

Chapter XXV

On Technological Specialization in Industrial Clusters

Herbert Dawid

Bielefeld University, Germany

Klaus Wersching

Bielefeld University, Germany

ABSTRACT

In this chapter an agent-based industry simulation model is employed to analyze the relationship between technological specialization, cluster formation, and profitability in an industry where demand is characterized by love-for-variety preferences. The main focus is on the firms' decisions concerning the position of their products in the technology landscape. Different types of strategies are compared with respect to induced technological specialization of the industry and average industry profits. Furthermore, the role of technological spillovers in a cluster as a technological coordination device is highlighted, and it is shown that due to competition effects, such technological coordination negatively affects the profits of cluster firms.

INTRODUCTION

Regional or local agglomeration of firms can be identified in almost every economy of the world: Hollywood, Silicon Valley, and Route 128 in the United States, the finance sector in London (GB) or Frankfurt (D), and the pharmaceuticals near Basel (CH) are only a few examples. Since Marshall (1920), the economic rationales for agglomeration of firms are discussed in the economic literature, and more recently there

emerged an amount of literature which focused on the relationship between agglomeration and innovation (see Audretsch, 1998; Asheim & Gertler, 2005).

Main arguments in favor of a geographic concentration of economic activity are positive externalities associated with the proximity of related industries (e.g., Porter, 1998). Beside transactional efficiencies, knowledge spillovers are one form of these externalities. The concentration of firms and workers allows the

exchange of tacit knowledge, which is characterized as vague, difficult to codify, and uncertain in its economic use (Dosi, 1988). Because of these properties tacit knowledge is best transmitted via face-to-face interaction and through frequent and repeated contact. Examples of transfer channels of knowledge spillovers are planned or unscheduled communication between people or the flow of workers from one company to another. Despite the advances in telecommunication technology, there is evidence that geographic proximity leads to a faster diffusion of knowledge (e.g., Jaffe, Trajtenberg, & Henderson, 1993) and that the costs of transmitting tacit knowledge rise sharply with geographical distance (Audretsch, 1998). Hence geographical proximity favors the flow of knowledge.

Arguably, the flow of knowledge between companies is, however, not only influenced by their geographical but also by their technological distance. Accordingly, the degree of technological specialization in a cluster should be of relevance for the intensity of technological spillovers, and several authors have studied the impact of technological specialization on the size of local knowledge spillovers.

One view of the topic was described as the Marshall-Arrow-Romer model by Glaeser, Kallal, Scheinkman, and Shleifer (1992). It is argued that technological specialization facilitates knowledge spillovers between firms of the same industry. The similarity of knowledge and activities promotes the learning effect between individuals and firms. Empirical support for these claims was given, for example, by van der Panne (2004). In a recent study Cantner and Graf (2004) provide further empirical evidence concerning specialization and cooperation. In their work, cooperation is measured in the way that the number of participating firms on assigned patents is counted. The authors find that technological moderately specialized

regions show the highest number of research cooperatives, and the higher a region's specialization, the more cooperatives are formed between partners outside that region. Taking cooperatives as a proxy for knowledge spillover, this result indicates that the exchange of knowledge is highest in a moderately specialized cluster.

By contrast, Jacobs (1969) argues that knowledge may spill over between complementary rather than similar industries. Ideas developed by one industry can be useful for other industries, and therefore technological diversity favors knowledge spillovers. According to Jacobs, a variety of industries within a cluster promotes knowledge externalities. The diversity thesis was also supported in empirical works (e.g., Feldman & Audretsch, 1999).

Although there is no complete consensus, there is some evidence that some technological specialization among firms of the same industry in a cluster has positive effects on spillovers. In this chapter we adopt this view, but also take into account that firms in a cluster are not only producers and receivers of knowledge flows, but also competitors in the market. Strong technological specialization within a cluster leads to little differentiation between the products of the cluster firms and hence to increased competition among them. This is particularly true if we think of clusters which primarily serve local markets, or industry-dominating clusters like the Silicon Valley. Hence the positive effect of intensive knowledge exchange in specialized clusters may be countered by negative competition effects. Competition considerations are also an important factor in determining which firms decide to enter a cluster in the first place. Knowledge spillovers always flow in two directions. Thus a firm cannot prevent knowledge from spilling over to possible competitors in the cluster. A firm inhabiting a particularly profitable market niche or enjoying

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