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REGULAR ARTICLE

Industry innovativeness, firm size, and entrepreneurship: Schumpeter Mark III?

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Abstract Emphasizing the dynamics in economies and industries, Schumpeter points to entrepreneurs carrying out 'new combinations'. His work, and in particular the Theory of Economic Development, is often interpreted as praising individual entrepreneurs setting up new firms to contribute to an industry's innovativeness. This has come to be referred to as the Schumpeter Mark I perspective. Later, however, in his Capitalism, Socialism, and Democracy, Schumpeter has rather suggested that large incumbents are best positioned to contribute to an industry's innovativeness (Schumpeter Mark II). In this discussion, however, the possibly different effects of structural as opposed to dynamic industry competitiveness is often not taken into account. In addition, the contribution of new and small firms to industry innovativeness are often conflated. Using New Product Announcements as a measure of innovation, we find that industries dominated by small firms prove consistently and significantly more innovative than industries where large firms dominate. Taking account of industries' structural and dynamic levels of competition, we find that high existing and increasing levels of new firms entering an industry, exercising what Schumpeter called the 'entrepreneurial function', actually decrease industry

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innovativeness. We conclude that the contribution of small firms in terms of industry innovativeness is different from that of large as well as new firms, suggesting a Schumpeter Mark III perspective.

Keywords Entrepreneurship · Innovation · Industry innovativeness · Industry dynamics · Firm entry · Small firms · Large firms · New-product announcements · Schumpeter Mark III.

JEL Classifications D22 · L10 · O33

The question what determines industry innovativeness has drawn much attention from both scholars and policy makers. In particular, the question which type of firms promotes *industry* innovativeness – large incumbents or new entrepreneurial firms – is much discussed and is an issue of great policy concern. In contrast, research in the domain of management focuses more on *firm* innovativeness (see Fontana et al. 2012).

Schumpeter was one of the first to address this question, and has famously provided *two* answers. His first answer is exemplified in the following quote:

> "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.66, emphasis added)

In addition to this answer emphasizing the role of new firms exercising the entrepreneurial function, bringing dynamics to an industry, Schumpeter has also given a second answer. His second answer argues that industries dominated by large incumbent firms are most likely to be innovative.

> "As soon as we go into details and inquire into the individual items in which 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 he 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 1934, p.81, emphasis added)

In the subsequent discussion this has come to be known as, respectively the Schumpeter Mark I and Schumpeter Mark II positions (Malerba and Orsenigo 1997; Malerba 2002).

Evidence is found for both these positions. Acs and Audretsch (1988), for instance, have tested econometric models relating a sector's innovativeness to a number of variables that capture the structure of an industry, including entry barriers to industries and size of firms in an industry. They have found, amongst others, that innovations are to be expected in industries dominated by large firms: creative accumulation of the Schumpeter Mark II type. Others have found evidence for a Schumpeter Mark I position, however, particularly when focusing on radically new products (e.g. Chandy and Tellis 2000, Dolfsma and Van der Panne 2008), or remain inconclusive (Acs and Audretsch 1986).

What could be called the Schumpeterian Innovation Puzzle has thus perplexed the innovation literature for some time now (cf. Fontana et al. 2012). Too often, however, small firms are readily equated to entrepreneurial firms. In the quotes from Schumpeter above this is apparent (see also Schumpeter 1934, p.229), and is it is an assumption that is central to the argument developed by Baumol (2010) and Aghion and Howitt (1992) as well. The contribution to industry innovativeness can be different for small firms when compared to new entrepreneurial firms. This has not been tested empirically in the literature to date, as far as we know. In addition, the discussion of the characteristics of firms in an industry most conducive to industry innovation often is implicitly conflated with the discussion about the effects of differing levels of competition in an industry. When the effect of industry competition on industry innovativeness is explicitly addressed, a limited view is taken of what indicates industry competitiveness. In this paper we employ structural as well as dynamic indicators of industry competitiveness and we analyze the possibly different effects of large, new, and small firms in an industry on industry innovativeness. Such an analysis should, we submit, provide additional insights into the Schumpeterian Innovation Puzzle.

Given the nature of the controversy, it is appropriate to analyze this issue using rich micro-level data on the innovativeness of identifiable firms (Kleinknecht et al. 2002). Given the emphasis on “new combinations [which] mean the competitive elimination of the old” (Schumpeter 1934, p.67) new-product announcements provide an appropriate measure that especially captures the more radical innovations in an industry. This measure is close to the spirit of the Oslo Manual for innovation studies developed by the OECD (1992).

We advance the literature in two key respects. Measuring firm size in a number of different ways, for the sake of robustness, first we determine how it impacts industry innovation. Secondly, building on the literature on the Industry Life Cycle (or: ILC; see, a.o., Klepper 1996; Klepper and Graddy 1990), a literature that offers a related but different view of the effect of competition on industry dynamics and innovativeness, we specifically determine the extent to which, at an aggregate industry level, entrepreneurship in the sense of firm entry contributes to industry innovativeness. We find that innovative industries contain relatively many small firms, rather than new firms (or a growing number of new firms) and large firms. Rather than the Schumpeter Mark I or the Schumpeter Mark II perspectives which point to entrepreneurial firms and large firms as sources of innovation, we, thus, suggest a Schumpeter Mark III position where established small firms are seen as a source of industry innovativeness.

1 Industry innovativeness: new, large or small firms?

Will an industry in which large firms dominate be successful at innovation because of the resources that these have and the complementary assets that they can muster, or will an industry structure in which new firms dominate be more likely to do so due to their flexibility and lack of vested interests? Should one subscribe to the 'creative accumulation' (Schumpeter Mark II) or to a 'creative destruction' (Schumpeter Mark I) view?

This Schumpeterian Innovation Puzzle actually relates to two different but related discussions of what stimulates innovation. One discussion is about how competition affects innovativeness at the industry level, and whether a structural or dynamic perspective should be adopted. The other discussion is what types of firms will contribute to industry innovativeness: large, new or small firms. The first view is about what environment provides the incentives most conducive to innovation. The second view is about the characteristics that firms have to allow them to innovate. These two views are related, but we will discuss them in turn since their effects might be different. The connection between these two discussions is clear in this quote from Schumpeter:

> "In industries in which there is still competition and a large number of independent people we see first of all the single appearance of innovation – overwhelmingly in businesses created *ad hoc* – and then we see how the existing businesses grasp it with varying rapidity and completeness, first a few, then continually more" (Schumpeter 1934, p. 229).

In recent years what has come to be referred to as the Schumpeter Mark I position has become the position many subscribe to (Baumol 2010), for instance, emphasizes that entrepreneurs are especially likely to introduce the more radically new products since they might have a bigger incentive to do so (Arrow 1962). Discussing the 'entrepreneurial function' in general, Schumpeter (1934, p.77) indicates that this function in practice "always appears mixed up with other kinds of activity" and that anyone can be an entrepreneur (ibid, p.78), even if they are "dependent employees of a company" (ibid., p.75). At the same time, however, he argues that when firms grow (ibid., p.78) or grow old (ibid., p.66) the entrepreneurial character is lost. Small firms and new entrepreneurial firms may thus not be similar in relevant respects – Schumpeter and much of the subsequent literature has not elaborated upon this, however. As with the relation between firm size and industry innovativeness, so with the relation between industry competition and industry innovativeness. As Table 1 shows, the findings for the relation between industry innovation and competition are inconclusive (Fontana et al. 2012).[1] There are a number of reasons why the findings have differed between these studies. Different measures are used to proxy competition and innovation. More important, however, may be that the approaches used in these studies have focused on the effect on industry innovativeness of either the static industry structure on the one hand, or the (technological) dynamic in an industry as discussed in the Industry Life Cycle theory on the other hand. While innovation might be conceptualized differently in these studies, the literature certainly conflates structural conceptions of industry competition with dynamic one. No study has

[1] Some have looked at the reverse, to determine if innovativeness affects industry structure. (Geroski and Pomroy 1990), for instance, argue that innovation will over time lead to less concentrated markets.

Table 1 Competition and innovation-findings from selected key 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)	Relation 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

included measures for both these views on industry competition. Ambiguity remains in the literature on the exact nature of the relation between industry competition on the one hand, and industry innovativeness on the other hand (Reinganum 1989).

This paper combines industry structure as well as dynamic Industry Life Cycle variables as a proxy for industry competition, on the one hand, and firm characteristics (size), on the other hand, as complementary and theoretically well-founded perspectives on what might explain industry innovativeness.

One way to conceive of competition is to highlight the structural aspects of an industry. Until well into the 1990s the relation between the structure of an industry and its competitive pressure was believed to be straightforward. The Structure-Conduct-Performance (SCP) model developed by Scherer and others (cf. Scherer and Ross 1990) postulated a direct influence from industry structure on the conduct of players in an industry, and then to performance indicators. Anti-trust law, for instance, hinges on this perspective of competition in an industry (Baker 2003). This line of work was largely followed in the pioneering work of Acs and Audretsch (e.g. 1988; see also Dolfsma and Van der Panne 2008). In this line of research the effects of industry characteristics on innovativeness is investigated. Industry characteristics that suggest decreased competitive pressure for firms, possibly through higher entry barriers, or the possibility of some stakeholders to seek rents, may hamper industry innovativeness. Thus, for instance, unionization, capital intensity, concentration and advertising will negatively impact innovation. Effects of indicators for the fierceness of competition on innovation at the industry level are surprisingly similar over time and across countries (Acs and Audretsch 1988; Dolfsma and Van der Panne 2008).

An important bone of contention in this literature has been the issue of whether the presence of large or small firms in a sector is conducive to innovation (cf. Van Dijk et al. 1997). Large firms might have the advantage of scale, having more resources available to develop new knowledge and new products (Cohen and Klepper 1996; Cohen 2010). They may also have benefits of scope, and so developing multiple products in different markets from a single piece of newly created knowledge is easier for larger firms (Granstrand et al. 1997). Small and entrepreneurial firms are believed to have a stronger incentive to innovative, however (Baumol 2010). They may not be restricted as much to an existing customer and knowledge base and might be more adapt at exchanging relevant knowledge within the firm (cf. Szulanski 1996).

Theoretically, no decisive arguments were found with respect to the relative benefits of either small firms or large ones for industry innovativeness (Vossen 1998), and empirically, too, differing findings have been reported (e.g., Acs and Audretsch 1988; Chandy and Tellis 2000; Dolfsma and Van der Panne 2008). Further empirical analysis is clearly needed, detailing more closely the effects of firm size and better distinguishing what contribution to industry innovativeness may be expected from small firms as opposed to large firms in particular.

A second line of thought about the way in which industry competition and innovativeness might relate has developed in more recent years. Literature on life cycles of industries suggests that industries may go through largely similar cycles (Cohen 2010; Fontana et al. 2012; Jovanovich and MacDonald 1994); Peltoniemi (2011). Drawing inspiration from the idea of the product life-cycle, this idea of industry life cycles (ILC) takes a longitudinal approach to industry development, arguing that an industry's 'competitive regime' changes as an industry evolves, as apparent from a number of relevant indicators (Cohen 2010; see Peltoniemi 2011 for an overview). Throughout an industry life cycle, patterns in sales, R and D expenditure, emphasis on product vs. process innovations, number of new products developed, investment outlays required, and firm entry / exit rates are found to move in a predictable manner. The Industry Life Cycle (ILC) idea has gained a considerable measure of empirical validity too. Much of this literature has focused on a single industry (Klepper 1996, 1997; see also Klepper and Graddy 1990), however, while some has been cross-sectional (Audretsch 1987; Fontana et al. 2012).

In the early phase of an ILC, according to the literature, R and D expenditures in an industry are substantial, skilled labor plays a major role, net firm entry is high, and competition for the dominant product design is fierce. Product innovations dominate, and these are more likely to involve radical innovations. Scale economies will not play a role at this stage as investments are not specific (yet). As a dominant product design emerges (Abernathy and Clark 1985; Abernathy and Utterback 1978; Tushman and Anderson 1986; Henderson and Clark 1990), competitive pressure moves to reducing price and a push to reduce cost of production through process innovation is undertaken (Klepper 1996). Scale economies are sought by the different parties in an industry. Consolidation in an industry may be expected to take place as net entry rates quickly decline or even become negative. Growth of output volumes continues, however. In the subsequent phase, growth of output levels off and may then decline. Consolidation continues, while capital investments continue apace with investments in advertising. Few product innovations occur, and the number of process innovations may decrease (further). The ILC literature provides explanations for empirical regularities that do not, however, have the status of law-like truths. Indeed, (Klepper 1997) has indicated some important exceptions to the general picture. The insights from ILC are important nonetheless. The ILC literature strongly suggests that the way in which certain structural characteristics of an industry relate to specific performance outcomes at industry level, including industry innovativeness, differs over an industry's lifetime.

The contribution that firms of different hue – large, new, or small – make to industry innovativeness is, however, also known to depend on industry structure and industry competition (Stock et al. 2002; Pla-Barber and Alegre 2007; Vaona and Pianta 2008). Findings can thus differ by sector in part because industries can be in different stages in their life cycle (Cáceres et al. 2011). This means that including indicators of industry structure and dynamics is important - stylized facts, for instance, as input for simulation exercises – may not be specific enough (cf. Kwasnicky 1996). Previous studies have dealt with this issue by studying the issue of industry structure and dynamics, firm size, and innovativeness within a single industry (Cohen 2010; Pla-Barber and Alegre 2007). This paper, by including a number of indicators of industry structure and dynamics, can pursue a cross-sectional analysis of the issue at hand, determining if large, new, or small firms contribute to industry innovativeness (Vaona and Pianta 2008).

Large companies can expect to benefit from economies of scale in R and D, spreading R and D costs over a larger base (Acs and Audretsch 1987; Cohen 2010; Stock et al. 2002). Spreading R and D costs is more readily possible for incremental and process innovations, which is what larger firms tend to focus on more than smaller firms (Cohen 2010). Large firms can more easily train their employees or allow them to develop skills and capabilities that might not give rise to immediate benefits (Cáceres et al. 2011; Cohen 2010), because they have more resources ready at hand or more easily available from the financial market (Pla-Barber and Alegre 2007; Uhlaner et al. 2013). Specialization of knowledge through division of labor is thus more readily pursued in large firms, possibly through more professional collaboration with other firms (Cáceres et al. 2011), giving rise to better managerial (Uhlaner et al. 2013) and technical capabilities (Stock et al. 2002). What innovations are developed in large firms may be brought successfully to the market because more complementary assets and capabilities are available in a large firm, even though they may actually be less likely to be recognized (Cohen 2010; Stock et al. 2002). As a result, too, innovations that have developed may be more readily exploited both in different yet related markets, including internationally (Cohen 2010; Pla-Barber and Alegre 2007), but also possibly in non-related markets (Granstrand et al. 1997). Once innovations are developed to a stage where they can be brought to the market, the possible gains to be made are higher for large firms (Cohen 2010). For these reasons, industries in which large firms are present may be expected to be more innovative than other industries.

Large firms tend to be contrasted with newly set-up firms in the literature (in Schumpeter, as discussed above; see also Cohen 2010). Large firms need to spend a lot of resources socializing new employees (Uhlaner et al. 2013). While large firms may be able to tap into a pool of information that is more varied (Cáceres et al. 2011), transfer of relevant knowledge within a large firm is not obvious (Aalbers et al. 2014; Szulanski 1996). As a result, while there may be more opportunities arising in large firms to develop innovations, there may actually be fewer of these to actually be recognized in a large firm as compared to a new firm (Stock et al. 2002). This can in part be due to the bureaucracy in place in large firms, bureaucracies that hamper transfer of knowledge in itself, but that can also stifle the motivation that people have to transfer relevant knowledge to others for them to be more innovative (Cohen 2010; Stock et al. 2002; Uhlaner et al. 2013). In newly established firms, both the entrepreneur as well as the few employees are more motivated to contribute to innovation efforts, and also notice the effects of their contribution more directly (Uhlaner et al. 2013). Alternatively put, principal-agency problems are less likely to arise in newly set up firms – newly set-up firms might more efficiently use what resources they have (Pla-Barber and Alegre 2007). As a result, the volume of resources invested in R and D by large firms might not actually mean that large firms are more R and D intensive (Cohen 2010; Shefer and Frenkel 2005). Industries which experience relatively high levels of new firm entry may for these reasons be expected to be more innovative (Christensen 1997).

What benefits newly set-up firms might have, will mostly also hold true for small firms that have been set-up earlier. In addition to these advantages, however, smaller firms that are older can also have accumulated a number of crucial skills and capabilities over time (cf. Cohen 2010). These skills and capabilities may be technical, or can be managerial. The R and D productivity benefits attributed to newly set-up can thus be even larger for smaller firms that have had more experience running a firm – industries in which small firms that have had time to accumulate experience dominate may for these reasons be expected to be more innovative.

Taking account of both industry structure and industry dynamics as indicators of industry competitiveness, we surmise, will deliver additional insights to help explain the innovativeness of industries and the contribution to that by (1) new and entrepreneurial, (2) large, or (3) small firms.

2 Data and model

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

Dependent variable-Innovativeness We use data on newly announced products as a measure for industry innovativeness (Coombs et al. 1996; Kleinknecht and Bain 1993). Before discussing the advantages and disadvantages of this Literature-based Innovation Output (LBIO) indicator, we first discuss the way in which the data were compiled. The measure we use in this paper, is, arguably, one of the more objective proxies for the output of innovation: new-product announcements (Kleinknecht and Bain 1993; Kleinknecht et al. 2002). Other indicators, mostly of measuring inputs into (formal) R and D, but also some that may indicate (intermediate) output of R and D to a degree, such a patents, have a number of generally recognized drawbacks. As the efficiency of R and D efforts remains unknown, R and D input measures are generally less accurate in measuring innovativeness. Large and manufacturing firms are over-represented when such data are used. Another often-used proxy is patent data. Patents are, however, not the ultimate output of the R and D process for firms, even though some firms do sell or license patents that they do not use themselves. Many patents do not have commercial value (Lemley and

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 studies the extent to which current sales is due to recently introduced products is used as an indicator. This type of data, included in the Community Innovation Survey (CIS), tends to be subjective and may neglect innovations that turn out to be commercially unsuccessful later, but that possibly are important for follow-up innovations and that also are indicative of industry innovativeness. Percentage of sales from recent innovations as an indicator is also likely to substantially underreport innovation in services (Van der Panne 2007).

Two successive volumes of 43 specialist trade journals, covering the vast majority of industries in the Dutch economy, were carefully screened in the period from August 2000 to September 2002 to count the number of new-product announcements in editorials. Only announcements reported on in editorials, published on the editors' authority, rather than reported on in advertisements, are counted. In the editors' expert opinion, these products had to embody surplus value in comparison to preceding versions or to possible substitutes; at least one feature had to be mentioned on which the new product or new service was deemed superior. Newly announced products thus were required to have improved functionality, versatility or efficiency. This reduces the risk of including spurious counts of innovations.

The Literature-based Innovation Output (LBIO) approach to collect data is conservative in the sense that it rather excludes a count of innovation than include one that is not a clear case of an innovation by a firm. In this sense, as indicated above, the LBIO approach is more in line with the Oslo Manual as well as, arguably, with the spirit of Schumpeter's interest in economics dynamics. Innovations announced in trade journals have passed several rounds of selection, in the firm, on the market and by trade journal editors, giving clearer indication of their technical and commercial value. The expert opinion of editors of trade journals is arguably more objective than advertisements sponsored by the firm. 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. Consequently, the products' degree of innovativeness surpasses 'mere' incremental product differentiation.

New-product announcements, difficult to collect data for, are likely to disregard mere incremental innovations, but are an attractive measure for innovation since it seems most in line with the Oslo Manual for collecting and interpreting technological innovation data (OECD 1992, p.42). There are possible drawbacks to this measure. While Van der Panne (2007) provides a detailed discussion about the LBIO data collection procedures as well as the validity of the data thus gathered, we would like to elaborate on procedures to collect such data here as well. Since the data collection procedure focused on innovations announced in trade journals, our data may, possibly, be similarly biased against process innovations as other studies (Van der Panne 2007). Our data takes product innovations as a measure of innovativeness and may be biased against pure intangible service innovations, as most innovation indicators are (Dolfsma 2004; Van der Panne 2007). Our data does include product innovations by firms classified as service firms. Indeed some 46 % of reported innovations were introduced by service firms – mostly in wholesale, across the full range of service industries. The spread of innovations across industries in our database is not biased (see also Van der Panne 2007).

By including firms with fewer than 10 employees as well – firms that the Community Innovation Survey (CIS) data do not cover (Mairesse and Mohnen 2010) – we prevent a possible bias against small firms in our data (see Van der Panne 2007, and Fig. 1 Appendix). Indeed, as Table 2 suggests, the CIS data that tend to be used in many studies of industry innovativeness indeed present a picture that may be biased against small firms (see also Kleinknecht and Reijnen 1991). As established in a number of studies, LBIO data can be considered a full-fledged alternative to traditional innovation data, more in line with the OSLO manual, not relying on self-reporting and closer to the actual test of an innovation's value in the market (Coombs et al. 1996; Kleinknecht and Bain 1993; Kleinknecht et al. 2002; Van der Panne 2007).

All 1585 firms whose innovations were announced in an editorial of any of the trade journals over the two year period for which we collected data were surveyed. Out of 1056 responding firms, 658 (response rate 62.3 %) reported that the announced innovation were imported rather than developed in-house within the Netherlands. The share of foreign products to the total per sector randomly varies across industries, ranging from zero to 100 percent (Van der Panne 2007). The 'import innovations' often had been instigated in the foreign mother company, or were produced under a license. As we are concerned with innovativeness of industries in a particular country, we excluded 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 the 2-digit SIC industry level. Since this paper studies what determines industry innovativeness, our dependent variable is the number of innovating firms in an industry, rather than the number of innovations in an industry.[2] These 48 industries cover almost the entire Dutch economy – some industries, such as agriculture, primary metals, natural resources, and food and beverages, are not included because of a lack of appropriate trade journals. Propensities to announce the innovation in a journal need not be equal across industries because of differences in editorial policy. Industries that serve narrowly defined and small-sized markets may not be inclined to issue an announcement but rather use more direct communication channels. This has been shown, however, not to severely affect the reliability of LBIO data (Kleinknecht and Bain 1993). Although some industries lack a trade journal in which new products are announced, comparative analysis shows that the distribution of innovators across industries does not systematically differ between LBIO and CIS data. Figure 1 gives indication of this. We include (10) service industries ignored by the influential study of Acs and Audretsch (1988). While their contribution to the knowledge economy may be smaller than the average firm (Leydesdorff et al. 2006),

[2]Assuming that each firm has a single innovation in the period studied could be seen to under-represent the contribution of large firms to industry innovativeness. The size distribution of firms in the country studied indicates that it will be unlikely (see Leydesdorff et al. 2006 for the Netherlands): very few firms are large. By separately including variables for firm and industry size we further control for the possible bias in the findings. In addition, as Van der Panne (2007) has shown, LBIO data tends to over-emphasize the role of large firms for industry innovativeness.

Table 2 Comparing CIS and LBIO

			CIS (Mairesse and Mohnen 2010)	LBIO (this study)
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 %

firms in service industries are still innovative. Their innovativeness may go unnoticed in innovation studies (cf. Dolfsma 2004), however.

Our database, uniquely, covers the complete population of new-product announcing firms in a country. In line with the purpose of our paper, data for the independent and control variables we use in our analyses are at the level of the 2-digit SIC industry level. This means that we cannot exploit the full potential of our data, but rather have an set of 48 counts (industries). Industry data were acquired from CBS – Statistics Netherlands.

Independent variables The data on industry characteristics we use are similar to the data used by often-cited studies by Acs and Audretsch (e.g. 1988).

We use several measures to characterize an *industry's economic structure*. The average capital intensity is measured as capital assets relative to industry output. Remarkably, there turns out to be no difference in the results if one would have taken fixed assets only, or in combination with current assets. Acs and Audretsch (1988) 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 – thus having a normalized 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 (1988) have measured it, as the percentage of employees who are a member of a union. Marketing expenditures divided by company output provide a proxy for advertising intensity.

The influence of *size of firms* in an industry on innovativeness has been a particular focus for a number of studies. As was highlighted above, results differ across studies. It is for this reason, and since the data we have allow for it, that we analyze the influence of size in two different ways, allowing us to go beyond the rather crude method proposed by Acs and Audretsch (1988) using a threshold 500 employees above which firms are defined as large. Employment share in an industry of large firms is then measured as the number of employees at large firms divided by the total number of employees. We present findings using a threshold of 350 employees for a firm to be considered large, but we have varied the threshold from 75, to 150, to 350, and, subsequently, to 625. We found an increasingly negative and increasingly significant effect of large firms employment share on industry innovativeness as we increased the threshold. The results for these analyses are available upon request. Alternatively, firm size is also included as a continuous variable, in line with the literature on firm growth (Garnsey 1998), as well as industry dynamics and the Industry Life Cycle theories referred to above. To determine whether the relation between firm size and industry innovativeness follows a possibly inverted-U pattern, the square of firm size was included as well.

As indicators of industry dynamics we include R and D expenditures. The percentage of employees who have obtained a degree at bachelor or master level indicates the level of skill available. The latter 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, however. 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 include net entry rate (firms entering an industry as a percentage of the total, average for the 2000–2002 period[3]). To be able to grasp the influence of changes in the net rate of firms entering a sector we include entry-squared. In line with Schumpeter (1934), Klepper (1996, 1997) and others one would expect sectors that show a high (increasing) net entry rate to be more innovative.

Several *control variables* are included. Effects due to differences in industry size are controlled for by including a variable for total sales. We have, in contrast to Acs and Audretsch (1988), added a further control variable for the size of the population 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 and Dolfsma 2003; Van der Panne 2004). This effect can but need not be related to industry size.

2.1 Model specification

Because of the focus on the industry level, the number of observations equals the number of industries. The count of innovating firms per industry follows a Poisson distribution, suggesting the use of a count data model. For reasons of over-dispersion, the negative binomial regression model is more appropriate (Cameron and Trivedi 1986).[4] Using the data as described above, we thus estimate the

[3]Changing the period chosen does not change the findings.

[4]In the case of over-dispersion, i.e. $\sigma_i > \mu_i$, a Poisson model under-estimates dispersion, resulting in downward biased standard errors (Cameron and Trivedi 1986). The negative binomial regression model

following model for industry innovativeness using a negative binomial regression method:

$$\mathrm{LBIO_i} = \alpha + \beta\,(\mathrm{X_i}) + \gamma\,(\mathrm{Y_i}) + \delta\,(\mathrm{Z_i}) + \varepsilon_\mathrm{i}$$
$$\mathrm{i} = 1 \ldots 48\text{industries} \tag{1}$$

Here, X are various variables indicating Industry Structure, variables in Y proxy for Industry Dynamics, and Z are control variables, as discussed above. A negative binomial regression model is a conservative estimation method to deal with over-dispersion in the data. We standardized coefficients to make it possible to compare results between models in Table 3.

2.2 Robustness

Table 4 Appendix presents a correlation matrix for the variables used in this paper. Model fit indicators for all models presented in this paper are all well within acceptable bounds. VIF values are well below threshold levels indicating that multicollinearity did not constitute a concern. Unfortunately, we cannot exhaustively address the potential problem of endogeneity with the data at our disposal. The relevant theory discussed above suggests that industry structure and industry dynamics as well as firm characteristics help explain industry innovativeness rather than the other way around. In addition, for each of the variables included as Independent Variable in our models we have performed a Durbin-Wu-Hausmann test. The outcomes of these tests indicate that endogeneity is not likely to be an issue, statistically (outcomes of tests available from the authors upon request).

By analyzing our model for different subsets of industries we can indicate the robustness of our main findings in Table 3–(Peltoniemi 2011) has suggested that this would both be a good test for ILC literature and would lead to new insights, referring to services in particular. Table 6 Appendix provides the results of our analyses for manufacturing industries, services, and low tech industries, separately. We also compare the main findings we present in this paper with results for industries where we found, in our data set at micro level, the 33 % most and 33 % least R and D intensive firms (cf. Shefer and Frenkel 2005). To further indicate robustness, we also, separately, analyzed our models for service industries, manufacturing industries and what the OECD classifies as low-tech industries. Our findings for these robustness checks are largely similar to our main findings. In addition to our analysis using negative binomial regressions, we replicated our analysis using OLS and found largely the same results. These results are available upon request from the authors.

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.

Table 3 Schumpeters Puzzle: Industry Innovativeness, Firm Size, and Entry

	Firm Size (threshold)	Firm Size (continuous)	Firm Size (nonlinear)	Entry	Entry (nonlinear)
Model:	(I)	(II)	(III)	(IV-a)	(IV-b)
Capital Intensity	−79.5	−72.9	−72.0	−73.0	−52.4
	(0.007)***	(0.072)*	(0.079)*	(0.072)*	(0.344)
Industry	−91.7	−91.7	−83.8	−91.2	−78.4
Concentr.	(0.001)***	(0.002)***	(0.073)*	(0.006)***	(0.090)*
Unionization	−20.0	−39.3	−37.3	−38.6	−25.5
	(0.537)	(0.145)	(0.155)	(0.162)	(0.280)
Advertising	−72.4	−79.9	−78.1	−79.8	−79.3
intensity	(0.040)**	(0.015)**	(0.029)*	(0.015)**	(0.009)***
Industry R&D	198.5	190.8	179.4	190.1	187.6
	(0.002)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Skilled labor	216.2	162.2	142.4	158.4	179.6
	(0.001)***	(0.090)*	(0.115)	(0.102)	(0.021)**
Industry size	272.0	363.0	341.9	361.1	377.7
	(0.009)***	(0.012)**	(0.015)**	(0.013)**	(0.003)***
Firm population	22.1	16.2	21.9	15.3	-3.0
	(0.487)	(0.69)	(0.594)	(0.706)	(0.926)
Large-firm	−71.9	–	–	–	–
share††	(0.001)***				
Firm Size	–	−70.7	135.9	−69.9	−58.2
(continuous)	(0.006)***	(0.743)	(0.011)**	(0.050)**	
(Firm Size	–	–	−92.2	–	–
continuous)^2			(0.468)		
Entry	–	–	–	−7.3	−89.2
				(0.826)	(0.089)*
(Entry)^2	–	–	–	–	−98.0
					(0.056)*
n	48	48	48	48	48
McFadden's R^2	0.19	0.183	0.187	0.183	0.202

Two-tailed; Regression of total number of innovators, 2-digit SIC industry level. * 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).

Our study focuses on the industry as our level of analysis, and so the number of innovative firms (innovators) in a sector is our dependent variable indicating the dynamics of a sector. Alternatively, from a more managerial and not so much a policy point of view, one may remark, as one reviewer has, that a firm may have introduced several innovations in a sector in the period we look at. While this does not make the sector more innovative per se, the competition dynamics might be altered perhaps. We believe that this effect is limited, if present at all. Our main findings draw on data covering two years and 48 sectors. Unfortunately, data we have about the number of innovations (rather than the number of innovators) is for the first year of our study only and covers 26 sectors. The number of innovations introduced in a year, we find, highly correlates with the number of innovative firms ($B = 0.994$, $p < 0.0001$). In addition, Table 5 Appendix reproduces model II from Table 3, comparing results for an analysis based on number of *innovators* in a sector on the one hand (model App2-a) with one for the number of *innovations* in a sector on the other hand (model App2-b). The results in these models are both largely comparable to the results in model II in Table 3, providing further indication that a focus on innovativeness at the industry level, focusing on the number of innovative firms rather than the total number of innovations, does not introduce biased results.

Further descriptives are presented in Table 2. The firms identified by the LBIO method engage more often in R and 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 and D-intensity, innovation commitment, patenting behavior, and R and D-output both in terms of improved as well as for new products that are higher than indicated by CIS data.

3 Results

Table 3 presents our main findings. The findings for the variables indicating economic structure of industries are remarkably similar to comparable studies and remain so as we expand our model (Acs and Audretsch 1988); (Dolfsma and Van der Panne 2008). Capital intensity, Concentration ratio, and Advertising intensity all negatively affect industry innovativeness. Different from the findings of Acs and Audretsch (1988) unionization does not impact industry innovativeness in a statistically significant manner. Given that this analysis pertains to a country (the Netherlands) where labor laws favor incumbent employees more than in some other countries in the developed world, and given that any company above a threshold size are legally obliged to have a board of employee representatives that has a number of rights, this may not be a surprising finding. Firms cannot disregard a central agreement between the union and industry representatives arrived at on the national level – the degree of unionization of an industry does not affect this procedure.

Industry R and D levels consistently positively affect innovativeness, and so does skilled labor. Spill-over effects may be involved. Industry size, but not industry firm population, positively influences innovativeness.

Our findings on the effect of firm size, proxied in different ways, on industry innovativeness are remarkable and quite robust. Using different thresholds to indicate firms as large, or taking size as a continuous variable did not alter our findings. Industries dominated by large firms are significantly less innovative than industries in which small firms dominate ($B = -71.9$; $p<0.01$). Only results for the 350 employee threshold are shown in Table 3 (Model I). As the threshold increased from 75, to 150, then to 350 and finally to 650 employees, the effect (beta) of this variable on industry innovativeness becomes increasingly negative and statistically increasingly significant. Using firm size as a continuous variable results in a statistically highly significant negative coefficient as well ($B = -70.7$; $p<0.01$). The relation between size and industry innovativeness is thus a firmly negative one. A Schumpeter Mark II perspective, arguing in favor of creative accumulation, is thus to be rejected based on our findings.

When including the square of industry firm size per industry, to test for the non-linear, (inverted) U shaped relation between firm size and industry innovativeness (Aghion *et al.* 2005), we find a non-linear result but one that is by no means statistically significant ($B = -92.2$; $p>0.10$). What is more, including this term also means that average firm size as a variable itself stops being a meaningful variable in the model. Contrary to the findings of (Aghion et al. 2005) the idea that there might be a particular disadvantage of a firm being middle-sized does not find support in our study.[5]

What is most striking in models IV-a and IV-b is that adding net firm entry to a sector into the model (model IV-a) has a negative ($B = -7.3$; $p>0.1$), though not statistically significant, effect on industry innovativeness. Also entry-growth affects sector innovativeness negatively, in exactly the opposite way as expected in the ILC literature – in model IV-b beta's for both entry ($B = -89.2$; $p<0.1$) and entry-squared ($B = -98.0$; $p<0.1$) are both negative. This clearly does not confirm Schumpeter's (Mark I) suggestion that industry innovativeness is to be expected by or be due to newly established entrepreneurial firms. This finding also contrasts with Audretsch's knowledge spill-over theory of entrepreneurship, where newly set up firms are argued to take advantage of knowledge spilling over from large firms, thus being better able to innovate and develop new products and services (Audretsch and Keilbach 2007, 2008).

Our findings suggest that one may not expect industry innovativeness to be stimulated by entrepreneurial start-ups. Small firms and newly entering firms are clearly different, certainly in how they affect industry innovativeness: presence of (many) small firms contributes to industry innovativeness while firm entry or presence of (many) large firms does not.

[5]Using the Lerner Index or price-cost margin as a measure of competition and patents as a measure of innovation, Aghion et al. (2005) find that innovativeness was highest when competition was either low or high. In part, the different findings we present may be due to the different measures used. Our data, which includes information on patent ownership, does not indicate that firms size and patent ownership is somehow correlated, however.

4 Conclusions

Schumpeter developed competing views about what would explain industry innovativeness. In what may be referred to as Schumpeter's Innovation Puzzle, a Schumpeter Mark I and a Schumpeter Mark II view are distinguished. The issues of industry structure and dynamics to indicate competition levels on the one hand, and firm characteristics on the other hand have tended not to be clearly distinguished in this discussion, however. In our analysis, we conceptually discuss and empirically integrate different views of how industry competitiveness, on the one hand, for which we both have structural and dynamic indicators, and on the other hand characteristics of firms in an industry give rise to industry innovativeness. The discussion about firm characteristics conducive to industry innovation has focused on firm size in particular. In our attempt to contribute to the Schumpeterian Innovation Puzzle, we thus distinguish between the effects of having relatively more large, newly set-up, or small firms in an industry.

Using new-product announcements in trade journals – the LBIO approach as arguably the more appropriate measure for (industry) innovativeness, in line with the Oslo manual - we find that, in a number of different and robust model specifications, the contribution of a presence of large firms to industry innovativeness is distinctly negative for industry innovativeness, suggesting that the Schumpeter Mark II perspective should be rejected. We also find no indication of non – linear effects of firm size on industry innovativeness.

Today Schumpeter is better remembered for arguing that entry into an industry by entrepreneurial firms stimulates industry innovativeness. Entry and entry growth in an industry, however, actually have a *negative* impact on industry innovativeness. The Schumpeter Mark I suggestion is thus not supported by our findings either. This finding contrasts with some central tenets in both the Industry Life Cycle and much of the entrepreneurship literature. Stimulating entrepreneurship may actually be questionable public policy when industry innovativeness is a goal to pursue (cf. Shane 2009).

Small firms, however, consistently, positively and significantly contribute to industry innovativeness. The findings differ little across model specifications and are thus robust. We suggest that there may be a need to identify a third position concerning the relation between firm size and entry by entrepreneurial firms on the one hand, and industry innovativeness on the other hand. A Schumpeter Mark III view would suggest that small firms, rather than large or new firms, stimulate industry innovation. This view is, we suggest, in line with the work of Schumpeter, but not explicitly developed in sufficient detail yet. Further research, in particular using micro level data, is needed to determine what may be some of the underlying mechanisms that produce these effects at an aggregate level.

Appendix

Table 4 Correlation Matrix

	Mean	S.d.	Min.	Max.	LBIO (innov)	Indu. R and D	Cap. Intens.	Concentr.	Union.
LBIO (innov)	12.71	22.33	0	99					
Indu. R and D	94.31	172.55	0.1	853	0.4292**				
Cap. Intens.	0.45	0.44	0.01	3.01	−0.1836	−0.1961			
Concentr.	0.66	0.61	0.05	3.31	−0.0076	−0.2104	−0.1473		
Union.	28.6	10.97	6	56	−0.3253**	−0.1486	0.3979**	−0.3787**	
Advert.	9.71	15.24	0.01	71	0.5565**	0.5677**	−0.2200	0.2553	−0.3600**
Skilled Labor	21.44	9.88	7	44	0.0289	−0.0854	0.0622	−0.4688**	−0.3990**
Size	65	131	0	1250	−0.1172	0.0248	0.1891	−0.5856**	0.3613**
Sector Size	18589	31765	19	196480	0.6640**	0.2364	−0.1869	0.752	−0.2853**
Firm Pop.	22006	44972	27	207303	0.3378**	−0.0297	−0.1641	0.6755**	−0.4011**
Entry	−9.6	12.2	−57.7	25.9	−0.1267	−0.1629	0.1382	−0.4174**	0.3378**
		Advert.		Skilled labor		Av. Firm Size	Sector Size		Firm. Pop.
Skilled labor		0.0783							
Firm size		0.0845		−0.2151					
Sector size		0.7448**		−0.1476		−0.1235			
Firm Pop.		0.4875**		−0.2825		−0.3334**	0.5622**		
Entry		−0.3504**		0.2335		0.2243	0.1307		−0.3990**

N = 48; * Significant at 10 %; **significant at 5 % level; *** significant at 1 % level

Table 5 Innovativeness: Innovators vs Innovations

	Innovators (LBIO-all sectors)	Innovators (LBIO)	Innovations
Model:	(II – Table 3)	(App2-a)	(App2-b)
Capital Intensity	−72.9 (0.072)*	−51.0 (0.00)***	−8.3 (0.532)
Industry Concentr.	−91.7 (0.002)***	−95.7 (0.00)***	−66.6 (0.039)**
Unionization	−39.3 (0.145)	−52.3 (0.017)**	−42.5 (0.036)**
Advertising intensity	−79.9 (0.015)**	−65.6 (0.175)	−21.7 (0.703)
Industry R and D	190.8 (0.000)***	106.3 (0.007)***	77.0 (0.026)**
Skilled labor	162.2 (0.090)*	89.3 (0.011)**	−17.0 (0.479)
Industry size	363.0 (0.012)**	143.4 (0.100)	4.7 (0.917)
Firm population	16.2 (0.69)	104.3.1 (0.036)**	180.0 (0.026)**
Firm Size ctd	−70.7 (0.006)***	−67.2 (0.00)***	−47.7 (0.004)***
n	480.19	26	26
McFadden's R^2		0.241	0.196

Percentage change in expected counts per standard deviation increase in explanatory variables. Twotailed;Regression of total number of innovators, 2-digit SIC industry level. (.) Replication of analysis using the number of innovations as dependent variable. * Significant at 10; **significant at 5 level; *** significant at 1 level; p-values in parentheses.

Table 6 Innovativeness: Innovators vs Innovations

Model:	Services	Manufacturing	Lo-Tech	RD Intensity (33 % Least)	RD Intensity (33 % Most)
Cap. Intens	0.232	4.202	−67.4)	−26.7	−61.71
	(1.330)	(2.691)	(0.179)*	(0.587)	(0.057)*
Concentr.	−2.811	−7.626	−90.4	−96.9	−83.2
	(0.867)	(2.226)***	(0.008)***	(0.000)***	(0.005)***
Union.	0.0160005	−0.0244	−44.3	−51.0	*−34.6
	(0.0159)	(0.0281)	(0.163)	(0.067)	(0.243)
Advert.	−0.363	−0.054	−83.1	−54.8	−66.9
	(0.0799)***	(0.0375)	(0.011)**	(0.193)	(0.036)**
Industry R and D	0.0388	0.0061869	156.2	154.4	172.6
	(0.00687)	(0.00112)***	(0.000)***	(0.006)***	(0.003)***
Skilled labor	0.203	†	150.8	65.5	112.1
	(0.0306)***	(0.136)	(0.263)	(0.026)**	
Industry size	0.000144	−0.000026	438.9	150.6	166.7
	(0.0000283)***	(0.0000268)	(0.012)**	(0.096)*(0.026)**	
Firm pop	−0.0000114	0.00019	14.6	77.9	19.8
	(4.35e-06)***	(0.000072)***	(0.731)	(0.069)*(0.467)	
Firm Size ctd	−0.086	−0.0864	−63.6	−88.6	−69.9
	(0.0366)**	(0.0287)***	(0.0200)**	(0.000)***(0.096)*	
n	22	26	43	48	48
McFadden's R^2	0.526	0.274	0.186	0.251	0.218

Percentage change in expected counts per standard deviation increase in explanatory variables. Two-tailed; regression of total number of innovators, 2-digit SIC industry level. * Significant at 10 %; **significant at 5 % level; *** significant at 1 % level; p-values in parentheses. † Not included due to multicollinearity

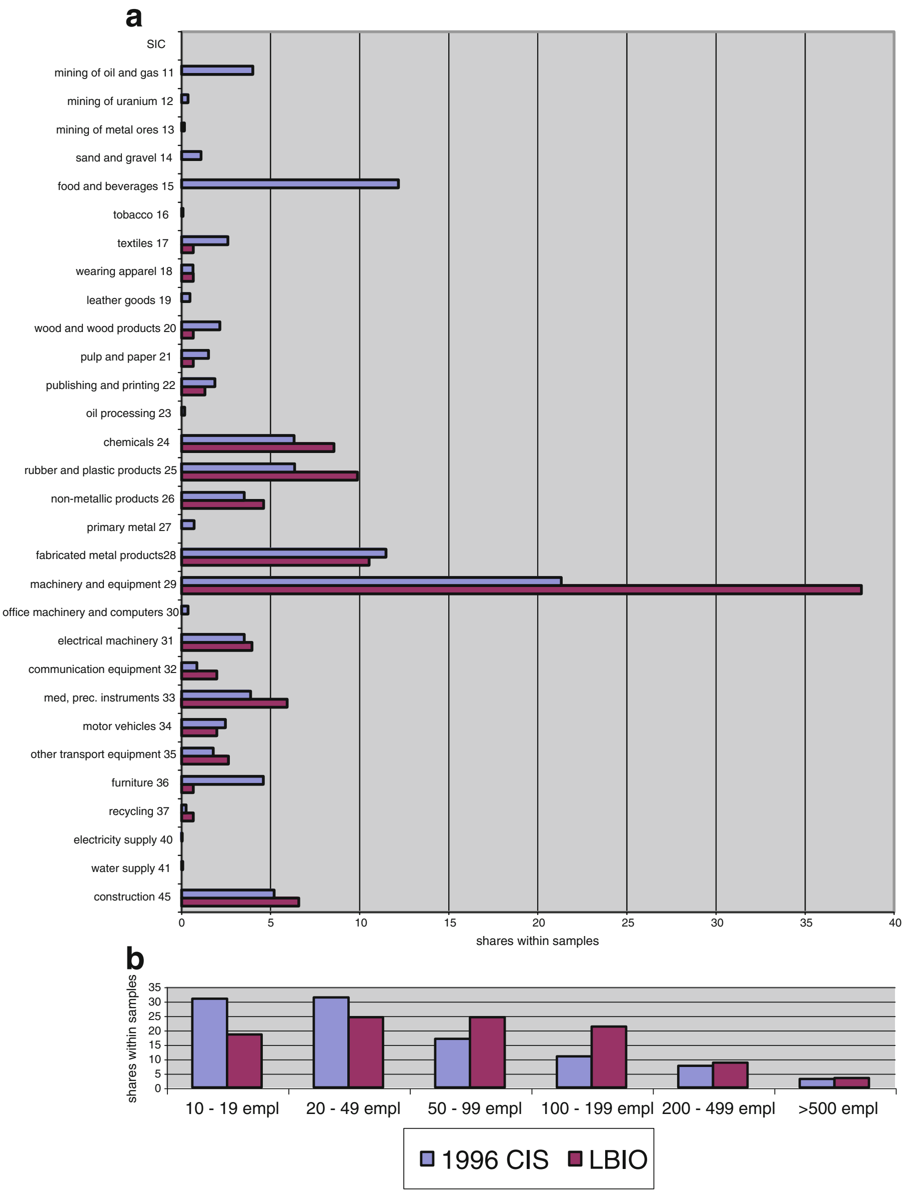

Fig. 1 Innovation counts by **a** industry, and **b** firm size: CIS versus LBIO database†b)

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