Paper to be presented at the annual AEA meetings, New Orleans, La., January 3-6, 2008

Innovations from SMEs or Large Firms?

Sector Structure and Dynamics

Wilfred Dolfsma[1] & Gerben van der Panne[2]

Draft – please do not quote without permission from the authors;

comments are most welcome

The question which industry structure is most conducive to innovation has drawn much attention from both scholars as well as policy makers. Schumpeter was one of the first to draw attention to this question, and has famously provided two answers. His first answer was that an industry where small firms thrive will see more innovation.

> "New combinations are, as a rule, embodied, as it were, in new firms which generally do not arise out of the old ones but start producing beside them; in general it is not the owner of stage-coaches who build new railways." (Schumpeter 1934, p.)

He has also given a second answer, one where large firms, and industries dominated by them, are believed to contribute most to innovation.

> "As soon as we go into details and inquire into the individual items in which

[1] Utrecht School of Economics, w.dolfsma@econ.uu.nl & wdolfsma@gmail.com

[2] Delft University of Technology, Economics of Innovation, g.vanderpanne@tudelft.nl

> progress was most conspicuous, the trail leads not to the doors of those firms that work under conditions of comparatively free competition but precisely to the doors of the large concerns…and a shocking suspicion draws upon us that big business may have had more to do with creating that standard of life than with keeping it down." (Schumpeter 1943, p.)

This has become known as the Schumpeter Mark I vs. Mark II discussion (Malerba & Orsenigo 1997). Evidence was found for both these views, and so the Schumpeterian Innovation Puzzle has perplexed the economics of innovation literature for some time now. Acs & Audretsch (1988) have tested an econometric model relating a sector's innovativeness to a number of variables denoting entry barriers. They have found, a.o., that innovations are to be expected from sectors where large firms dominate: creative accumulation of the Schumpeter Mark II type. Others have found evidence for a Schumpeter Mark I (xxx). In a recent study, using new product announcements as indicator for innovativeness as the studies by Acs & Audretsch did too, we have analyzed this issue again (Dolfsma & Van der Panne 2008). The results, using similar but much less noisy data for the Netherlands, were remarkably similar except for the findings on firm size. Sectors where SMEs predominate are more innovative – creative destruction of the Schumpeter Mark I type. Still others believe that there is an inverse U-shaped relation between innovation and the dominance in an industry of firms of a specific size (Aghion *et al*. 2005; Acs & Audretsch xxxx).

This paper will further analyze the issue by doing two things. First the exact way in which firm size is implicated is analyzed by taking size as a continuous variable. Given the richness of our data, we are able to take several proxies for firm size, giving us information about what aspect of size matters. This does not resolve

Schumpeter's Innovation Riddle completely, however. More importantly are sector dynamics (Klepper 1996). As the economic and technological dynamics are complex and will differ between sectors (Klepper & Graddy 1990) they should be incorporated for a fuller understanding. The contribution of these insights has not been tested empirically so far in a cross-sectoral analysis, however. We thus investigate empirically the following issues:

- Does industry involvement in R&D, through overall levels of R&D expenditure or through the hiring of skilled labor, impact its innovativeness?
- How does net entry into a sector effect its innovativeness? Does growth of firm entry have an impact?
- Are Low-tech sectors different due to worse opportunities for innovation?
- To what extent are differences between firms' R&D intensity explanatory?

In developing and testing models that incorporates variables for both the economic structure of sectors as well as their (differing) economic dynamics we use the most appropriate indicator for innovation: New Product Announcements.

1. Industry Structure & Industry Dynamics

The relation between competition and innovation has drawn a substantial amount of attention in the economics literature at least since Schumpeter. Do many small firms in an economy or an industry ensure a highly innovative economic dynamics, and should we thus subscribe to the 'creative destruction' view as espoused by Schumpeter? Or, should we rather believe that firms need the resources to invest and thus expect large firms to deliver innovation? In the latter case, one would follow the later Schumpeter in advocating 'creative accumulation'. It is only in recent decades that empirical evidence has accumulated to shed light on this issue.

Competition can, however, be apparent in a number of different ways. One is to focus on the structural aspects of an industry. This line of work has largely followed the cue of the pioneering 1988 article by Acs & Audretsch (see also Dolfsma & Van der Panne 2008). In this research the effects of industry characteristics on innovativeness is investigated. The argument developed 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. An important bone of contention in this work has been the issue of whether or not the presence of large firms in a sector is conducive to innovation (cf. Van Dijk *et al*. 1997). Effects of many indicators for levels of competitiveness at the industry level used in these studies are surprisingly similar over time and across countries (Acs & Audretsch 1988; Dolfsma & Van der Panne 2008). As theoretically, no decisive arguments were found with respect to the relative benefits of either small firms or large ones (Vossen 1998), this is a significant finding.

Another way of defining competition is inspired by the advent of game theory in the Industrial Organization literature. This literature has argued that industry structure does not determine firm conduct to shape overall industry performance in terms for instance of innovativeness. This line of thought would rather focus on outcome indicators of competition such as the margin of price over costs that firms in a sector may be able to sustain. Aghion et al. (2005), for instance, have followed Boone (2000) in this respect.

A third approach has also developed in recent years. It is to point to the remarkable insight that sectors go through cycles that are similar among them. Drawing inspiration from the product life cycle, this idea takes a longitudinal approach to industry development. The cycles are apparent from growth patterns in sales, R&D expenditure, new products developed, investment outlays required, and entry / exit rates. This Industry Life Cycle (ILC) idea has gained a measure of empirical validity too with the work of mostly Klepper (1996, 1997; see also Klepper & Grady 1990, Audretsch 1987). In the early phase of an ILC R&D expenditures in an industry are substantial, skilled labor plays a major role, net entry is high, and competition for the dominant product design is fierce. As a dominant design emerges (xxx), competitive pressure moves to reducing price and thus a push to reduce cost of production through process innovation is undertaken. Consolidation in the industry takes place as net entry rates plummet. There may even be net exit. Growth of output volumes continues, however. In the decline phase, growth of output levels off or may turn to a decline. Consolidation continues, while capital investments continue apace with investments in advertising. Few product innovations occur, and even the number of process innovations slumps. Needless to say, the ILC provides empirical regularities that do not have the status of a law-like truth. Indeed, Klepper (1997) has indicated some important exceptions to the general picture.

Table 1: Competition and Innovation Related - Findings from selected studies

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

As Table 1 shows, the findings for the relation between innovation and competition are inconclusive.[3] There thus remains quite a bit of ambiguity in the literature on the exact nature between industry structure, or competition, on the one hand, and on the other hand innovativeness. This has been the conclusion that Reinganum (1989) drew, and it remains valid to date. Obviously, there are a number of reasons why findings have differed. One of them is the diferent measure for competition used. Another is the data used. In this paper we will thus combine the first and third approaches discussed above. Factors associated both with a firm's market structure and the development of its technological environment determine whether or not large firms have relatively more or less advantages in being innovative (Acs & Audretsch 1987).

[3] Some have looked at the reverse as well: does innovativeness affect industry structure? Geroski & Pomroy (1990) argue that innovation will lead to less concentrated markets.

Studies of particular industry cases (e.g. Christensen 1997), or regions (e.g. Saxenian 1994) have indicated that patterns may differ across industries.

Industry structure and dynamics combined, thus, we surmise, will deliver additional insights into the innovativeness of industries and the relationship between competition and innovation. Not just the focus on the longitudinal development of specific industries in the work of Klepper provides a firm basis for developing this line of work, cross-industry analysis by Audretsch (1987) indicates this as well. We believe that adopting the second approach might have certain advantages, but overall is not to be prefered. Aghion et al. (2005) for instance point to the international nature of competition that firms in their UK sample face. Industry characteristics in the UK – they consider concentration ratio or Herfindahl index – might then not provide a clear indication of competition levels. Firms, and especially when one takes the full range of sectors and does not exclude very small firms, will still be facing other industry characteristics that affect them. In addition, taking industry structure rather than outcome indicators for competition makes sure that interaction between different dependent and independent variables can be excluded as much as possible.

2. Data & Model

This section defines the endogenous and exogenous variables, and discusses how the relevant data is collected. The model to be tested is developed and the statistical methods to be used are detailed.

Endogenous variable - Innovativeness. In this paper, we use the only objectively given proxy for the output of innovation: new product announcements (Kleinknecht & Bain 1993; Kleinknecht *et al*. 2002). As it is unknown how effectively money or time spent on R&D will be to generate marketable innovations, input measures are generally less useful even when the data may be readily available. Large and manufacturing firms are over-represented when such data is used. Another often-used proxy is patent data. Patents are, however, not the ultimate output of the R&D process, even though some firms do sell or license them. Many patents do not have commercial value (Lemley & Shapiro 2005). If they do, their value is due to the production process to which they help contribute – their value is thus a derived value. In some instances the extent to which current sales are due to products introduced in the last, say, 5 years is used as an indicator. This type of data tends to be subjective and tends to neglect innovations that turned out to be unsuccessful thus introducing a bias. New product announcements are thus the superior measure for innovation, and indeed as a proxy for innovation this indicator is most in line with the Oslo Manual for collecting and interpreting technological innovation data (OECD 1992, p.42).

Data collection procedure. According to the Literature Based Innovation Output (LBIO) method to obtain such data, two successive volumes of 43 specialist trade journals were screened to count the number of new-product announcements. Only announcements published on the editors' authority are counted. In the editors' expert opinion, these products had to embody surplus value in comparison to preceding versions or to possible substitutes. The expert opinion of editors of trade journals is obviously much more objective than 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 underrepresented in this sample.

Two-thirds of innovations reported by the trade journals in editorials as national innovations were *not* invented by the company reported in the advertisement. Out of 1056 responding firms, 658 (62.3%) reported that the announced innovation were imported rather than developed in-house within the Netherlands.[4] The share of foreign products to the total per sector randomly varies across industries, ranging from zero to 100 percent. The 'import innovations' often had been instigated in the foreign mother company, or may be produced under a license. As we are concerned with innovative firms only, we excluded such imported innovations from the sample. Having thus cleaned up the database, we have 398 valid counts of new-product announcing firms, covering 48 industries at 2-digit SIC. These 48 industries cover almost the entire Dutch economy – primarily agriculture and logistics are not included.

As such, our database comes as close to covering the complete population of new-product announcing firms as is possible. The data on the output of innovations at the company level is unique, even when it can only be used at the relatively aggregated level of the 2-digit industry level, providing 48 counts. Where necessary, given the research objective we adopt, we may use information on the level of individual firms to take the analysis further.

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

Exogenous variables. The data for industry characteristics we use in this paper are similar to the data used by Acs & Audretsch (e.g. 1988). The data that refer to individual companies was collected by one of the authors in 2000-2002; and when it pertains to an industry as a whole, was acquired from CBS – Statistics Netherlands.

We use several measures to characterize an ***industry's economic structure***. The average capital intensity is measured as capital assets relative to industry output (CAP.INTENS.). Acs & 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 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 (CONCENTR.) – 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 & Audretsch 1999). Unionization is measured in the same way as percentage of employees who are a member of a union (UNION.). Marketing expenditures divided by company output provide a proxy for advertising intensity (ADVERT.).

The influence of **size of firms** in an industry on innovativeness has been a particular focus of many studies, and since results have differed widely in this regard. It is for this reason, and since the data we have allow for it, that we present analyze the influence of size in three different ways. The first of these is to follow Acs & Audretsch (1988) in taking a threshold above which large-firm employment share of an industry is measured. Large-Firm employment share is indicated by the share in total industry employment accounted for by companies larger than 500 employees

(LARGE-FIRMSHARE). This cut-off point was chosen by Acs & Audretsch for convenience: this is how data are made available.[5] For practical reasons, we had to use different cut-off points, but 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 results. Only the one with a cut-off point of 350 employees is presented (as model II in Table 3). While model I by Acs & Audretsch (1988) is not perfectly comparable with our model II, since a different statistical procedure was adopted, in all other respects we offer a very similar analysis.

Secondly, for model III, firm size as a continuous variable is introduced (FIRM SIZE CTD). Industry averages for firm size are taken, from Statistics Netherlands. To find out if the relation between industry innovativeness and size follows an inverted-U pattern, thirdly, for model IV the square of firm size was taken. Given that model IV does not show any statistical relationship between either of the two size variables on the one hand and innovativeness on the other, where in all other models in this and our previous study (Dolfsma & Van der Panne 2008) every coefficient for the influence of firm size on innovativeness was always statistically significant, we have taken model III as a base model in Table 4. Table 4, to wit, explores further the effects of industry dynamics on innovativeness.

In addition to using measures for an industry's economic structure and to making size continuous, we include into our analysis indicators for ***industry dynamics***. Thus, we have data on an industry's R&D expenditures (INDUSTRYR&D). The percentage of employees who have obtained a degree at bachelor or master level indicates the level of skill available (SKILLEDLABOR).

[5] Personal communication, D. Audretsch.

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. Both these measures are shown by Audretsch (1987) to relate to the early phases of the ILC, when product innovation is rife.

In line with ILC literature, we have included net entry rate into a sector as a measure of (ENTRY, and ENTRY-squared). In line with Klepper and others one would sectors that show a high (increasing) net entry rate to be more innovative. Innovatiness is believed to be higher in the early phase(s) of the ILC. Our use of the LBIO measure – more likely to measure product as compared to process innovations – should constitute a specific bias favoring an ILC inspired finding in models V-a and V-b. The specific way in which we have operationalized the Entry variable – by taking the percentage growth over the 2000 to 2007 period of the number of firms in any sector – should also favor an ILC hypothesis as differences between sectors are more pronounced than when yearly averages for firm entry were taken.[6] Product innovations are believed to dominate the early phases of an ILC, while process innovations dominate later phases.

Several ***control variables*** are included. Effects due to differences in industry size are controlled for by including a variable for total sales (INDUSTRYSIZE). We have, in contrast to Acs & Audretsch, added a further control variable for the size of the population of firms in an industry (FIRMPOPULATION). 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 2004).

[6] In actual fact, however, taking the yearly average percentage growth rate over the 2000 to 2007 period does not change the findings.

This effect can but need not be related to industry size. The latter control variable was included by Acs & Audretsch.

Some descriptives give an impression of the kind of data we use (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). The distribution of innovations included in our database is not biased according to economic activity in terms of industries. The 48 industries at two-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 underrepresented in innovation studies as surveys constructed to measure innovative activity tend to neglect small firms. In Europe, the CIS survey does not cover firms employing fewer than 10 people. 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. We have not drawn a sample, nor did we ignore smaller firms with less than 10 employees. The differences between our data and the data used in other studies might compromise the comparability of the findings in this study with that of other studies somewhat, except for the study by Acs & Audretsch. At the same time it would seem that our findings might be more in line with reality.

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 (re)new(ed) products is 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 both in terms of improved as well as for new products that are higher than indicated by the CIS data.

Table 2: Descriptive Statistics

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

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

$$LBIO_i = \alpha + \beta (X_i) + \gamma (Y_i) + \delta (Z_i) + \varepsilon_i \, . \qquad \text{[Eq. 1]}$$

$i = 1 \ldots 48$ industries

Here, X are the various variables indicating Industry Structure, variables in Y proxy for Industry Dynamics, and Z are control variables.

Because of the relatively small number of observations, we use a count model.[7] We are unable to perform an ordinary regression analysis as it cannot be assumed that variables are distributed in a normal fashion. We do, however, and contrary to for instance Acs & Audretsch, standardize coefficients so as to make the comparison of our results in Tables 3 and 4 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 & Trivedi 1986).[8] Statistically an exceptionally conservative estimation method, a negative binomial regression model yields results that are comparable to a regression analysis. The measure for model fit with the data, pseudo R^2, hovers around 20% - to be expected for a study in the social sciences.

3. Industry Innovativeness & Structure, and Size in Particular

Table 3 presents some first findings. The point of departure has been the 1988 Acs & Audretsch study. The main focus there was to analyse the effects of industry structure on industry innovativeness. They did include two variables that one may also perceive of as indicators of industry dynamics. An earlier study has also reported on these findings, remarking how similar they are despite the fact that a twenty year period separates the times when the data were collected and despite the fact that different countries are concerned. The major difference between the findings reported upon by

[7] Negative binomial regression model (see Cameron & Trivedi 1986).

[8] In the case of over-dispersion, i.e. $\sigma_i > \mu_i$, the Poisson model under-estimates 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.

Acs & Audretsch (1988) as compared to Dolfsma & Van der Panne (2008), relating to the issue of firm size, was further explored by looking at a number of different subcurrents in the river of innovations that the general model presents. This has resulted in some remarkable insights.

Table 3: Exploring Firm Size

(Regression of total number of innovators, 2-digit SIC industry level)

	Acs & Audretsch	LBIO Netherlands†	Size as ctd. var.†	Inverted-U †
Model	**(I)**	**(II)**	**(III)**	**(IV)**
Industry Structure:				
Cap. Intens.	-/-,	-79.5 (0.007)***	-72.9 (0.072)*	-72.0 (0.079)*
Concentr.	-/-, **	-91.7 (0.001)***	-91.7 (0.002)***	-83.8 (0.073)*
Union.	-/-, **	-20.0 (0.537)	-39.3 (0.145)	-37.3 (0.155)
Advert.	-/-,	-72.4 (0.040)**	-79.9 (0.015)**	-78.1 (0.029)**
Large-firm share††	+/+, **	-71.9 (0.001)***	-	-
Firm Size ctd	-	-	-70.7 (0.006)***	135.9 (0.743)
(Firm Size ctd)^2	-	-	-	-92.2 (0.468)
Industry Dynamics:				
Industry R&D	+/+, **	198.5 (0.002)***	190.8 (0.000)***	179.4 (0.000)***
Skilled labor	+/+, **	216.2 (0.001)***	162.2 (0.090)*	142.4 (0.115)
Control variables:				
Industry size	+/+, **	272.0 (0.009)***	363.0 (0.012)**	341.9 (0.015)**
Firm pop.	-	22.1 (0.487)	16.2 (0.69)	21.9 (0.594)
N	247	48	48	48
R^2	0.48	0.19	0.183	0.187

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

Building on our earlier study (Dolfsma & Van der Panne 2008), which, a.o., compared models I and II of Table 3, we find that taking size as a continuous variable does not change the findings reported upon there. The relation between size and industry innovativeness is firmly a negative one. Where earlier we followed the original Acs & Audretsch (1988) model specification closely in taking several threshold, we here take size as a continuous variable and still find a statistically highly significant negative correlation. In other respects the models are surprisingly similar: signs and sizes of betas are largely comparable. Significance levels for model III are lower, suggesting that the use of a cut-off point(s) may be somewhat more meaningful, if only when one aims to understand the relation between elements of industry structure on the one hand, and industry innovativeness on the other hand.

When including the square of average industry firm size per industry our model behaves in an unexpected manner. We find that including the square of AVERAGE SIZE indeed negatively affects industry innovativeness, but that the beta is by no means statistically significant. What is more, including this term also means that firm size stops being a meaningful variable. The idea that there might be a particular disadvantage of a firm being middle-sized is thus to be rejected. This finding, of course, does not impact directly on that of Aghion et al. (2005) who talk of an inverted-U relationship between competition and innovativeness[9]: average industry firm size and competitive pressure are imperfectly related.

Findings for models I through IV are, in other respects, again, surprisingly similar. Capital intensity, Concentration ratio, and Advertising intensity all negatively affect innovativeness. Different from the findings of Acs & Audretsch (1988)

[9] Using the Lerner Index or price cost margin as a measure of competition, Aghion et al. (2005) find that innovation was highest when competition was either low or high. Using indicators of industry structure to proxy for competition in a sector, as we do hrere, makes it methodologically difficult to test their findings even when using new product announcements as the preferable measure for innovativeness.

unionization does impact innovativeness in a statistically significant manner. Given that this analysis pertains to a country where labor laws favor incumbent employees more than in many other countries in the developed world, and given that any company above a threshold level is to have a board of representatives from among the employees that has a number of rights, this may be a surprising finding. Industry R&D levels always positively affect innovativeness, and so does skilled labor. Spill-over effects may be involved in this. Industry size, irrespective of number of firms within the sector, positively influences innovativeness.

4. Exploring Industry Dynamics

Now, however, we want to explore, as argued in section 1 above, the relation between innovation and competition further by bringing to bear a second theoretical perspective. In addition to analyzing the impact of industry structure on innovativeness, we are interested in discussing the effects of an industry's dynamics on its innovativeness. The latter discussion draws on insights from the ILC literature. Table 4 presents the relevant findings.

Table 4: Further Exploring Industry Dynamics

(Regression of total number of innovators, 2-digit SIC industry level)

	Size as ctd. var.†	Sector Growth (Entry)†		LoTech†	R&D Intensity †	
Model	**(III)**	**(V-a)**	**(V-b)**	**(VI)**	**(VII-a)** 33% Least	**(VII-b)** 33% Most
Industry Structure:						
Cap. Intens.	-72.9 (0.072)*	-73.5 (0.092)*	-79.3 (0.008)***	-67.4 (0.179)	-26.7 (0.587)	-61.7 (0.057)*
Concentr.	-91.7 (0.002)***	-90.6 (0.005)***	-91.7 (0.000)***	-90.4 (0.008)***	-96.9 (0.000)***	-83.2 (0.005)***
Union.	-39.3 (0.145)	-43.8 (0.112)	-37.2 (0.191)	-44.3 (0.163)	-51.0 (0.067)*	-34.6 (0.243)
Advert.	-79.9 (0.015)**	-77.2 (0.026)**	-82.0 (0.002)***	-83.1 (0.011)**	-54.8 (0.193)	-66.9 (0.036)**
Firm Size ctd	-70.7 (0.006)***	-71.4 (0.013)**	-72.8 (0.005)***	-63.6 (0.0200)**	-88.6 (0.000)***	-69.9 (0.096)*
Industry Dynamics:						
Industry R&D	190.8 (0.000)***	170.8 (0.000)***	173.2 (0.000)***	156.2 (0.000)***	154.4 (0.006)***	172.6 (0.003)***
Skilled labor	162.2 (0.090)*	117.1 (0.198)	187.9 (0.025)**	150.8 (0.136)	65.5 (0.263)	112.1 (0.026)**
Entry	-	51.2 (0.144)	25.2 (0.495)	-	-	-
$(\text{Entry})^2$	-	-	-78.6 (0.015)**	-	-	-
Control variables:						
Industry size	363.0 (0.012)**	305.6 (0.025)**	402.9 (0.001)***	438.9 (0.012)**	150.6 (0.096)*	166.7 (0.026)**
Firm pop.	16.2 (0.69)	11.0 (0.797)	2.3 (0.935)	14.6 (0.731)	77.9 (0.069)*	19.8 (0.467)
N	48	48	48	43	48	48
R^2	0.183	0.188	0.211	0.186	0.251	0.218

Two-tailed. * Significant at 10%; **significant at 5% level; *** significant at 1% level; p-values in parentheses. † Percentage change in expected counts per standard deviation increase in explanatory variables.

Since Model III, taking firm size as a continuous variable, makes most sense from the perspective of industry dynamics, we use this as a base model. In Table 4 we do three different things. The ***first*** is to see if entry of new firms (net), or the uptake of firm entry, affects industry innovativeness. Models V-a and V-b investigate this. ***Secondly*****,** we analyze whether type sector makes a difference. Thus, model VI duplicates the analysis of model III for sectors classified as low-tech by the OECD.[10] The ***third*** exercise is presented in models VII-a and VII-b. From our original sample, the relative R&D intensity of firms was used to create subsets – innovation counts in industries were correspondingly adjusted and regressed against the variables as described. We will briefly discuss these models in the remainder of this section.

What is most striking in models V-a and V-b is that adding net firm entry to the model has a negligible effect on the model outcomes. The findings for the Capital Intensity and Skilled Labor variables are less significant. Entry as a variable itself seems not to have an effect, and even less so when entry growth is included. This seems in contrast with Schumpeter's suggestion, in the quote above, that innovation is to be expected by or due to newly established firms. This finding also contrasts with Audretsch knowledge spill-over theory of the firm where newly set up firm take advantage of knowledge spilling over from large firms, thus able to innovate and develop new products and services. Our findings thus seem to suggest that care should be taken not to confuse an expectation of innovation to be stimulated by presence of small firms in an industry on the one hand, and the expectation that entry of newly set up firms in a sector will spur innovativeness on the other hand.

[10] To wit, the OECD defines sectors where 4.5% of sales is spent on R&D, as an industry average, as high-tech.

The effect of introducing the Entry growth variable is important to note. While adding Entry growth does not affect the findings for other variables in the model, it is remarkable that innovativeness is affected by that variable in exactly the opposite way as expected. Our findings thus stand in stark contrast to an ILC inspired hypothesis – a remarkable finding. ILC literature expects innovativeness and firm entry rates to be positively correlated, and certainly when a measure for innovativeness is used that seems to be bias to some degree to product innovation.

Zooming in on low-tech industries, again we find surprisingly similar results for the model as a whole, although Capital Intensity and Skilled Labor disappear as significant variables. In an earlier study Acs & Audretsch (1991) found that low-tech industries show increasing returns to firm size for innovative activity. We cannot replicate these findings: in every model we have run, including this one, firm size negatively affects industry innovativeness.

Finally we investigate the effects of firm level differences: do industries where the most R&D intensive firms cluster behave differently from industries where the least R&D intensive firms are to be found? Industries in which the most R&D intensive firms are proportionately clustering are more responsive to the use of Skilled Labor. Advertising affects them more than it does industries in which low R&D intensive firms are predominantly present. The latter, surprisingly, are not affected so much by Capital Intensity, or by Advertising intensity. Advertising not having an effect is special as this is the only model in which this is so. Large firm presence in a sector as well as unionization seem to hurt low R&D intensive sectors particularly, while these do not benefit from the use of Skilled Labor. Model VII-a is the only model in which Unionization shows up as a significant variable.

It is clear that sectors where firms cluster that are least R&D intensive do not overlap fully with the set of sectors that the OECD classifies as Low-Tech by comparing models VI and VII-a. Especially the different effects of the variables Advertising and Unionization are remarkable. Also, the control variable of Firm Population is significant in model VII-a only. Sectors where the least R&D intensive firms cluster seem to benefit more from having lots of firms around instead of from having ample market opportunities (Industry Size).

Overall, then, we find that a model that specifies competition in structural terms explains industry innovativeness well. The findings differ little across model specifications and are robust over time (when compared to the Acs & Audretsch 1988 study). Capital Intensity, industry Concentration rates, Advertising Intensity, and Firm Size (either as an average or using a threshold) all negatively affect innovativeness. The latter finding is different from earlier studies. What is surprising too is that Unionization does not affect innovativeness. Overall industry R&D boosts innovativeness, as to be expected, while the use of Skilled Labor does so too in most model specifications. Only when the available absorptive capacity of firms in an industry is likely to be low to start with does Skilled Labor not contribute.

When information at the firm level was used to create subsets of firms more theoretically as well as statistically significant differences in the findings show up. This suggests that that firm-level differences might be at least as important as industry level differences; a suggestion that an earlier study confirms (Dolfsma & Van der Panne 2008).

4. Conclusions

In this paper we deepen our understanding on the effects of industry structure – as a proxy of competition – on an industry's innovativeness. We do so for several reasons. First of all we we use the most appropriate measure for innovativeness: new product announcement. Secondly, by replicating the seminal analysis that Acs & Audretsch have presented, we are able to determine to what extent their findings actually hold over time and across countries. It can, largely, and this is a significant finding. Thirdly, for the one measure where our findings depart from those of Acs & Audretsch – the effect of firm size – we have very robust findings indicating that increasing firm size hurts industry innovativeness. This latter issue obviously takes the analysis into the direction of industry dynamics.

To further substantiate these findings, and to explore the possible explanations of them, we have developed the models further to incorporate variables that indicate industry dynamics inspired by the literature on Industry Life Cycles. If anything, Firm Entry has an impact that contrasts with the ILC literature. Findings for Low-Tech industries are largely in line with earlier models presented, and where they depart it is as to be expected (notably the absence of an effect of Skilled Labor due to a lack of absorptive capacity for these firms). Using firm level data to create subsets of industries where the least and the most R&D intensive firms cluster indicates that firms are heterogeneous and respond differently to the external circumstances they face. Even when the playing field is level, some do better than others.

References

Z.J. Acs and D.B. Audretsch (1988) “Innovation in Large and Small Firms: An empirical analysis” *American Economic Review* 78(4): 678-690.

---- (1987) “Innovation, Market Structure, and Firm Size” *Review of Economics and Statistics* 59(4): 567-574.

----, (1986) “Innovation in Large and Small Firms” *Economics Letters* 23: 109-112.

Z.J. Acs, D.B. Audretsch and M.P. Feldman (1994) “R&D Spillovers and Recipient Firm Size” *Review of Economics and Statistics* 76(2): 336-340.

Ph. Aghion, N. Bloom, R. Blundell, R. Griffith and P. Howitt (2005) “Competition and Innovation: an inverted U relationship” *Quarterly Journal of Economics* 120: 701-728.

Audretsch, D.B. (1987) “An Empirical Test of the Industry Life Cycle” *Weltwirtschaflisches Archiv* 123(2) 297-308.

D.B. Audretsch and Z.J. Acs (1991) “Innovation and Size at the Firm Level” *Southern Economic Journal* 57(3): 739-744.

D.B. Audretsch & M. Keilbach (2008) “Knowledge Spillover Entrepreneurship and Innovation in Large and Small Firms” in J.B. Davis & W. Dolfsma (eds.) *The*

Companion to Social Economics. Cheltenham: Edward Elgar.

Blundell, R.W., R. Griffith & J. van Reenen (1995) "Dynamic count data models of technological Innovation" *Economic Journal* 105: 333-344.

Boone, J. (2000) "Competitive pressure: the effects on investments in product and process innovation" *RAND Journal of Economics* 31(3): 549-569.

Caballero, R.J. & A.B. Jaffe (1993) "How high are the giants' shoulders: an empirical assessment of knowledge spillover and creative destruction in a model of economic

Cameron, A.C. & P.K. Trivedi (1986) "Econometric Models Based on Count Data: Comparisons and applications of some estimators and tests" *Journal of Applied Econometrics* 1: 29-53.

W.M. Cohen & S. Klepper (1996) "A Reprise of Size and R&D" *Economic Journal* 106(July): 925- 951.

Christensen, C.M. (1997) *The Innovator's Dilemma When New Technologies Cause Great Firms to Fail*. Harvard Business School Press.

B. van Dijk, R. den Hertog, B. Menkveld and R. Thurik (1997) "Some evidence on the determinants of large- and small-firm innovation" *Small Business Economics* 9: 335-343.

Dolfsma & Van der Panne (2008) Currents and Subcurrents in the River of Innovations:

Feldman, M.P. & D.B. Audretsch (1999) "Innovation in Cities: Science-based diversity, specialization and localized competition" *European Economic Review* 43: 409-429.

Geroski, P.A. (1990) "Innovation, technological opportunity, and market structure" *Oxford Economic Papers*, 42, 58 6-602.

Geroski, P.A. & R. Pomroy (1990) "Innovation and the evolution of market structure" *Journal of Industrial Economics* 38(3): 299 -314.

Kamien, M.I. & N.L. Schwartz (1975) "Market structure and innovation: a survey" *Journal of Economic Literature* 13(1): 1-37.

Kleinknecht, A. & D. Bain, eds. (1993) *New concepts in innovation output measurement.* London: Macmillan & New York: St. Martin's Press.

Kleinknecht, A., K. van Montfort & E. Brouwer (2002) "The non-trivial choice between innovation indicators" *Economics of Innovation and New Technology*, 11: 109-121.

Klepper, S. (1997) "Industry Life Cycles" *Industrial and Corporate Change* 6: 145 – 182.

----, (1996) "Entry, Exit, Growth, and Innovation over the Product Life Cycle" *American Economic Review* **86**(3): 562-583.

Klepper, S. & E. Graddy (1990) "The Evolution of New Industries and the Determinants of Market Structure" *RAND Journal of Economics* **21**(1): 27-44.

M.A. Lemley & C. Shapiro (2005) "Probabilistic Patents" *Journal of Economic Perspectives* 19(2): 75-98.

Leydesdorff, L., W. Dolfsma, G. van der Panne (2006) "Measuring the 'Knowledge Base of an Economy in terms of Relations among 'Technology, Organization, and Territory'" *Research Policy* 35(2): 181-199.

Malerba, F. & L. Orsenigo (1997) "Technological regimes and sectoral patterns of innovative activities" *Industrial and Corporate Change* 6: 83-117.

Organisation for Economic Co-operation and Development / European Commission / Eurostat (1992) *The Measurement of Scientific and Technological activities – Proposed guidelines for collecting and interpreting technological innovation data* ('Oslo manual'). Paris: OECD.

Schumpeter, J.A. (1934) *The Theory of Economic Development*. Harvard UP.

Schumpeter, J.A. (1943) *Capitalism, Socialism, and Democracy*. Peter Smith Publisher.

Symeonidis, G. (2001): *Price competition, innovation and profitability: theory and UK evidence*. CEPR Discussion Paper, 2816.

Van der Panne, G. 2004 "Agglomeration externalities: Marshall versus Jacobs" *Journal of Evolutionary Economics* 14(5): 593-604.

Van der Panne, G. & W. Dolfsma (2003) "The Odd Role of Proximity in Knowledge Relations – High-tech in the Netherlands" *Journal of Economic and Social Geography* 94(4): 453-462.

Reinganum, J. (1989) "The timing of innovation: research, development, and diffusion, in: R.

Schmalensee & R.D. Willig (red.), *Handbook of Industrial Organization*, vol. 2, Elsevier.

R.W. Vossen (1998) "Relative Strengths and Weaknesses of Small Firms in Innovation" *International Small Business Journal* 16(3): 88-94.