Innovation Pattern Heterogeneity

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The firm's ability to innovate is one of the usual suspects for explaining differences in firm performance according to a strong and diversified theoretical framework. Innovation facilitates the high rate of growth of ‘‘superstars’’ as well as the establishment and continued existence of profitable companies that do not seek to become large enterprises Understanding the diversity that exists within the population of innovative firms is essential for developing appropriate innovation policies. By applying factor analysis to a wide array of survey variables and a large sample of firms, we identified eleven typical approaches to innovation.

technological change | innovation survey | factor analysis | business strategies | intra-industry heterogeneity

1. Introduction

The firm's ability to innovate is one of the usual suspects for explaining differences in firm performance according to a strong and diversified theoretical framework [1][2]. Innovation facilitates the high rate of growth of ‘‘superstars’’ as well as the establishment and continued existence of profitable companies that do not seek to become large enterprises [3]. Understanding the diversity that exists within the population of innovative firms is essential to develop appropriate innovation policies. The researchers study explored the diversity of innovation patterns among Norwegian firms and identified typical approaches to innovation, which connect innovation inputs and outputs at the firm level.

The mechanisms linking R&D, innovation success, and firm performance are largely indebted to the Schumpeterian endogenous growth representation, according to which firms strive to innovate so that they can enjoy monopoly rents [4]. The forward-looking firm makes a decision about its level of research input, based on the expected returns to R&D (in terms of sales or directly in terms of profits), which affects the stochastic innovation process. Innovation success, in turn, automatically raises the firm's profitability or productivity level [5][6]. Such stochastic and optimizing representation has, however, been challenged by models in which agents constrained by bounded rationality search for more productive techniques in an uncertain environment, where the impact of innovation on firm growth is itself random [7]. In such a framework, firms are heterogeneous in their ability to innovate, not only because of their financial resources, but also because they differ in terms of their ability to exploit technological opportunities. Path dependency explains the concentration of many innovations in the hands of a limited number of firms [1], while there may also be growth pattern heterogeneity for the same levels of R&D due to the uncertain nature of the R&D process [8]. Even among successful innovators, heterogeneity persists: while innovators are likely to enjoy superior employment growth compared with non-innovators, the bulk of this differential derives from the exceptional job creation activities of a few firms [9].

If policy-makers are willing to help different firms (incumbents or entrants), a first way to group the target firms is by the type of products and processes they deal with, which, in turn, roughly defines the economic sector to which the firms belong. At high levels of aggregation, product-based classifications of sectors such as the NACE system have often been considered impractical for understanding the sectoral dynamics of innovation. Therefore, other classifications have been suggested for this purpose, which use a finer disaggregation level as a basis for new definitions of economic sectors. Pavitt [10] proposed a four-sector taxonomy based on size, innovation patterns, and sources of innovation: scale-intensive, supplier-dominated, science-based, and specialized supplier. Miozzo and Soete [11] proposed removing services from the supplier-dominated category in Pavitt's original classification and suggested four additional categories: supplier-dominated services, physical network services, information network services, and knowledge-intensive business services. This led to an eight-fold taxonomy including four manufacturing and four service sectors; the taxonomy was later subjected to further aggregation by Castellacci [12].

However, these taxonomies have still grouped data at the level of industry rather than that of firms. Such a choice ignores the fact that firms in the same industry may have a very different technological base. This issue was raised by Archibugi [13], who said that "[h]opefully, over the next few years more statistical and econometric work will be carried out to group firms, as opposed to industries, into the taxonomic categories [.] according to their intrinsic characteristics such as the rate and direction of technical change and their sources of innovation" ([13] p. 420). Their hope was partially misplaced, since data limitations have often constrained the researchers in innovation studies into using output-based sectoral definitions. In the researchers study, the researchers used firm-level data from the Innovation Survey conducted in Norway in 2018 to identify various approaches to innovation. Drawing on De Jong and Marsili [14] and Leiponen and Drejer [15], the researchers employed a factor analysis to reveal typical patterns of innovation behavior by analyzing correlations in the answers to the survey. Unlike in previous studies, the researchers did not aim to label each firm as having one specific approach to innovation, but the researchers allowed for the coexistence of several approaches to innovation within the same firm. The eleven innovation patterns the researchers identified are therefore eleven different, but not exclusive, ways for a firm to be innovative.

the researchers took stock of the findings by Baregheh et al. who collected different definitions of innovation from various disciplinary literature and, following a content analysis, proposed that "Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace". This definition helps us to reaffirm, on one hand, that innovation is a process rather than a discrete act and, on the other hand, that the presence of an aim is necessary to reconnect the rhetoric
of innovation to its strategic contexts. The researchers analysis uncovered the innovation patterns of Norwegian firms by studying not only the variables associated with innovation inputs and outputs, but also variables describing the goals and hindrances in the innovation process, as emerging from the answers to the 2018 Norwegian Innovation Survey.

2. Innovation Pattern Heterogeneity

Empirical studies and practical experience have often revealed a variety in the sources, nature, and use of innovation. One of the pioneers was Pavitt [10], who proposed classifying industries according to a four-sector taxonomy based on size, innovation patterns, and sources of innovation: scale-intensive, supplier-dominated, science-based, and specialized supplier. Similarities and differences amongst sectors in the sources, nature, and impact of innovation were defined by the sources of knowledge inputs, by the size and principal lines of the activity of innovating firms, and by the products and main uses of the innovation sectors. The dataset comprised 2000 significant innovations, and the corresponding innovating firms existed in the UK from 1945 to 1979. Notably, these data covered only eleven 2-digit industries. The data did not measure the significance of innovations, nor did they precisely capture incremental innovations. The four sectors resulting from the analysis by Pavitt (1984) are:

- Scale-intensive (SI), which includes both complex and consumer durables (food, chemicals, motor vehicles) and processed raw materials (e.g., metal manufacturing, glass and cement). Firms tend to be large and to rely mainly on internal resources for their innovations;
- Supplier-dominated (SD), which includes industries where firms mostly produce technologically simple goods (e.g., textiles, leather goods, pulp and paper), where the capital and intermediate components suppliers are the main sources of innovation;
- Science-based (SB), which includes industries where innovation is linked directly to advances in academic research (e.g., pharmaceuticals, electronics, scientific instruments). Innovation rates are particularly high. Carrier industries in the ICT paradigm; and
- Specialized supplier (SS), includes equipment building, design, and mechanical engineering, where innovation typically emerges from informal activities. Firms in this group tend to be small, and innovation rates are particularly high. Supportive of the Fordist paradigm.

Miozzo and Soete [11] proposed withdrawing services from the supplier-dominated category in Pavitt’s original classification and suggested four additional categories: supplier-dominated services, physical network services, information network services, and knowledge-intensive business services, defined as follows:

- Supplier-dominated services (SDS) rely on the purchase of capital goods for their innovation. They are mostly small companies providing services directly to customers (e.g., hotels, restaurants, rental services and personal services). Innovation rates are particularly low;
- Physical network services (PNS), which, which include all transport, retail, and wholesale trade-related services;
- Information network services (INS), which include all information-intensive activities (communication, financial intermediation, insurance, real estate). Firms tend to be large and to innovate in interaction with suppliers and users; and
- Knowledge intensive business services (KIBS), which include R&D services, consultancy, and computer-related activities. Firms tend to be small and medium-sized firms and to generate their own innovation. Innovation rates are particularly high.

The taxonomy by Pavitt [10] is often considered in studies of innovation patterns and industrial dynamics, both directly to categorize firms in empirical studies, and indirectly to frame the theoretical relations between industries in innovation models or innovation processes within firms. For instance, Paananen [16] used the taxonomy to investigate the balance between internal and external sources of knowledge for firms belonging to a given sector. Inter-industry differences in technological trajectories, as represented by Pavitt's taxonomy, were taken into account by Spithoven [17] in his study of firm sales from product innovation. Di Berardino and Onesti [18] explained the international processes of deindustrialization by considering Pavitt's taxonomy as an empirically based framework of vertical linkages between industries. Ascani et al. [19] categorized inward foreign direct investments according to Pavitt's taxonomy when inspecting which types of investments could be a systematic source of knowledge inputs, on the assumption that foreign activities are inherently industry-specific. Dosi et al. [20] considered the sectoral patterns of innovative activities identified by Pavitt [10] to disentangle the sectoral patterns of job-creation/destruction. Labor markets were also the object of analysis for Felice et al. [21], who relied on the Pavitt taxonomy (as revisited by [22]) to analyze the impact of additive manufacturing technology on employment. Schneider et al. [23] adopted a sectoral perspective to examine the influence of human capital on innovation performance, noticing that the criteria used by Pavitt [10] to classify sectors implied that sectors had different skill requirements.

Bonaccorsi et al. [24] combined the taxonomies by Pavitt [10] and by Miozzo and Soete [11] to cluster new firms on the basis of the characteristics of their innovation patterns to study the impact of the scientific specialization of universities on local new firm creation (the researchers call this joint taxonomy the "Pavitt–Miozzo–Soete", since it evolved directly from the original taxonomy by Pavitt; see also [25]). On a similar topic, Baroncelli and Landoni [26] conducted a comparative analysis of university-level support practices and entrepreneurial behavior of spin-offs; they also used the taxonomies by Pavitt [10] and by Miozzo and Soete [11] to classify the technologies embodied and exploited by the spin-offs of their sample. Consoli and Rentocchini [27] identified structural characteristics of industry-specific know-how, and understood their results in light of "Pavitt's renowned taxonomy, a point of reference for virtually all industry classifications" ([27] p. 1122) and of the Miozzo and Soete (2001) extension of the taxonomy to services. The Pavitt–Miozzo–Soete taxonomy was also adopted for studies of open innovation [28] and of regional development [29][30], while Flikkema et al. [31] only used sectoral categorization by Miozzo and Soete [11] for services, without its manufacturing counterpart, when studying trademark activities.

The Pavitt–Miozzo–Soete taxonomy was aggregated further by Castellacci [12], who took up the challenge of explicitly addressing the relationships between manufacturing and services. In this latter study, supplier-dominated goods and supplier-dominated services appeared together at the final stage of an ideal knowledge chain, at a position where they were able to implement new technologies created elsewhere in the economy. At the other end of the chain, there were the "advanced knowledge providers": specialized manufacturing firms and knowledge-intensive business services, both characterized by great technological capability and a significant ability to manage and generate complex technological knowledge. All the other industries were divided between the "supporting infrastructure services" sector, upon which business and innovative activities in the whole economy were based, and the "mass production of goods" sectors, which are carriers of knowledge in the form of scale-intensive and science-based firms.

The aforementioned taxonomies have grouped data at the industry level rather than the firm level. This choice, however, ignores the fact that firms in the same industry may have a very different technological base. Micro-founded definitions of economic sectors could provide a foundation for a better understanding of the innovation processes and the development of more targeted innovation policies [13]. This empirical path was opened by Cesaratto and Mangano [32], who analyzed data from an extensive innovation survey conducted among Italian manufacturing firms and identified six main clusters or dominant technological firm profiles. The authors stated that a degree of technological determinism predominates in the model by Pavitt [10], while an established tradition in organization theory (see, e.g., [33]) has also emphasized the "strategic choice" available to firms for manipulating their internal and external environments. Applying cluster analysis to data on technological inputs and outputs and the impact of innovation on sales, Cesaratto and Mangano [32] identified the following six clusters of firms:

- Cluster 1 represents the case of struggling companies competing in dynamic R&D-intensive technological trajectories;
- Cluster 2 shows a smaller group of aggressive companies competing in dynamic trajectories through a blend of R&D, industrial design, and investment policy;
- Cluster 3 contains firms that are less resolute in their innovative strategies;
- Cluster 4 is representative of technological trajectories based on industrial design and incremental technical change; and
- Clusters 5 and 6 both show embodied technical change as the main innovation channel, with Cluster 5 representing a more traditional component of the industrial landscape and Cluster 6 blending heavy capital accumulation and some in-house innovative activities.

In the words of the authors, "[t]he intersectoral nature of clusters seems to attest to the existence of a considerable degree of choice in company strategy as compared to the more marked sectoral determinism emerging from Pavitt's taxonomy" ([32] p. 252).

Strategy also constitutes an important element for the subsequent micro-based taxonomy designed by De Jong and Marsili [14], who employed data from computer-assisted telephone interviews with managers and entrepreneurs of small- and micro-enterprises. The interviews aimed at capturing novel relevant variables such as managerial attitude, innovation planning, and external orientation. The focus on the bottom of the firm size distribution is motivated here by the disproportionate attention paid to large firms by previous studies including the study by Pavitt [10]. Somewhat surprisingly, after running a cluster analysis on their survey data, De Jong and Marsili [14] obtained a taxonomy of small- and micro-firms, which closely resembled the taxonomy of Pavitt [10]. Three of the four original categories were even defined under the same names as used in Pavitt [10], although they displayed additional qualities: supplier-dominated firms appeared to be relatively open, consulting on average with more than three external parties; specialized suppliers reached high levels of product innovation through more intensive use of specialized labor; and science-based firms were managed with a strongly positive attitude toward innovation, frequently accompanied by a written plan. The firms in the fourth category, called "resource-intensive" firms, allocated financial and time resources to innovation, but they limited their use of personnel employed in innovation and of external networks; their main difference from the "scale-intensive" firms in the Pavitt taxonomy consists of their not being associated with a large firm size. No clear-cut relationship emerged between industrial sectors and clusters of firms: following a definition introduced by Caves and Porter [34], De Jong and Marsili [14] also confirmed that different “strategic groups” coexisted within industries.

Leiponen and Drejer [15] used a similar approach to assess whether industry boundaries truly defined the boundaries of technological regimes. Again, the intuition behind their work lies in the idea that intra-industry heterogeneity may derive from strategic diversity. Importantly, their theoretical foundation strongly emphasizes the myopic trajectories followed by some firms, which, especially under rapidly changing conditions, must make strategic decisions under very limited knowledge conditions. Differences in knowledge could then pair up with differences in skills to produce different innovation patterns within industries. Their empirical analysis is based on cross-sectional Community Innovation Survey (CIS) datasets containing data on manufacturing and service firms located in Denmark and Finland covering the period 1994–1996. The study was conducted in two phases: first, a factor analysis was performed on a set of survey variables; then, the scores obtained from the factor analysis were input into a cluster analysis with the aim of grouping the firms into distinct categories, as homogeneous as possible with respect to factor dimensions. Both the factor analysis and the subsequent cluster analysis pointed to four types of innovative behavior that displayed a partial overlap with the Pavitt categories. Indeed, the analysis by Leiponen and Drejer [15] showed the existence of supplier-dominated firms; in Finland, suppliers are often direct collaborators with these firms, whereas in Denmark, they act simply as sources of information. On the other hand, market-driven firms tend to open new markets and extend current ones, sourcing information intensively from clients. Collaboration with universities, often associated with patenting, instead mark the behavior of science-based firms, while production-intensive firms mainly focus on improving existing products. Finally, one cluster in each country was termed “ad hoc”; its firms do not draw much on any sources nor are they driven by clear objectives in their innovation activities. Notably, only half of the four-digit (Denmark) and five-digit (Finland) NACE industries, with six or more observations, had more than 50% of firms associated with one cluster. In other words, about half of the industries did not have a dominant cluster, suggesting that firms have more room for strategic choice than is commonly believed in the innovation literature.

The researchers work follows directly on from Leiponen and Drejer [15] by conducting a factor analysis on the innovation survey data and by complementing the analysis with additional information from other data sources. the researchers particularly stress the advantage of factor analysis over rigid clustering techniques, in that the researchers were able not only to avoid restrictions from existing industry-based taxonomies (which represent the benchmark throughout the researchers study), but also pointed out cases where several types of innovation behavior coexist. the researchers conducted the researchers factor analysis on a wide array of survey variables and on a large sample of firms to obtain a fine-grained view of the firms’ approaches to innovation.

The taxonomy by Pavitt [10] assigned a main role to firm size, to the point that one of the categories identified bears the name “scale-intensive”, to associate innovation processes to industries characterized by specific economies of scale. Miozzo and Soete [11] also showed that in services, firm size may concur to define the innovation patterns of a macro-sector, as in the case of “physical network services”. However, De Jong and Marsili (2006) argued that some smaller firms (which they labeled “resource-intensive”) may recreate similar innovation processes as scale-intensive firms.

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