



Performance differentials within geographic clusters

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ABSTRACT

Increasing evidence indicates that firms benefit from a location in a geographic cluster of similar firms. The literature is nearly silent, however, on whether agglomeration economies accrue symmetrically across clustered firms. Drawing from the knowledge-based view, we investigate which firms benefit most from agglomeration and discuss how the implications for entrepreneurs are significant if some firms benefit more from geographic agglomeration than others. We investigate three particular firm attributes that may accentuate or mitigate benefits tied to participation in a cluster. We test our hypotheses on a sample of biotechnology firms and find strong evidence that firms benefit asymmetrically. Younger firms and firms with higher knowledge stocks benefit more from agglomeration.

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1. Executive summary

A large body of research shows that many firms are located close to their competitors, a fact reflected in well-known examples of regional concentrations of technology companies, such as semiconductor firms in Silicon Valley, biotechnology firms in the San Diego, California or Cambridge, England areas, and software firms in Bangalore, India. These clustered firms may benefit from agglomeration externalities that are created by spatial concentration of groups of related firms. Economies of agglomeration suggest that “the net benefits to being in a location together with other firms increase with the number of firms in the location” (Arthur, 1990:237), and these benefits may include greater access to specialized labor, specialized inputs, and knowledge spillovers.

The prevalence of this phenomenon has spurred a great deal of academic research linking firm performance to agglomeration. Increasing evidence indicates that, on average, firm performance improves with more agglomeration; however, it is not clear whether all firms benefit equally from their participation in a geographic cluster. That is, the literature is nearly silent on whether agglomeration economies accrue symmetrically across clustered firms. We believe there are several reasons why it is important to understand whether firms benefit equally from geographic agglomeration. First, the development of knowledge resources to support innovation is a critical factor in developing competitive advantage, especially in high-technology industries. Second, there are significant implications for entrepreneurs who seek to understand the causal relationship between their location decisions and firm performance. Third, the empirical record has not considered important firm characteristics that may moderate a firm's ability to benefit from clustering, and we believe that the inclusion of firm-level moderating effects may help to clarify the accumulating empirical evidence around the relationship between firm performance and agglomeration.

Like prior research, we expect that agglomeration benefits can be approximated by evidence that firms benefit more from participation in larger clusters and clusters with greater knowledge stocks. However, we contribute to the agglomeration literature by drawing from the knowledge-based view of the firm to argue that these effects will be moderated by firm-level attributes or capabilities associated with differential abilities to access and generate knowledge. For example, we expect that firms with higher absorptive capacity, younger age, and more strategic alliances will benefit more from agglomeration in building their combinative

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capabilities (Kogut and Zander, 1992). We anticipate that firms who have larger knowledge stocks will have higher absorptive capacity (Cohen and Levinthal, 1990) and be able to benefit more from clustering because of their superior ability to take in knowledge spillovers. We expect that firm alliances may also enhance a firm's combinative capabilities, creating higher marginal performance benefits from agglomeration. These alliances may also provide an effective means for firms to exploit the knowledge gained from proximate competitors (Grant and Baden-Fuller, 2004). Finally, we recognize that prior theorizing and commentary (e.g., Acs et al., 1994; Saxenian, 1994) argues that clustering is especially beneficial for younger firms who may be better able to take advantage of knowledge spillovers and who depend more critically on proximate resources. Thus, we investigate whether the relationship between clustering and patenting performance is stronger for more youthful firms.

Using a sample of United States biotechnology firms, we examine the impact of clustering on these firms' patenting performance during the period of 1973–1998. Patenting activity provides a good performance proxy in young industries in which sales and profits may not be generated for a significant time during firms' developmental stages. Furthermore, superior performance in high-technology industries, such as biotechnology, is strongly related to the firms' underlying knowledge.

Consistent with prior work, we find evidence of a link between agglomeration and firm performance. Specifically, we find that both larger cluster size and larger cluster knowledge stocks are associated with increased probability of patenting across our sample. We also find evidence that firms do not benefit equally from agglomeration. Firms with higher knowledge stocks, as reflected by their stock of prior patents, demonstrate a significantly stronger clustering-performance relationship. We also find that younger firms benefit more from agglomeration. We find no support for a stronger relationship for firms with larger numbers of alliances.

Our findings have implications for both research and practice. From a research perspective, they indicate that scholars should be aware of the need to consider additional measures of the richness of individual clusters beyond just the number of firms. Furthermore, they should consider potential moderators of this relationship, as it appears that particular firms may benefit more from clustering. This finding is of particular interest for a number of reasons. First, it points to the existence of asymmetries in the ability to develop knowledge-based competitive advantage through firm agglomeration. This competitive advantage will be particularly relevant in high-technology industries that require constant innovation to successfully compete. These findings also relate strongly to recent speculation about the potential for adverse selection in agglomerations (e.g., Shaver and Flyer, 2000). According to this view, those firms who are most likely to generate agglomeration externalities may want to avoid clustered locations because their relative advantage may suffer. Our results point to a countervailing force, namely that these very same firms may benefit more from clustering, raising the question of whether their relative advantage will in fact decline. From a practical perspective, our research informs both firm decision makers and policy makers. For those deciding whether to locate in an agglomeration or for those attempting to recruit firms to an agglomeration, it provides advice on those firms that are most likely to benefit.

2. Introduction

The last two decades have seen a marked increase in research concerning the geographic agglomeration of economic activity and the expectation that agglomeration improves firm performance through improved access to knowledge spillovers and specialized resources. These benefits have been championed by notable scholars such as Krugman (1991a,b), Saxenian (1994), and Porter (1998a,b). While there is empirical evidence that such performance benefits exist, in total, the evidence is somewhat inconsistent (Martin and Sunley, 2003). This is rather surprising given that agglomeration theory clearly advocates that “the net benefits to being in a location together with other firms increases with the number of firms in the location” (Arthur, 1990). We wonder, however, whether this paradox is at least partly attributable to the implicit assumption that *all firms benefit symmetrically from agglomeration*. It seems reasonable that some firms might have unique characteristics that enable them to obtain greater benefits from knowledge spillovers or specialized inputs.

Our expectation of heterogeneous clustering benefits rests upon the knowledge-based view (KBV) of the firm (Kogut and Zander, 1992, 1996; Grant, 1996). The KBV sees knowledge as the most strategically important resource of the firm and argues that managers must frequently adapt their knowledge base to keep pace with dynamic environments (Grant, 1996). Most importantly, this view suggests that the key to generating competitive advantage is *differential* abilities to access and generate knowledge both from internal and external sources. For clustered firms, one key external source is the pool of knowledge spillovers generated by co-located competitors, suppliers, and supporting institutions. If firms have differential ability to benefit from these spillovers, there are significant implications for firm performance inside of clusters.

We theoretically and empirically consider whether firm-level factors identified as critical by the KBV literature influence how firms benefit from knowledge spillovers. Our hypotheses build upon three firm characteristics that underlie firms' combinative capabilities (Kogut and Zander, 1992): knowledge stocks, alliance experience, and firm age. We argue that these characteristics influence the firm's learning ability and organizing principles and will therefore moderate the benefits to agglomerating near similar firms. By investigating these moderating influences, we contribute to agglomeration theory with our consideration of how firms might asymmetrically benefit from agglomeration. In particular, we extend prior literature drawing from the KBV that examines the *main* effects of cluster strength on performance (e.g., DeCarolis and Deeds, 1999). Our research also complements recent literature that has implicitly argued such moderating relationships might exist (e.g., Acs et al., 1994; Shaver and Flyer, 2000). Moreover, it contributes to recent studies that consider when newness might actually be an advantage to firms rather than a liability (e.g., Autio et al., 2000; Choi and Shepherd, 2005). Finally, it augments work that has examined the factors that moderate knowledge spillovers (Rosenkopf and Almeida, 2003) but has not linked such spillovers to firm-level generation of patents. We

contend that consideration of firm-level factors that may moderate the benefits to agglomeration can add clarity to the empirical record on the benefits of clustering.

We follow a research tradition that tests whether firm performance improves with the size or the capacity of high-technology clusters in such industries as biotechnology, medical devices, and semi-conductors, among others. Of course, an emphasis on high technology is not necessary because it is well-known that clusters are robust to other contexts, such as manufacturing (Shaver and Flyer, 2000), footwear production (Sorenson and Audia, 2000), and garment production (Visser, 1999). Nevertheless, our emphasis on heterogeneous benefits in high-technology clusters is particularly interesting because knowledge spillovers are regarded as a principal benefit, and competitive advantage in these industries is partially determined by firms' abilities to absorb and apply knowledge from their external environments. We use a sample of biotechnology firms to investigate whether firm-level attributes moderate the performance effects from location in an agglomeration of similar firms.

This issue should be of principal importance to scholars of entrepreneurship or strategic management wondering about the relationship between location and competitive advantage. This research may provide insight for firms trying to decide whether clustering makes sense given their unique firm profile. For firms that have decided to cluster, it helps inform them as to which clusters might be the most advantageous. Policy makers attempting to increase economic development through clustering strategies will also find value in this work as it may help them in trying to decide the best types of firms to target for attraction.

3. Theoretical background

Geographic agglomerations have been recognized as an important characteristic of the industrial landscape since at least the time of Alfred Marshall, who described them as an “industry concentrated in certain localities” (Marshall, 1920: 268). In general, agglomeration refers to the geographic concentration of companies within certain industries. In some cases, the particular geographical or climatic characteristics of an area provide an easy explanation for the concentration of similar firms. Indeed, Marshall (1920) posits that unique physical conditions, such as a grouping of firms around a limited natural resource, are the chief cause for the localization of industries. Unique geographical features do not explain the presence of all agglomerations. In fact, Ellison and Glaeser (1999) found identifiable natural advantages present in only 20% of the clusters they studied. The remaining 80% received some agglomeration benefits distinct from any quality of the particular geographical location.

The popularity of the term “cluster” to describe the agglomeration phenomenon is a relatively recent development most often associated with the work of Michael Porter. Porter (1998a) describes clusters as a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities. Geographic proximity and interconnections create agglomeration externalities such that the net benefits to locating with similar firms increase as the number of firms in the location grows. The act of grouping together serves to create externalities that all firms within the cluster might enjoy. Marshall (1920) described three important types of agglomeration externalities in clusters of similar firms: (i) access to specialized labor, (ii) access to specialized inputs, and (iii) access to knowledge spillovers.² As a cluster grows, these benefits are thought to grow as well. As these arguments have been articulated before, we only briefly review them here.

Krugman (1991a) observes that clusters create a pooled market for *specialized* workers, benefiting both hiring firms and workers. A larger market serves to reduce risk for specialized workers able to attain work from multiple employers, while also benefitting employers by reducing the risk premium and search cost components of workers' wages (David and Rosenbloom, 1990). Specialized laborers may also be more willing to invest in industry-specific human capital when they believe they have a greater ability to appropriate the benefits (Rotemberg and Saloner, 1990), a condition more likely to occur when there are multiple firms pursuing the services of similar laborers.³ Many of the same reasons that clustered firms have improved access to specialized laborers also create improved access to specialized suppliers, such as universities, distributors, consulting, market research, testing services, and even specialized angel investors or venture capitalists (Folta et al., 2006). Reduced transportation costs and the potential for gaining economies of scale also provide explanations for the clustering of producers and users of intermediate inputs (Krugman, 1991b).

Improved access to knowledge spillovers is a final way firms might benefit from larger clusters. This benefit is thought to be particularly pertinent for firms competing in industries where knowledge is the basis for any competitive advantage. Jaffe, Trajtenberg, and Henderson (1993) found evidence that geographic proximity is linked to the transfer of knowledge by observing a relationship between the place of patenting and the citation of that patent. Geographic proximity might facilitate the transfer of tacit knowledge because it increases the likelihood of face-to-face contact, which is a particularly efficient medium for the transfer of such knowledge (Daft and Lengel, 1986). It might also facilitate the transfer of tacit knowledge through formal means such as licensing, technology partnerships, strategic alliances, and supply contracts, or via informal means such as social networks that might serve as a medium to transfer information, expertise, workers, and contacts (Pouder and St. John, 1996; Almeida and Kogut, 1997). DeCarolis and Deeds (1999: 956) noted that, “social interactions, both formally and informally, stimulate information exchange about such topics as competitor's plans, developments in production technology, and recent developments with the local

² Marshall also observed that firms may benefit from increased demand created by the agglomeration. This demand-related externality is particularly relevant in cases where consumers physically visit the firms to inspect the firm's products prior to purchase. In our empirical context, this externality is not a relevant force.

³ Higher levels of human capital investment are consistent with the findings of Henderson (1986) and Ciccone and Hall (1996), who found support for an association between spatial concentration and labor productivity.

university's labs." These interactions can occur through employees' joining community groups, residing in the same neighborhoods (Yates, 1983), and participating in local industry events (Saxenian, 1990; Almeida and Kogut, 1999).

In general, the reviewed theory in agglomeration research is uncontroversial in its tenor — externalities available to clustered firms increase with the size of a cluster. Nevertheless, the literature is relatively silent on whether these externalities accrue symmetrically to all clustered firms. This silence is particularly concerning given the knowledge-based view's (e.g., Kogut and Zander, 1992, 1996; Grant, 1996) clear suggestion that firms have differential abilities to generate knowledge from external sources.

The knowledge-based-view considers knowledge as the firm's most significant strategic resource (Grant, 1996), and its proponents argue that heterogeneous knowledge bases are the main determinants of sustained competitive advantage and superior performance (DeCarolis and Deeds, 1999; Winter and Szulanski, 1999). Knowledge-based resources are particularly difficult to imitate because they often rest on a foundation of causal ambiguity, especially when the resource consists, at least in part, on tacit knowledge. The accumulation of knowledge can be a path dependent and socially complex process as well, making imitation difficult. Overall, the ability of the firm to create and sustain a competitive advantage is critically dependent on its ability to generate knowledge according to the KBV.

The knowledge-based view is particularly relevant to agglomeration research given the importance of knowledge spillovers as an explanation for clustering benefits in high-tech industries. To the extent that competition is becoming more knowledge-based, especially in high-tech industries and advanced economies, knowledge acquisition and management become increasingly critical. These environments also require firms to extend their knowledge generation activities beyond firm borders to access external knowledge, a fact emphasized by Tripsas (1997) with her findings that firms' abilities to adapt their knowledge base in the face of radical technical change depended upon their capability to access and integrate external knowledge. One key source of potential external knowledge is knowledge spillovers generated within a cluster, as prior research indicates an association between spatial proximity and knowledge transfer. Most importantly, for our purposes, the KBV suggests that competitive advantage flows from differences in ability to generate knowledge from internal and external sources.

While agglomeration research has yet to reflect a focus on asymmetric benefits as suggested by the KBV, many studies have investigated agglomeration benefits in general. Below, we review the empirical literature examining the relationship between cluster size and firm performance. Despite agglomeration theory's clear expectation that geographic co-location increases performance, the empirical record is decidedly controversial.

3.1. Empirical evidence of clustering benefits

Prior empirical studies of agglomeration can be roughly grouped into two categories. The first group examines whether industrial activity exhibits clustering tendencies. The evidence is overwhelming that it does, even in the absence of some exogenous factor that might otherwise drive the spatial concentration (such as the presence of a unique natural resource).

The second group of work is more to the heart of our current study. It focuses on how agglomeration bears upon firm performance. The record here is not nearly as deep or coherent. A number of studies do support a positive relationship. In a study of United Kingdom manufacturing firms, Beaudry and Swann (2001) noted a positive association between firm growth and total employment within the cluster in the firm's own industry. DeCarolis and Deeds (1999) demonstrated a positive relationship between US biotechnology firms' IPO valuations and a measure of the richness of the firms' locations, where the measure of richness included factors such as the proportion of similar firms, high-tech employees, National Institute of Health grants, and number of related educational institutions in the same Metropolitan Statistical Area as the firm. Folta et al. (2006) also found that US biotechnology companies in larger clusters had higher rates of attracting alliance and private equity partners. The record also provides some support for the role of clusters in fostering knowledge-based outcomes. Baptista and Swann (1998) found that UK manufacturing firms were considerably more likely to innovate if own-sector employment in its home region was strong (and found no effect of strong employment in other industries) while Folta et al. (2006) found higher rates of patenting for clustered US biotechnology companies.

This literature on the relationship between agglomeration and performance is closely related to a second body of work to which we have already referred — the role of geography on the transfer of knowledge across boundaries. It has not only yielded support for the idea that knowledge spillovers are geographically bounded, but it is suggestive that firms differ in their ability to tap this knowledge. For example, like Jaffe et al. (1993), Rosenkopf and Almeida (2003) noted a positive relationship between geographic proximity and knowledge flows between firms as revealed by patent citation data. Moreover, they hypothesized that employee mobility and strategic alliances might moderate the relationship between geographic proximity and knowledge flows between firms. They found that while employee mobility enhanced knowledge flows, strategic alliances did not. Acs, Audretsch, and Feldman (1994) found that product innovations were also correlated with geographically proximate knowledge. They also found that this effect was more pronounced for small firm innovation than for large firm innovation, presumably because small firms were less able to tap into resources outside their location, or because their birth was more dependent upon proximate capabilities.

The empirical record also indicates, however, that clustering may not have a uniformly positive influence. For example, Folta et al. (2006) found no association between the size of clusters and rates of initial public offering for biotech firms, and Martin and Sunley (2003: 22) note that evidence of a positive association between clustering and innovation is not consistent. Moreover, studies such as Folta et al. (2006) have also found that firms located within clusters have *higher* failure rates. Similarly, Staber (2001) found higher failure rates for German knitwear firms as higher numbers of similar firms were located within a 10 km radius. Shaver and Flyer (2000) also discovered higher failure rates for greenfield manufacturer entrants to manufacturing clusters in the United States. They further observed that larger entrants were less likely to cluster and theorized that

these “strong” firms would increasingly opt out of larger clusters because, relative to “weak” firms, they have more technology to lose via spillovers.

In summary, there are several important features of empirical work to this point. First, the record is not uniformly coherent around the fundamental premise of agglomeration theory — that organizational performance increases with cluster size. Second, this work has not examined whether there are factors that may mitigate the relationship between cluster size and firm performance. This is surprising given that some work is suggestive that knowledge flows may be contingent upon firm characteristics, such as firm size or alliance activity. In the next section, we hypothesize about firm-level characteristics that may moderate the benefits firms accrue due to their agglomeration with other similar firms, drawing from the knowledge-based view of the firm.

4. Hypotheses

Our focus on cluster size and firm performance invites consideration of what is meant by “larger clusters” and by “higher performance” because these constructs are likely to have different meanings across different contexts. Given our focus on high-technology firms, we use patent production to approximate firm performance. It is obvious to consider a firm's production and protection of knowledge as being a pertinent performance indicator in many of the high-technology industries that typically form clusters. Many firms are young or small and may not generate sales and profits for significant periods of time, making alternative proxies less applicable. Even if such proxies were available, the link between competitive advantage and superior performance in the biotechnology industry is strongly dependent on knowledge and ideas. For example, Calabrese, Baum, and Silverman (2000) found that patenting activity significantly affected the rate of firm births in the Canadian biotechnology industry. Patents provide an indication of a firm's underlying knowledge stocks that may eventually be converted into final products. They also reflect the firm's ability to protect that developed knowledge from expropriation. Finally, the accumulation of patents can send a signal to potential partners regarding the strength of the firm, allowing the firm to attract more resources that help foster their growth. Overall, the ability to generate patents is a significant indicator of performance for these firms. Consequently, we follow precedent (e.g., Calabrese et al., 2000; Folta et al., 2006) by using a firm's patent production as our measure of high-technology firm performance. We also acknowledge that a number of authors have argued that relationships such as the ones we study might be affected by spatial selection effects driven by non-random firm location decisions. We address this potential alternative explanation in our results section, ultimately concluding that selection effects do not appear to be driving our results.

We have already articulated the uncontroversial expectation that larger clusters will produce greater externalities and, as a result, greater firm patenting performance. While supported in prior work (e.g., Beaudry and Breschi, 2003; Folta et al., 2006), we repeat it here because our subsequent hypotheses build from it.

Hypothesis 1a. *There will be a positive relationship between the total number of firms in a cluster (cluster size) and firm patenting performance.*

Given our focus on firms' ability to build competitive advantage by generating knowledge from external sources, we introduce an alternative measure of the extent of agglomeration. We believe an important indicator of the potential for knowledge spillover externalities in high-technology clusters is not merely the number of firms in the cluster, but the relative stock of patents in a geographic region. Consider two separate clusters (A and B) with the same number of firms. If cluster A is populated by firms having 250 patents while cluster B is populated by firms having 100 patents, it seems reasonable to argue that cluster A appears to have a greater stock of knowledge that might spill over between the firms. This expectation is consistent with findings from Beaudry and Breschi (2003) who found an association between cluster-level stock of knowledge and level of patenting in a sample of United Kingdom and Italian firms. They found that employment levels within similar firms in the cluster had no effect on performance, while employment levels within innovative firms in the cluster had a positive effect on patenting. Thus, we expect that greater levels of knowledge richness within clusters are associated with more firm patenting.

Hypothesis 1b. *There will be a positive relationship between the total number of patents in a cluster (cluster patents) and firm patenting performance.*

Subsequent hypotheses will adopt both the region's number of firms (cluster size) and the region's number of patents (cluster patents) as approximations for the theoretical construct, the extent of agglomeration in a region.

4.1. Within-cluster heterogeneity

The central theme of this research is that firm differences create varying capacities to draw benefits from agglomeration externalities. To motivate hypotheses around this theme we draw on the knowledge-based view of the firm (e.g., Kogut and Zander, 1992), which clearly suggests that firms might have differential abilities to generate knowledge. Research in the KBV tradition not only identifies the characteristics that impede knowledge replication by competitors that might erode a market position, but also those that spur knowledge creation and replication by a firm's own members so as to speed its rate of growth. This emphasis on knowledge creation and replication is particularly pertinent to the study of high-technology agglomeration because of the expectation that firms will benefit from knowledge spillovers. If firms have differential ability to benefit from spillovers, there are significant implications for firm performance inside of clusters.

To guide the development of our hypotheses, we build on the role of the firm's "combinative capability" (Kogut and Zander, 1992). Combinative capabilities are the intersection of the capability of a firm to exploit its knowledge and the unexplored potential of its technology, and they serve to generate new applications from existing knowledge. It is argued that they are a function of its internal learning (e.g., reorganizing, accidents, experiments), its external learning (e.g., acquisitions, alliances, new people), and its organizing principles (Kogut and Zander, 1992). Our hypotheses build upon three firm characteristics that relate to learning capability and organizing principles: knowledge stocks, alliance experience, and firm age. Although we fully expect that these factors will individually have main effects on firms' production of knowledge consistent with prior KBV work, we focus here on how these factors might moderate the relationship between agglomeration and knowledge generation. Not only do these characteristics coincide with our theoretical development, but they are among the most frequently examined characteristics in the organizational learning literature, one of the foundations of the knowledge-based view (Eisenhardt and Santos, 2002).

4.1.1. Learning capability

According to the knowledge-based view, a firm's existing knowledge stock will largely determine the growth of its future knowledge. This is because combinative capabilities cannot be abstracted from current abilities (Kogut and Zander, 1992). Absorptive capacity (Cohen and Levinthal, 1990) is a concept related to combinative capabilities, and it emphasizes even more the extent to which prior related knowledge guides the direction and the rate of growth of a firm's future knowledge. We expect that firms with higher stocks of knowledge should have higher combinative capability or absorptive capacity and be able to benefit more from available knowledge spillovers. A number of researchers have found evidence supporting this view. For example, Pisano (1991) reported that firms with expertise in a particular research domain display higher absorption levels from external knowledge sources. Ahuja and Katila (2001) found higher post-acquisition innovation rates when acquirors had a knowledge base more similar to that of the acquiree.⁴ In a study of business units within two large multinational corporations, Tsai (2001) reported an association between absorptive capacity, as measured by the units' intensity of R&D spending, and innovation rates. Finally, consistent with a view of absorptive capacity providing firms greater ability to benefit from external knowledge, Dushnitsky and Lenox (2005) found that of U.S. public firms that invested in corporate venture capital initiatives in the 1990s, those with higher levels of absorptive capacity (as measured by patent stock and technological proximity) tended to invest greater amounts. Overall, we expect that firms with higher levels of combinative capability or absorptive capacity, as reflected in larger patent stocks held by the firm, would have higher levels of prior related knowledge and would be better able to absorb and benefit from knowledge spillovers.

Hypothesis 2a. *The relationship between cluster size and firm patenting performance will be accentuated for firms with larger stocks of patents.*

Hypothesis 2b. *The relationship between cluster patents and firm patenting performance will be accentuated for firms with larger stocks of patents.*

Strategic alliances represent another important external source of knowledge contributing to a firm's combinative capability (Kogut and Zander, 1992). Organizational learning is often cited as one the key motives for entering into alliance relationships (Kogut, 1988), and there is a wealth of literature that identifies the sharing of knowledge as a dominant objective in alliance formation (e.g., Inkpen and Crossan, 1995; Mowery et al., 1996; Khanna et al., 1998; Dyer and Nobeoka, 2000; Kale et al., 2000). While alliances may not always be initiated for the purposes of organizational learning, in certain contexts, such as biotechnology, this assumption is more reasonable because alliances can overcome the limits of firms in encompassing highly differentiated knowledge integration processes (Powell et al., 1996).

In addition to their *direct* role as a source of external knowledge, alliances can also enhance the firm's ability to benefit from other knowledge sources. First, firms having initiated more prior alliances should have higher absorptive capacity leading to higher combinative capability because they have been more exposed to learning opportunities and will have had the opportunity to refine their skills at extracting knowledge from their partnerships. Second, Grant and Baden-Fuller (2004) argue that alliances facilitate the *exploitation* of knowledge gained from other sources by allowing the firm to access partner stocks of knowledge in order to exploit complementarities. They contend that this facilitation function (which they label "knowledge accessing") is the predominant motive for alliance formation, especially within knowledge-based industries. As a result, we expect firms with more alliances will have higher combinative capability and will benefit more from the knowledge spillovers available in agglomerations.

Hypothesis 3a. *The relationship between cluster size and firm patenting performance will be accentuated for firms with more alliance experience.*

Hypothesis 3b. *The relationship between cluster patents and firm patenting performance will be accentuated for firms with more alliance experience.*

We note that there may be an alternative hypothesis around alliances. Alliances may (at least partially) substitute for face-to-face communication as a means for knowledge transfer, which reduces the benefits to geographic clustering. Knowledge sourced through alliances and knowledge spillovers available within a cluster may serve as partial substitutes because they may generate

⁴ The authors found a U-shaped relationship indicating that as the two parties' knowledge bases approached total overlap, little innovation-related benefit flowed from the acquisition.

redundant information. That is, with knowledge transfer occurring through formal alliance channels, knowledge sourced from the informal channels fostered by clustering is more likely to include some redundant information and therefore provide lower marginal benefit. This view is consistent with Singh (2005) who found that geographic co-location had little additional effect on the probability of knowledge flows between inventors who already had close network ties.

4.1.2. Organizing principles

Kogut and Zander (1992) argue that as firms age, they must develop organizing principles to replace individual skills of the entrepreneur in order to maintain their combinative capabilities. These higher-order principles represent the firm's ability to coordinate internal groups and transfer knowledge among them. Organizing principles are an example of what Cyert and March (1963) refer to as *organizational routines*. They are necessary to improve information flow and are particularly important in socially complex organizations. The maturing firm needs a “widely-held and shared code by which to orchestrate *large numbers of people*, and potentially, varied functions” [emphasis added] (Kogut and Zander, 1992, p. 390). Thus, older and larger firms' ability to take advantage of external knowledge spillovers will be constrained by the level of development of their organizing principles.

It is an obvious extension to consider that small and young firms are in less need of organizing principles because information flows more freely than in older, larger organizations. Henderson and Clark (1990) have noted that younger firms may be more innovative because new knowledge need not pass through organizational routines and structures that are not well-suited for that purpose. Even if organizing principles or routines were equally necessary regardless of firm age, the nature of organizing principles likely differs. Young firms are likely to be more flexible than old organizations in adopting new routines (Hannan and Freeman, 1984), which may be a critical to continue to generate knowledge in dynamic environments. Newness can be related to strategic flexibility and enhance learning capacity in new areas (Autio et al., 2000; Sorenson and Stuart, 2000; Choi and Shepherd, 2005; Katila and Shane, 2005). As indirect evidence that younger firms absorb more knowledge in clusters, Saxenian (1994) argues one of the potential reasons for the success of the Silicon Valley area relative to the Route 128 area in Boston was the presence of larger numbers of young flexible firms in Silicon Valley while Route 128 institutions were more rigid and hierarchical. Thus, we believe that knowledge spillovers will be more efficiently transferred into younger firms. Since larger and more knowledge-rich clusters are expected to have more knowledge spillovers, the marginal benefits to younger firms should be higher.

Hypothesis 4a. *The relationship between cluster size and firm patenting performance will be mitigated by firm age.*

Hypothesis 4b. *The relationship between cluster patents and firm patenting performance will be mitigated by firm age.*

5. Methods

5.1. Sample

The sample consists of 806 biotechnology firms founded in the United States between 1973 and 1998. With its broad coverage of the biotechnology industry, BioScan was the main source for identifying firms. Because it was only first published in 1987, we also searched Lexis/Nexis for company registration filings with the Securities and Exchange Commission. We augmented these data sources with information from Dow Jones Interactive where necessary to determine firm founding dates, alliance activity, and involvement in industry sectors from firm founding to exit (through either liquidation or acquisition) or to the end of 1998. The U.S. Patent database provided data on the patenting activity of each firm.

Determining a method for identifying clusters is not an uncontroversial task. A number of researchers have defined clusters at a broad geographic level such as a U.S. state (e.g., Audretsch and Feldman, 1996; Prevezer, 1997; Shaver and Flyer, 2000) while others have selected a narrower scope such as the Metropolitan Statistical Area (MSA) (e.g., DeCarolis and Deeds, 1999; Folta et al., 2006) or the Bureau of Economic Analysis Functional Economic Area (Zucker et al., 1998). The essential question in defining cluster boundaries is over how far of a distance will the benefits of specialized labor, inputs, and knowledge spillovers extend. Porter (2000: 16) echoes this approach noting that “the geographic scope of a cluster relates to the distance over which informational, transactional, incentive, and other efficiencies occur.” We anticipate that the costs and benefits of clustering will be more associated with metropolitan areas rather than states so we elect to define cluster boundaries at the MSA level. This approach allows multiple clusters to exist within a state. Moreover, a focus on the MSA is more consistent with empirical evidence that has revealed that the effects of knowledge spillovers seem stronger over shorter geographic distances. For example, Jaffe et al. (1993) found evidence of localization of knowledge spillovers at both the state and Metropolitan Statistical Area levels, with the effects being stronger at the MSA level. We assigned firms to MSA based on the location of the firms' headquarters determined by zip code. We identified location in all but 17 cases, reducing our sample to 789 firms; exclusion of firms with missing data resulted in a final sample of 783 firms. The sample includes both private and public firms. The top ten clusters as of 1994, roughly the peak of the industry in terms of the number of firms, account for nearly 75% of the firms in the industry and are comparable to the biotechnology clusters identified by Burrill and Lee (1993) and used by DeCarolis and Deeds (1999).

5.2. Dependent variable and model specification

As noted earlier, we focus on a firm's ability to produce and protect knowledge as our response variable. Our dependent variable is a dichotomous variable coded “1” if the firm applied in a given year for a patent that was eventually granted, and “0”

otherwise.⁵ We elect to use the year of application rather than the grant year because the time of application more closely matches the time at which the knowledge was produced. Substantial delays can occur between application and grant. For example, Gans, Hsu and Stern (2008) report an average delay of just over 39 months from application to grant in the biotechnology industry. Popp, Juhl and Johnson (2004) report a similar lag of approximately 44 months for biotechnology patents. Over the approximately 24 years of the sample, firms in the sample generated over 5500 successful patent applications.

With a binary dependent variable, we elected to use logistic regression to test our hypotheses. The logistic regression model has the following form: $P(y_i = 1 | x_i) = \frac{\exp(x_i\beta)}{1 + \exp(x_i\beta)}$, in which x_i is a vector of independent and control variables described below. As indicated below, we considered and tested alternative empirical specifications of our theoretical model, but our results were robust to these alternatives.

5.3. Independent variables

Our hypotheses encompass two measures of cluster characteristics. First, we measure *Cluster Size* simply as the number of biotechnology firms located within the focal firm's MSA. Cluster size increases as new firms open within the MSA and decreases as firms liquidate or are acquired. The sample covers 85 MSAs, and cluster size ranges from 1 to 100 firms. Our second cluster characteristic measures the knowledge stock within the cluster. *Cluster Patents* is the natural log of the cumulative sum of patents held by all firms in the cluster, excluding those held by the focal firm. Prior to taking the log of these values, a constant of one is added to all values to avoid undefined transformations.

Our theory also considers three dimensions of potential heterogeneity among clustered firms: firm patenting activity, firm alliance activity, and firm age. A firm's knowledge stock (*Firm Patent Stock*) is measured with a logged sum of the total number of successful patent applications by the firm since its inception. Our use of patent stock as an indication of absorptive capacity is consistent with a number of prior studies in the absorptive capacity literature (e.g., Ahuja and Katila, 2001; Dushnitsky and Lenox, 2005, 2006; Penner-Hahn and Shaver, 2005; Wahdwa and Kotha, 2006).⁶ A firm's cumulative alliance stock (*Firm Alliance Stock*) is measured by logging the sum of the total number of alliances the firm has entered since its founding.⁷ *Firm Age* is measured as the number of years since the firm's founding. All independent variables were lagged one period.

5.4. Control variables

We include a number of control variables to account for other factors related to the cluster, the timing, and the firm that might provide alternative explanations for increased patenting by firms. Some authors (e.g., Pouder and St. John, 1996) have argued that the benefits of clustering might vary over the life cycle of the cluster, so we include *Cluster Age*, measured as the number of years since the first firm was founded in the MSA. The ability to produce knowledge may also be due to the availability of capital, which in the case of private equity, has been shown to be geographically bounded (Sorenson and Stuart, 2001). To capture the general availability of capital within a cluster, we include measures of the cumulative dollars raised by public offerings (*Cluster Public Offering Dollars*) within the cluster and the cumulative number of private placement events (*Cluster Private Placements*).

To control for time-specific macroeconomic and industry effects, we include year dummies in all specifications. The time dummies will capture any yearly variations in industry-level trends including factors such as overall industry size, total industry patenting rates, and total industry alliances. Firm-level controls include cumulative counts of both public and private offerings by the firm (*Firm Public Offerings* and *Firm Private Placements*) to account for firms that may have greater financial ability to engage in subsequent patenting, and dummy variables to indicate when firms were active in particular biotechnology sectors (*Therapeutic Sector*, *Diagnostic Sector*, *Ag-Bio Sector*, and *Other Sector*). Table 1 presents descriptive statistics for all independent variables.⁸

6. Results

6.1. Univariate analysis

It is illuminating to examine some descriptive statistics. Table 2 investigates the proportion of firms who engage in patenting activity in different cluster environments. In panel A, we split the sample based on low/high values of *Cluster Size* and in panel B,

⁵ As a first step, we are interested in whether our independent variables affect the dichotomous outcome of patenting versus not patenting. Robustness checks investigate whether these same independent variables affect the number of patents the firm generates.

⁶ One potential criticism of our measure of patent stock is that it has not been adjusted for size, as has been done in some studies. Data on employees, sales, and assets were unavailable for periods when firms were not public. We note, however, that our models include control variables for numerous factors that should be correlated to size, including age and access to private and public equity. The inclusion of these size-related variables mitigates the concern for a size-adjusted measure of absorptive capacity.

⁷ Again, we add a value of one to cumulative firm patents and alliances prior to log transforming.

⁸ Table 1 indicates that a number of our independent variables have relatively high correlations raising a potential concern of multicollinearity. Severe multicollinearity can lead to inflated standard errors, and inflated standard errors may lead to conclusions of insignificance in hypothesis testing. We calculated variance inflation factors for all of the coefficients involved in the hypotheses tests – in no case did any of the variance inflation factors exceed a value of 10, a standard critical value (Myers, 1990; Chatterjee and Price, 1991; Stevens, 2002). We also checked whether our coefficient estimates demonstrated instability across different random sub-samples and found no evidence of serious instability. Overall, it does not appear that multicollinearity materially affects the conclusions of our analysis.

Table 1

Descriptive statistics.

	Descriptive statistics				Correlation coefficients												
	Mean	Std. dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Cluster Size	34.37	29.56	1	100.00													
2 Cluster Patents	3.23	2.25	0	6.86	0.90												
3 Firm Patent Stock (log)	0.50	0.93	0	5.83	0.21	0.23											
4 Firm Alliance Stock (log)	0.65	0.98	0	4.56	0.22	0.27	0.58										
5 Firm Age	6.37	4.38	0	23.00	0.07	0.11	0.36	0.34									
6 Cluster Age	14.19	5.59	1	23.00	0.69	0.76	0.24	0.31	0.40								
7 Cluster Private Placements	32.15	42.30	0	179.00	0.80	0.78	0.25	0.29	0.19	0.72							
8 Cluster Public Offering Dollars	326.92	482.56	0	1795.00	0.80	0.74	0.24	0.27	0.18	0.68	0.93						
9 Firm Public Offerings	6.43	23.28	0	368.23	0.17	0.20	0.49	0.54	0.22	0.20	0.24	0.26					
10 Firm Private Placements	0.70	1.62	0	19.00	0.19	0.25	0.47	0.66	0.25	0.27	0.32	0.27	0.46				
11 Therapeutic Sector	0.48	0.50	0	1.00	0.19	0.21	0.13	0.27	−0.08	0.17	0.19	0.18	0.18	0.25			
12 Diagnostic Sector	0.47	0.50	0	1.00	−0.09	−0.08	0.01	0.03	0.07	−0.09	−0.11	−0.10	−0.02	−0.03	−0.09		
13 Ag-Bio Sector	0.23	0.42	0	1.00	−0.11	−0.15	0.10	0.18	0.10	−0.13	−0.14	−0.13	0.06	0.14	−0.02	0.06	
14 Other Sector	0.65	0.48	0	1.00	0.02	0.02	0.00	0.03	0.00	−0.01	0.00	−0.01	0.00	0.01	−0.12	−0.09	−0.04

Notes: $n = 7265$; correlations in excess of 0.025 are significant at the $p < 0.05$ level.

we split the sample based on low/high values of *Cluster Patents*. The panels denote the average proportion of firms patenting in each split of the sample. Consistent with the logic of the first two hypotheses, we see that firms in both larger and more knowledge-rich clusters have a higher probability of patenting in any given year. This univariate analysis reveals that in large clusters the proportion of biotechnology firms that engage in patenting activity is nearly double that of the proportion in small clusters. Firms in patent-rich clusters appear to enjoy a similar advantage over their counterparts in knowledge-poor clusters.

Table 3 allows a focus on how our firm-level variables relate to both *Cluster Size* (panel A) and *Cluster Patents* (panel B). In panel A, we split the sample by low/high values of *Firm Patent Stock*, *Firm Alliance Stock*, and *Firm Age* and show how the average probability of patenting differs for the whole sample regardless of cluster size (column 1) and across clusters of various sizes (columns 2–5). We note, for example, that the average probability of patenting increases from 0.05 for firms with no patents to 0.55 for firms with at least one prior patent. Moreover, as clusters increase in size, the relative advantage for “high” patent firms tends to increase (i.e., the difference increases from 0.31 to 0.59). This pattern supports our expectation in Hypothesis 2 for a stronger relationship between cluster size and patenting propensity for high-patent-stock firms. We see a similar pattern of findings for splits involving *Firm Alliance Stock* and *Firm Age*. In the case of alliances, the pattern is consistent with our prediction that alliance activity enhances the benefits of clustering; however, the results for firm age are opposite our expectations in Hypothesis 4: the relationship between cluster size and patenting productivity is accentuated for older firms. Examination of panel B reveals the same general pattern of findings as in panel A. Any conclusions based on these univariate statistics should remain tentative, as they do not control for possible relationships among the variables. For example, the contrary results for firm age might be influenced by the fact that younger firms tend to have fewer patents. To examine the nature of these relationships in a multivariate setting, we move on to the main part of the analysis.

Table 2

Univariate analysis comparing the probability of patenting across larger and smaller clusters.

Cluster dimension	Pr(patent)
<i>Panel A</i>	
Low Cluster Size	0.12
High Cluster Size	0.24
Difference	0.12
Z	13.63
p-value	<0.001
<i>Panel B</i>	
Low Cluster Patents	0.14
High Cluster Patents	0.25
Difference	0.12
Z	12.67
p-value	<0.001

Note: Low vs. high determined by above or below median value.

Table 3

Univariate analysis comparing the probability of patenting across larger and smaller clusters for different firm-level characteristics.

Firm dimension	Cluster Size (# of firms)				
	(1) Overall	(2) <5	(3) 5–24	(4) 24–61	(5) 61+
<i>Panel A</i>					
Firm Patent Stock					
Firm Patent Stock = 0	0.05	0.03	0.04	0.07	0.04
Firm Patent Stock > 0	0.55	0.34	0.52	0.59	0.63
Difference	0.50	0.31	0.47	0.52	0.59
Firm Alliance Stock					
Firm Alliance Stock = 0	0.09	0.07	0.06	0.11	0.11
Firm Alliance Stock > 0	0.36	0.19	0.32	0.39	0.43
Difference	0.27	0.12	0.26	0.28	0.31
Firm Age					
Firms below median age (<5)	0.11	0.06	0.09	0.14	0.13
Firms above median age (>5)	0.24	0.12	0.20	0.28	0.35
Difference	0.14	0.06	0.11	0.13	0.22
Firm dimension	Cluster Patents (# of patents)				
	(1) Overall	(2) <1	(3) 1–41	(4) 41–185	(5) 185+
<i>Panel B</i>					
Firm Patent Stock					
Firm Patent Stock = 0	0.05	0.04	0.05	0.06	0.05
Firm Patent Stock > 0	0.55	0.30	0.56	0.56	0.64
Difference	0.50	0.26	0.50	0.49	0.59
Firm Alliance Stock					
Firm Alliance Stock = 0	0.09	0.07	0.08	0.11	0.11
Firm Alliance Stock > 0	0.36	0.14	0.36	0.36	0.42
Difference	0.27	0.06	0.29	0.26	0.31
Firm Age					
Firms below median age (<5)	0.11	0.07	0.13	0.14	0.16
Firms above median age (>5)	0.24	0.09	0.22	0.26	0.35
Difference	0.14	0.02	0.09	0.11	0.20

Notes: Cluster size and cluster patent stock categories each established to create four equal size groups (divided at 25th, 50th, and 75th percentiles). All differences in bold are significant at $p < 0.05$ level.

6.2. Multivariate analysis

6.2.1. Agglomeration externalities

Table 4 includes analysis involving multivariate logistic regression on the probability of a firm filing a patent application in any given year. Because we have multiple observations for each firm, we utilize robust standard errors, clustered to adjust for intrafirm correlation. Model 1 is a base model including only control variables. In Models 2 and 3, we incrementally introduce the variables *Cluster Size* and *Cluster Patents*, to test [Hypotheses 1a and 1b](#), respectively. Using a likelihood ratio test, we find that in both cases the addition of these variables significantly improves ($p < 0.01$) model fit. Consistent with previous empirical studies and with the logic of [Hypothesis 1a](#), we find a significant positive effect associated with cluster size, indicating that the probability of a firm patenting increases with cluster size. The coefficient of 0.0099 indicates that growth in cluster size of one firm is associated with a nearly a 1% increase in the odds of patenting.⁹ We can also interpret logit coefficients in terms of their marginal effect, or how much a one-unit change in the variable changes the probability of patenting. Because the logit model is a non-linear estimator, the *Cluster Size* coefficient estimate is *not* the marginal effect. The marginal effect is estimated by $\beta_1[(e^{-X\beta})/(1 + e^{-X\beta})^2]$, and its magnitude is contingent on the values of all of the independent variables. To calculate the marginal effect, we follow the standard practice of setting all other independent variables at their mean value. The cluster size marginal effect indicates that an increase of one firm is associated with an increase of 0.001 in the probability of patenting. While this marginal effect may seem small, it represents a significant impact given the relatively low predicted rates of patenting in a given year as can be seen in panel A of [Fig. 1](#). An isolated firm (*Cluster Size* equal to one) has a predicted probability of patenting of 0.0887. Increasing *Cluster Size* by 10 raises the predicted probability of patenting to 0.097 or an increase of just under 10%. We can also compare the predicted probabilities of patenting in a given year for firms in a *Cluster Size* of 5 (the 25th percentile of *Cluster Size*) versus firms in a *Cluster Size* of 61 (the 75th percentile of *Cluster Size*). In this case, the probability of patenting increases from 0.0919 to 0.1498, an increase of 0.0579 or 63% from the base rate of 0.0919.

⁹ To interpret the coefficient in terms of its effect on the odds ratio, calculate $\exp(\text{coefficient})$ and subtract 1. $\exp(0.0073) - 1 = 0.99\%$.

Table 4

Pooled logit models testing for whether agglomeration affects the likelihood of a firm successfully filing a patent in a year.

Variables	Model 1	Model 2	Model 3	Model 4
Cluster Size		0.0099* (0.0044)		0.0025 (0.0051)
Cluster Patents			0.1785** (0.0582)	0.1617* (0.0676)
Firm Patent Stock	1.8037** (0.0680)	1.7969** (0.0678)	1.7931** (0.0677)	1.7923** (0.0677)
Firm Alliance Stock	0.4137** (0.0798)	0.4035** (0.0803)	0.4090** (0.0798)	0.4070** (0.0800)
Firm Age	−0.1124** (0.0192)	−0.1071** (0.0195)	−0.1007** (0.0195)	−0.1004** (0.0196)
Cluster Age	0.0285 (0.0195)	−0.0049 (0.0238)	−0.0225 (0.0256)	−0.0264 (0.0268)
Cluster Private Placements	0.0008 (0.0050)	−0.0008 (0.0053)	−0.0017 (0.0052)	−0.0019 (0.0053)
Cluster Public Offering Dollars	0.0001 (0.0004)	−0.0002 (0.0004)	−0.0001 (0.0004)	−0.0002 (0.0004)
Firm Public Offerings	0.0057 (0.0049)	0.0061 (0.0049)	0.0053 (0.0048)	0.0054 (0.0048)
Firm Private Placements	0.0591 (0.0450)	0.0667 (0.0460)	0.0564 (0.0435)	0.0586 (0.0445)
Therapeutic Sector	0.2735** (0.1024)	0.2798** (0.1032)	0.2670** (0.1021)	0.2694** (0.1022)
Diagnostic Sector	0.0656 (0.0984)	0.0708 (0.0986)	0.0600 (0.0990)	0.0620 (0.0989)
Ag-Bio Sector	−0.1831 (0.1127)	−0.1837 (0.1127)	−0.1418 (0.1134)	−0.1461 (0.1130)
Other Sector	−0.1770+ (0.1020)	−0.1980+ (0.1028)	−0.2112* (0.1036)	−0.2133* (0.1037)
Constant	−3.2251** (1.0612)	−3.1859** (1.0598)	−3.1522** (1.0591)	−3.1489** (1.0588)
Year dummies	Yes	Yes	Yes	Yes
Observations	7265	7265	7265	7265
Number of firms	783	783	783	783
Log likelihood	−2130.23	−2126.15	−2121.35	−2121.16
Chi-square	941.52**	940.48**	949.77**	949.35**
McFadden's pseudo R-squared	0.4044	0.4055	0.4069	0.4069

Robust standard errors in parentheses.

+ Significant at 10%; * significant at 5%; ** significant at 1%.

In Model 3, *Cluster Patents* has a significant coefficient of 0.1785, which supports [Hypothesis 1b](#)'s argument of higher firm patenting rates in geographic clusters that have richer knowledge stocks. The marginal effect indicates that a one-unit increase in the logged value of *Cluster Patents* within the cluster is associated with an increase of 0.0186 in the probability of patenting. This effect is also consequential in absolute terms. The relationship is shown graphically in panel B of [Fig. 1](#) with the probability of patenting rising from 0.0784 in clusters at the 25th percentile of *Cluster Patents* to 0.1604 in clusters at the 75th percentile of *Cluster Patents*. The impact of both *Cluster Patents* and *Cluster Size* is reduced in Model 4, which includes both measures. This result is unsurprising given the high correlation between *Cluster Patents* and *Cluster Size*.

We also note that all of the models in [Table 4](#) provide strong support for the main effect relationships predicted by our discussion of the knowledge-based view. Firms with higher patent stocks as well as those with more alliance experience have a higher likelihood of patenting. Furthermore, the negative significant coefficients on firm age indicate that younger firms enjoy a patenting advantage relative to their older competitors.

6.2.2. Firm-level differences in agglomeration externalities

[Table 5](#) tests our main hypotheses around heterogeneous benefits within clusters. Models 5–7 interact firm characteristics with *Cluster Size*, while models 8–10 interact these same characteristics with *Cluster Patents*. In contrast to ordinary least squares regression, conclusions about the sign and significance of the interaction can *not* be inferred by simply examining the coefficient of the interacted variable. In logistic regression, the magnitude and sign of the marginal effect of an interaction can vary across observations ([Huang and Shields, 2000](#); [Ai and Norton, 2003](#)). The non-linear nature of the logit model drives this non-intuitive result, and the interaction effect in such models is a function of the interaction coefficient as well as the coefficient of each interacted variable and the values of all the other independent variables. As [Hoetker \(2007: 336\)](#) notes, “the significance of the interaction effect cannot be determined just by the significance of the interaction coefficient. There can be a significant interaction effect for some observations even if the interaction coefficient is not significant.” Thus, the interaction effect must be calculated across all observations. To assess the significance of the interaction effect, we calculated the interaction effect for each observation

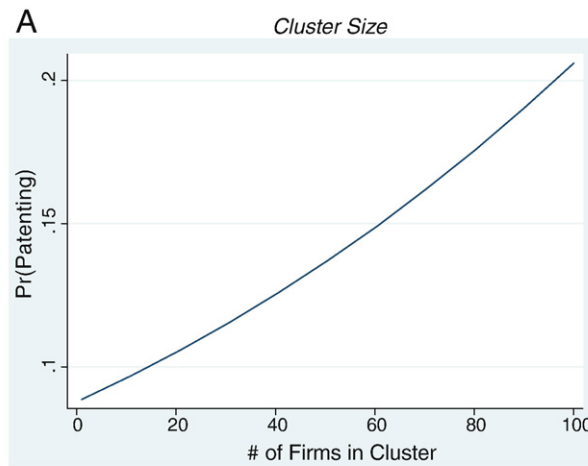


Figure was produced by using the estimated regression coefficients from Model 2 to calculate predicted probability of patenting across the range of x-axis values (all other variables set at mean values).

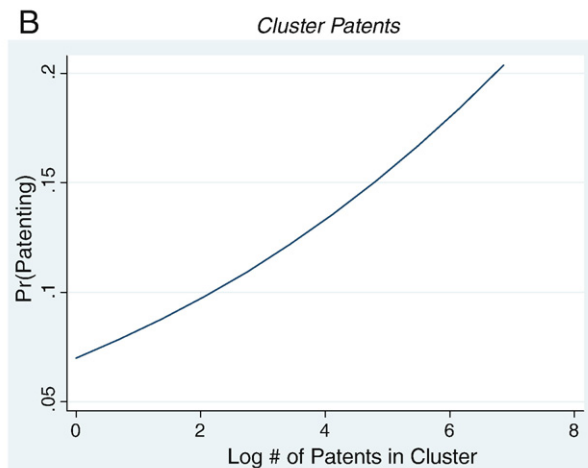


Figure was produced by using the estimated regression coefficients from Model 3 to calculate predicted probability of patenting across the range of x-axis values (all other variables set at mean values).

Fig. 1. Main effects of cluster size and cluster patents.

as suggested by Norton, Wang, and Ai (2004).¹⁰ Using this technique, we can ascertain what percentage of the sample has significant negative interaction effects, significant positive interaction effects, and no interaction effects. These results are reported at the bottom of Table 5.

Hypotheses 2a and 2b argue for a stronger agglomeration effect for firms with larger patent stocks. As a result, the interactions between *Cluster Size* and *Firm Patent Stock* and between *Cluster Patents* and *Firm Patent Stock* are expected to be positive. Examination of models 5 and 8 reveals that neither of the interaction coefficients is significant, but as noted above the interaction coefficient does not represent the interaction effect in the non-linear logit model. We find that the interaction effect between *Cluster Size* and *Firm Patent Stock* is positive and significant for 54.12% of the sample and the interaction between *Cluster Patents* and *Firm Patent Stock* is significant for 72.94% of the sample. We present diagrams showing the form of these interactions in panel A of Fig. 2. In each case, we set firm patent stock at the 10th percentile for the low value and the 90th percentile for the high value. In each graph, we see that the relationship between the cluster measure (*Cluster Size* and *Cluster Patents*, respectively) and patenting probability is stronger for the high-patent stock firm (the upper line has a higher positive slope). We do find evidence that the interaction effects are negative over part of the sample, but in both cases the predominance of effects are positive as expected. Thus, Hypotheses 2a and 2b receive ample support.

¹⁰ Interaction effects were calculated using the *inteff* command in Stata version 9.2.

Hypotheses 3a and 3b argue for an enhanced agglomeration effect when firms have many strategic alliances, with the belief that alliances may substitute for agglomeration benefits. Neither Model 6 nor Model 9 reveals significant coefficients, nor is there strong evidence of a positive interaction effect. For example, the interaction effect between *Cluster Size* and *Firm Alliance Stock* is positive for none of the sample and negative for 5.23% of the sample; the interaction between *Cluster Patents* and *Firm Alliance Stock* is positive for 17% of the sample and negative for 5.99% of the sample. In both cases, the predominance of observations has an insignificant effect (over 94 and 77% of the sample, respectively). We conclude very little support for **Hypotheses 3a and 3b**. Nor is there any strong support for the alternative, substitution view under which clustering would have lower marginal benefits for firms with more alliances.

Hypotheses 4a and 4b argue for stronger agglomeration effects for younger firms. Hence, we expect negative interaction effects. While neither Model 7 nor Model 10 reveals significant interaction coefficients, there is substantial support for significant negative interaction effects. Our tests confirm that the interaction effect between *Cluster Size* and *Firm Age* is negative for 73.27% of the sample, while the interaction between *Cluster Patents* and *Firm Age* is negative for 76.06% of the sample. Thus, we conclude that

Table 5

Pooled logit models testing for whether firm-level variables moderate how agglomeration affects the likelihood of a firm successfully filing a patent in a year.

Variables	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Cluster Size	0.0115** (0.0043)	0.0110* (0.0044)	0.0156** (0.0050)			
Cluster Patents				0.1991** (0.0573)	0.1875** (0.0602)	0.2727** (0.0749)
Firm Patent Stock	1.9045** (0.1152)	1.7947** (0.0681)	1.7975** (0.0677)	1.9033** (0.1419)	1.7917** (0.0679)	1.7890** (0.0674)
Firm Alliance Stock	0.4041** (0.0807)	0.4810** (0.1234)	0.4136** (0.0805)	0.4093** (0.0800)	0.4569** (0.1455)	0.4164** (0.0800)
Firm Age	−0.1071** (0.0195)	−0.1056** (0.0194)	−0.0709* (0.0282)	−0.1013** (0.0195)	−0.1000** (0.0194)	−0.0565+ (0.0337)
Cluster Size*Firm Patent Stock	−0.0025 (0.0022)					
Cluster Size*Firm Alliance Stock		−0.0019 (0.0024)				
Cluster Size*Firm Age			−0.0009 (0.0006)			
Cluster Patents*Firm Patent Stock				−0.0283 (0.0318)		
Cluster Patents*Firm Alliance Stock					−0.0132 (0.0325)	
Cluster Patents*Firm Age						−0.0115 (0.0077)
Cluster Age	−0.0065 (0.0238)	−0.0059 (0.0241)	−0.0154 (0.0236)	−0.0249 (0.0255)	−0.0234 (0.0255)	−0.0389 (0.0255)
Cluster Private Placements	−0.0003 (0.0052)	−0.0002 (0.0053)	−0.0002 (0.0053)	−0.0013 (0.0051)	−0.0015 (0.0052)	−0.0007 (0.0052)
Cluster Public Offering Dollars	−0.0002 (0.0004)	−0.0002 (0.0004)	−0.0002 (0.0004)	−0.0001 (0.0004)	−0.0001 (0.0004)	−0.0001 (0.0004)
Firm Public Offerings	0.0060 (0.0048)	0.0066 (0.0052)	0.0064 (0.0050)	0.0054 (0.0048)	0.0056 (0.0050)	0.0056 (0.0049)
Firm Private Placements	0.0690 (0.0457)	0.0645 (0.0460)	0.0636 (0.0451)	0.0586 (0.0429)	0.0570 (0.0432)	0.0573 (0.0429)
Therapeutic Sector	0.2706** (0.1044)	0.2769** (0.1040)	0.2750** (0.1035)	0.2602* (0.1037)	0.2645* (0.1031)	0.2616* (0.1027)
Diagnostic Sector	0.0721 (0.0983)	0.0639 (0.0994)	0.0821 (0.0981)	0.0626 (0.0987)	0.0567 (0.0997)	0.0718 (0.0983)
Ag-Bio Sector	−0.1959+ (0.1144)	−0.1819 (0.1131)	−0.1928+ (0.1138)	−0.1536 (0.1164)	−0.1434 (0.1139)	−0.1535 (0.1149)
Other Sector	−0.1958+ (0.1029)	−0.2013+ (0.1034)	−0.1880+ (0.1022)	−0.2095* (0.1039)	−0.2111* (0.1037)	−0.2026+ (0.1036)
Constant	−3.1945** (1.0629)	−3.1822** (1.0596)	−3.2315** (1.0596)	−3.1584** (1.0625)	−3.1492** (1.0588)	−3.1920** (1.0593)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7265	7265	7265	7265	7265	7265
Number of firms	783	783	783	783	783	783
Log likelihood	−2124.87	−2125.32	−2123.06	−2120.59	−2121.16	−2118.82
Chi-square	950.48**	940.21**	959.39**	956.61**	951.56**	965.00**
McFadden's pseudo R-squared	0.4059	0.4057	0.4064	0.4071	0.4069	0.4076
% Of observations with significant positive interaction	54.12%	0.00%	0.00%	72.94%	17.00%	0.03%
% Of observations with insignificant interaction	41.87%	94.77%	26.73%	20.58%	77.01%	23.91%
% Of observations with significant negative interaction	4.01%	5.23%	73.27%	6.48%	5.99%	76.06%

Robust standard errors in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

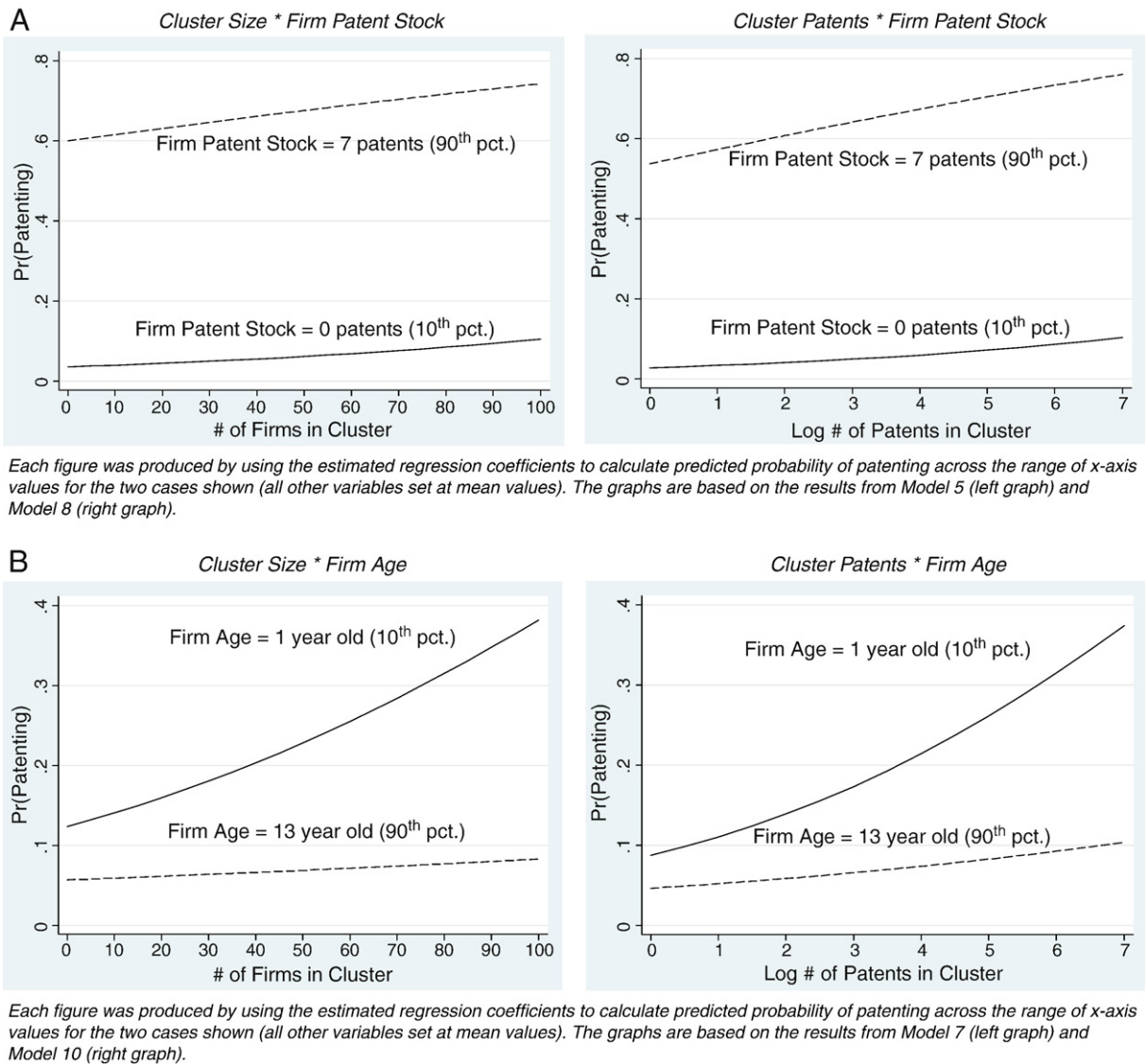


Fig. 2. Interaction graphs.

our results support [Hypotheses 4a and 4b](#). We present diagrams showing the form of these interactions in panel B of Fig. 2. In each case, we set firm age at the 10th percentile for the low value and the 90th percentile for the high value. In each graph, we see that the relationship between the cluster measure (*Cluster Size* and *Cluster Patents*, respectively) and patenting probability is stronger for younger firms (the upper line has a higher positive slope).

6.3. Robustness checks

To confirm the general pattern of our results, we conducted a number of robustness checks. First, we exploited the panel nature of the data set by performing a random effects logit specification.¹¹ To take into account potential unobserved differences across firms, the random effects approach assumes a different intercept for each firm but views the different intercepts as randomly deviating from an overall intercept. Tests indicated that the random effects model was superior to the simple logit models presented in Table 5. However, controlling for potential unobserved heterogeneity did not substantively affect the results for the main effects (as in the pooled logit models, when both main effects are in the model, cluster

¹¹ We rejected the fixed effects estimator because it can not be estimated for groups whose outcomes do not vary (firms who patent every year or never patent). These groups represent a large portion of the data, and their exclusion may potentially bias results.

Table 6

Random effects logit models testing for whether firm-level variables moderate how agglomeration affects the likelihood of a firm successfully filing a patent in a year.

Variables	Model 11	Cluster Size interactions			Cluster Patents interactions		
		Model 12	Model 13	Model 14	Model 15	Model 16	Model 17
Cluster Size	0.0052 (0.0056)	0.0163** (0.0048)	0.0168** (0.0049)	0.0193** (0.0055)			
Cluster Patents	0.2163** (0.0691)				0.2723** (0.0616)	0.2668** (0.0616)	0.3114** (0.0772)
Firm Patent Stock	1.5203** (0.0934)	1.6719** (0.1278)	1.5283** (0.0927)	1.5371** (0.0932)	1.6869** (0.1520)	1.5211** (0.0932)	1.5259** (0.0936)
Firm Alliance Stock	0.5094** (0.0808)	0.5061** (0.0807)	0.6438** (0.1148)	0.5138** (0.0806)	0.5102** (0.0807)	0.6138** (0.1327)	0.5138** (0.0805)
Firm Age	−0.0572** (0.0216)	−0.0645** (0.0214)	−0.0629** (0.0214)	−0.0343 (0.0291)	−0.0579** (0.0216)	−0.0573** (0.0215)	−0.0273 (0.0332)
Cluster Size*Firm Patent Stock		−0.0032 (0.0020)					
Cluster Size*Firm Alliance Stock			−0.0034+ (0.0020)				
Cluster Size*Firm Age				−0.0008 (0.0005)			
Cluster Patents*Firm Patent Stock					−0.0409 (0.0301)		
Cluster Patents*Firm Alliance Stock						−0.0277 (0.0285)	
Cluster Patents*Firm Age							−0.0081 (0.0064)
Cluster Age	−0.0430 (0.0302)	−0.0177 (0.0285)	−0.0174 (0.0285)	−0.0257 (0.0293)	−0.0390 (0.0292)	−0.0366 (0.0289)	−0.0475 (0.0308)
Cluster Private Placements	−0.0039 (0.0042)	−0.0012 (0.0041)	−0.0010 (0.0041)	−0.0006 (0.0042)	−0.0028 (0.0041)	−0.0031 (0.0042)	−0.0028 (0.0042)
Cluster Public Offering Dollars	−0.0001 (0.0004)	−0.0002 (0.0004)	−0.0002 (0.0003)	−0.0002 (0.0003)	0.0000 (0.0003)	0.0000 (0.0003)	0.0000 (0.0003)
Firm Public Offerings	0.0064* (0.0031)	0.0069* (0.0031)	0.0076* (0.0032)	0.0071* (0.0032)	0.0064* (0.0031)	0.0068* (0.0032)	0.0064* (0.0031)
Firm Private Placements	0.0696+ (0.0417)	0.0810+ (0.0417)	0.0790+ (0.0417)	0.0769+ (0.0416)	0.0689+ (0.0414)	0.0699+ (0.0417)	0.0675 (0.0414)
Therapeutic Sector	0.3896** (0.1371)	0.3954** (0.1367)	0.3959** (0.1369)	0.3998** (0.1361)	0.3765** (0.1371)	0.3767** (0.1370)	0.3790** (0.1362)
Diagnostic Sector	0.0153 (0.1296)	0.0212 (0.1291)	0.0117 (0.1295)	0.0304 (0.1286)	0.0153 (0.1296)	0.0077 (0.1296)	0.0221 (0.1289)
Ag-Bio Sector	−0.0620 (0.1610)	−0.1109 (0.1604)	−0.1033 (0.1604)	−0.1035 (0.1593)	−0.0673 (0.1613)	−0.0610 (0.1608)	−0.0592 (0.1599)
Other Sector	−0.2358+ (0.1321)	−0.2168+ (0.1316)	−0.2231+ (0.1319)	−0.2099 (0.1311)	−0.2316+ (0.1320)	−0.2323+ (0.1320)	−0.2272+ (0.1313)
Constant	−3.3790** (1.0629)	−3.3434** (1.0609)	−3.3612** (1.0612)	−3.3465** (1.0598)	−3.3481** (1.0625)	−3.3724** (1.0628)	−3.3499** (1.0611)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7265	7265	7265	7265	7265	7265	7265
Number of firms	783	783	783	783	783	783	783
Log likelihood	−2086.12	−2089.89	−2089.68	−2089.77	−2085.62	−2086.08	−2085.76
Chi-square	792.27	790.04	787.27	788.45	795.23	793.03	795.05
% Of observations with significant positive interaction		70.09%	14.43%	0.00%	75.87%	42.42%	0.03%
% Of observations with insignificant interaction		2.71%	74.95%	49.91%	15.09%	47.56%	40.96%
% Of observations with significant negative interaction		7.20%	10.63%	50.09%	9.04%	10.02%	59.01%

Standard errors in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

size loses significance while cluster patents maintains a positive significant relationship), or the significance of the interaction effects across all observations, which were generally quite similar to the pooled logit results reported above as shown in Table 6.¹²

As an additional robustness check, we also investigated an alternate dependent variable, the *count* of successful patent applications by a firm in a particular year, rather than just a dichotomous variable. Results for these models, which used negative

¹² Calculation of the interaction effects required estimates of the random effects. We utilized the gllamm package in Stata 9.2 to estimate these effects (the standard xtlogit, re command in Stata does not provide estimates of the random effects).

Table 7

Negative binomial models testing for whether firm-level variables moderate how agglomeration affects the number of patents successfully filed in a year.

Variables	Model 18	Cluster Size interactions			Cluster Patents interactions		
		Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Cluster Size	0.0014 (0.0042)	0.0094* (0.0037)	0.0082* (0.0040)	0.0140** (0.0040)			
Cluster Patents	0.1056+ (0.0610)				0.1691** (0.0486)	0.1323* (0.0624)	0.2525** (0.0589)
Firm Patent Stock	1.3363** (0.0459)	1.5001** (0.0767)	1.3321** (0.0465)	1.3292** (0.0431)	1.6200** (0.0998)	1.3352** (0.0480)	1.3262** (0.0436)
Firm Alliance Stock	0.2553** (0.0572)	0.2495** (0.0574)	0.3706** (0.0878)	0.2698** (0.0562)	0.2468** (0.0563)	0.3653** (0.1044)	0.2638** (0.0553)
Firm Age	−0.0825** (0.0150)	−0.0866** (0.0145)	−0.0833** (0.0149)	−0.0337 (0.0230)	−0.0851** (0.0146)	−0.0811** (0.0150)	−0.0186 (0.0280)
Cluster Size*Firm Patent Stock		−0.0035** (0.0012)					
Cluster Size*Firm Alliance Stock			−0.0027+ (0.0014)				
Cluster Size*Firm Age				−0.0012** (0.0004)			
Cluster Patents*Firm Patent Stock					−0.0678** (0.0199)		
Cluster Patents*Firm Alliance Stock						−0.0289 (0.0204)	
Cluster Patents*Firm Age							−0.0158** (0.0056)
Cluster Age	−0.0295 (0.0251)	−0.0204 (0.0225)	−0.0190 (0.0233)	−0.0315 (0.0231)	−0.0321 (0.0225)	−0.0282 (0.0240)	−0.0515* (0.0230)
Cluster Private Placements	0.0009 (0.0029)	0.0022 (0.0028)	0.0021 (0.0028)	0.0034 (0.0028)	0.0022 (0.0028)	0.0014 (0.0028)	0.0023 (0.0029)
Cluster Public Offering Dollars	−0.0002 (0.0003)	−0.0001 (0.0003)	−0.0002 (0.0003)	−0.0001 (0.0003)	−0.0000 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)
Firm Public Offerings	−0.0010 (0.0014)	−0.0003 (0.0015)	−0.0003 (0.0016)	−0.0005 (0.0014)	−0.0002 (0.0015)	−0.0006 (0.0015)	−0.0006 (0.0014)
Firm Private Placements	0.0000 (0.0247)	0.0094 (0.0242)	0.0044 (0.0240)	0.0026 (0.0238)	0.0072 (0.0241)	0.0019 (0.0242)	−0.0005 (0.0241)
Therapeutic Sector	0.1963* (0.0767)	0.2011* (0.0784)	0.2048** (0.0773)	0.2116** (0.0777)	0.1929* (0.0791)	0.1932* (0.0768)	0.1999** (0.0776)
Diagnostic Sector	−0.0470 (0.0770)	−0.0305 (0.0752)	−0.0489 (0.0770)	−0.0193 (0.0745)	−0.0246 (0.0741)	−0.0555 (0.0771)	−0.0226 (0.0744)
Ag-Bio Sector	−0.0786 (0.0944)	−0.1307 (0.0937)	−0.1114 (0.0942)	−0.1102 (0.0945)	−0.1174 (0.0990)	−0.0847 (0.1001)	−0.0786 (0.0990)
Other Sector	−0.2144* (0.0839)	−0.2082* (0.0819)	−0.2130* (0.0834)	−0.2029* (0.0818)	−0.2135** (0.0820)	−0.2127* (0.0838)	−0.2101* (0.0827)
Constant	−3.1038** (1.0172)	−3.1342** (1.0197)	−3.1190** (1.0162)	−3.1916** (1.0182)	−3.1210** (1.0236)	−3.1007** (1.0170)	−3.1662** (1.0203)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7265	7265	7265	7265	7265	7265	7265
Number of firms	783	783	783	783	783	783	783
Log likelihood	−4893.82	−4888.46	−4893.30	−4885.25	−4880.27	−4891.56	−4883.30
Chi-square	1990.81	1950.30	1960.47	2153.41	1988.58	1989.21	2100.52
% Of observations with significant positive interaction		15.95%	0.00%	0.00%	61.06%	0.00%	0.00%
% Of observations with insignificant interaction		84.03%	99.93%	7.64%	38.93%	100.00%	5.05%
% Of observations with significant negative interaction		0.01%	0.07%	92.36%	0.01%	0.00%	94.95%

Standard errors in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

binomial regression, are reported in Table 7. Aside from a weaker interaction effect between cluster size and firm patents, the results are similar to the results from the logit and random effects logit models.¹³

Prior to moving to a discussion of the results, we address one final issue related to causality in the relationship between agglomeration and firm productivity. In particular, if higher quality firms are more likely to be founded in or re-locate to a clustered region, our estimates of the benefits of agglomeration may be overstated.

¹³ We did not estimate a random effects negative binomial because estimates for the random effects are not available from the estimation procedure. The random effects are conditioned out in the estimation of this model (Hausman et al., 1984). Thus, we are unable to calculate the interaction effects because their values depend on the values of the random effects. No alternative estimation procedure (like gllamm for the random effects logit) is available. We did run a random effects negative binomial model that included the main effects of cluster size and cluster patents. The substantive results were similar to those generated by the other analyses.

We first consider the argument that firms with above-average productivity choose to locate in clusters, as has been contended by Baldwin and Okubo (2006). We do not believe this for a number of reasons. First, the theoretical claims surrounding this topic are unclear as to whether we should expect *positive* or *negative* selection. In their theoretical model, Baldwin and Okubo (2006) argue for positive effects (“better” firms will re-locate to clustered locations) while Shaver and Flyer’s (2000) arguments are the opposite (“better” firms should choose isolated locations). Second, the empirical record does not provide much support for positive selection effects. Shaver and Flyer (2000) present some evidence for *negative* selection effects with their findings that larger greenfield entries are less likely to occur in clustered locations. Stuart and Sorenson (2003) consider the potential for selection in the biotechnology industry, but the evidence they examine is inconsistent with this explanation (that is, there does not appear to be a selection effect at work). Third, it does not appear that *de novo* firm founders make location decisions to capitalize on agglomeration effects. Instead, the weight of the literature (e.g., Cooper, 1979; Cooper and Dunkelberg, 1987; Almeida and Kogut, 1997) indicates that new venture founders locate their new ventures in their current location. As Cooper and Folta (2000: 360) note, “technical entrepreneurs tend to start their new firms within commuting distance of where they were previously working and living.” Finally, the types of re-location events that would drive the results in Baldwin and Okubo’s (2006) model appear to be relatively rare events. For example, Klier (2006: 127) notes that “pure relocations, however, are rare” where pure relocations refer to relocations not driven by merger or acquisition. Of the 1245 large (greater than 2500 employees) public companies Klier (2006) identified in 1990, only 101 had moved their headquarters location by the year 2000. An examination of the location decisions of California biotechnology establishments (Zhang and Patel, 2005) showed similarly low levels of re-location choices. Of 5589 California biotech establishments, only 781 moved during the period 1990–2001. The probability that even this small number of moves was driven by agglomeration-seeking is likely low given that 566 of the 781 moves were relocations within the same county.

We also consider the argument that firms with above-average productivity are more likely to be founded in clusters. This might occur, for example, if higher quality universities spawn better firms (who in turn spawn additional, higher quality firms which may result from the tendency of entrepreneurs to found new firms near their former employers) leading to larger clusters consisting of better firms than those located in isolation. In this case, some of the effects that we attribute to agglomeration benefits might be driven by this unobservable heterogeneity. Our preference would have been to empirically control for selection effects by modeling the initial location choice of the firms within our sample; however, this was not possible as we have no information on firm qualities at founding to serve as predictors in a selection equation. Although the weight of the evidence appears to be inconsistent with a selection concern, our results are limited by our inability to explicitly control for this alternative explanation. However, we did take a number of steps to control for this alternative explanation. First, we included a broad set of control variables to capture heterogeneity among the firms. Second, we included a robustness check using a random effects panel estimator to control for unobserved heterogeneity. Finally, we conducted a number of empirical checks that did not support this alternative explanation.¹⁴

7. Discussion

This paper contributes to the understanding of asymmetric benefits of agglomeration by revealing that an asymmetry in firm learning capability leads to asymmetric benefits of knowledge spillover in an agglomeration. By theorizing and demonstrating empirically that firms benefit asymmetrically from cluster externalities, this paper offers a bridge between the literatures extolling the advantages of agglomeration and the literatures examining the determinants of superior performance. This work goes beyond prior work that has sought to demonstrate agglomeration effects matter and places an emphasis back on the firm. Combining the knowledge-based view with agglomeration theory, we believe there are persuasive reasons to suspect that returns are not symmetric for all firms in an agglomeration. Our results bear this out. We believe this is the strongest evidence yet that firm differences influence agglomeration externalities. Moreover, our focus on the role of combinative capability or absorptive capacity advances a growing body of literature that has examined how technical capabilities matter.

In particular, we find that agglomeration effects accrue asymmetrically to firms with a deeper knowledge stock and firms that are younger. The first finding is consistent with an absorptive capacity argument, in which firms with larger knowledge stocks benefit more from being located in knowledge-rich clusters. Our conjecture is that such firms are better able to benefit from knowledge spillovers present in such clusters. We should note that these results can be contrasted with the suggestion by Shaver and Flyer (2000) that the best firms (those with superior technologies, human capital, suppliers, distributors, etc.) will prefer to avoid clusters, resulting in adverse selection in agglomerations. They have argued that firms who are most likely to generate agglomeration externalities are least likely to join an agglomeration because their relative advantage will suffer. Using relative size as a proxy for the “quality” of the firm in generating externalities, they found evidence that “better” (i.e., larger) foreign greenfield investments were less likely to be located in highly agglomerated areas. While our evidence is consistent with one part of their argument, namely that “good” (i.e., high-knowledge stock in our context) firms contribute more to the generation of externalities (by increasing the stock of knowledge in the cluster), we also find evidence that these “good” firms may benefit more from being

¹⁴ We undertook two empirical tests to try to show our results were robust to this potential criticism. First, we ran our models excluding isolated firms. If better firms locate in clusters, limiting our sample in this way allows us to (at least) partially condition our results based on this selection effect. Indeed, our results proved robust, allowing us, at a minimum, to claim that even after controlling for selection of “better” firms into clusters, we find that there are significant firm-level differences in the extent to which firms benefit from agglomeration. The results are also robust to other splits in the sample, including by median cluster size. Second, to check whether firms founded in clusters appear to be of higher unobservable quality, we compared the number of first-year patent applications generated by firms founded in clustered locations to those founded in non-clustered locations. We observed no significant differences. We also compared number of first-year patent applications of those founded in larger clusters (greater than five firms) to those founded in smaller clusters (less than five firms). Again, we observed no significant differences. This evidence does not appear to be consistent with the idea that the quality of the firm is related to its initial location.

located in knowledge-rich clusters. While our paper does not explicitly test the adverse selection argument, the evidence it generates seems at odds with it.

The second finding worth highlighting is that younger firms seem to enjoy stronger clustering benefits. This result is consistent with prior scholars who have speculated that young firms might more effectively draw benefits from their clustered regions. Saxenian (1994) associated this advantage with more flexible organizational structures while Cooper and Folta (2000) pointed to young firms' greater need to rely on outside knowledge sources given their limited internal resources. In both cases, they argued that younger firms would benefit more from spatial concentration, and our evidence of greater knowledge production by youthful clustered firms matches their conjecture. As far as we know, this is the first direct evidence to support such speculation. These results are particularly impressive given that during the time of the sample the biotechnology industry was made up of mostly young firms. The average age of firms in the sample is just over seven years old. We cannot discern whether our results are driven by whether firms are more effective at accumulating knowledge spillovers or recruiting local talent or suppliers, or whether they merely rely more heavily on the geographic context for such resources.

In contrast to our expectations, firm alliance stocks did not influence the relationship between agglomeration and patenting activity. Thus, we cannot conclude that alliances enhance the benefits of clustering in generating knowledge. We offer this interpretation cautiously as our data set does not distinguish between intra- and inter-cluster alliances. Perhaps these two types of alliances have opposing effects. Intra-cluster alliances might serve as substitutes, weakening the effects of clustering while inter-cluster alliances might serve as complements, enhancing the relationship between clustering and performance. The differing role of intra- versus inter-cluster alliances is a potential area for additional research. Finally, we note that we used two measures to capture agglomeration effects (*Cluster Size* and *Cluster Patents*), and the nature of our results (i.e., interaction effects) is very similar across these measures. We draw encouragement from this consistency.

Our research has significant implications for entrepreneurs. It suggests that entrepreneurs may accrue particular benefits to agglomeration during the early phases of a firm. Our evidence suggests that a strategy of locating in cluster may be a way to offset other liabilities that may be associated with newness. The finding that young firms benefit more from agglomeration adds to an emerging body of work that has begun to investigate when and how newness might provide advantages to firms (e.g., Autio et al., 2000; Choi and Shepherd, 2005). Given the benefits available in clusters, it is puzzling why new firm founders are not agglomeration-seeking in their initial location choice (Cooper, 1979; Cooper and Dunkelberg, 1987; Almeida and Kogut, 1997). Entrepreneurs would be well served to consider the potential benefits of different geographic locations and compare those locations to the seeming default choice of locating near their home or prior job. It further suggests that entrepreneurs seeking to take advantage of a geographic location should emphasize internal processes to develop combinative capabilities within their firms. The marginal payoffs to such processes appear to be higher when they are embedded in knowledge-rich geographies.

Our research may also be of interest to policy makers attempting to build economic activity across certain sectors in their regions, whether it be at the state or metropolitan level or even at smaller units of analysis, such as the growing phenomenon of science parks and incubators (Phan et al., 2005). First, given the prominence of knowledge spillovers as a benefit to geographic agglomeration, policy makers should clearly communicate the strength of their local knowledge base as a source of such spillovers relative to other location options. Second, local officials might consider taking steps to build the potential pool of knowledge spillovers available to member firms by taking actions such as building stronger links with local universities and with other nearby agglomerations or science parks. Third, it may be beneficial for policy makers to counsel their firms about the necessity to build complementary skills in learning capabilities to take full advantage of available knowledge spillovers. Finally, sponsors of regional clusters and/or science parks may consider targeting recruiting efforts at those firms who will benefit most from location in an agglomeration.

Our results are not without qualification, however. First, our sample is limited to a single industry, which inevitably raises issues of generalizability. For example, one may speculate that knowledge spillovers may play a more important role in biotechnology, and may explain our findings around the potency using the number of patents in a cluster to approximate agglomeration externalities. Second, we only examine one measure of performance within this study; however, we might argue that patenting activity is the most important measure of performance for firms within this industry. We encourage future research to consider additional proxies for superior performance. Finally, we do not directly test particular agglomeration externalities. We argue that, for example, higher levels of cluster knowledge stocks will result in greater knowledge spillovers; however, our evidence of an association between cluster knowledge stocks and patenting probability could also be consistent with an explanation of higher cluster knowledge stocks attracting more specialized labor to the cluster, which in turn impacts firms' patenting propensity. Untangling the particular externalities driving clustering benefits is a promising area for additional research.

8. Conclusion

Consistent with prior work in agglomeration research, we find evidence of a link between spatial concentration and firm performance. Our results indicate that both larger cluster size and larger cluster knowledge stocks are associated with increased firm patenting activity in our sample of US biotechnology firms. Extending prior studies that have implicitly assumed that clustered firms benefit symmetrically from geographic agglomeration, we explicitly argued that firms may benefit asymmetrically from clusters, and our results confirmed this conjecture. Although we found no support for a stronger relationship for firms with larger numbers of alliances, firms with higher knowledge stocks and younger firms demonstrated significantly stronger clustering-performance relationships.

Overall, what emerges is a much richer picture of the performance implications of clustering. As a first step, our research provides substantial support for the idea that firms benefit asymmetrically from firm agglomeration in their quest to build knowledge-based competitive advantage. Additional theoretical and empirical work will help further clarify the potential for asymmetrical benefits from spatial concentration.

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