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THE PUZZLE OF INSULAR DOMAINS: A LONGITUDINAL STUDY OF KNOWLEDGE STRUCTURATION AND INNOVATION IN BIOTECHNOLOGY FIRMS

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ABSTRACT

In this study we explain the puzzle of insular domains: insular domains are niches where new innovation is built on the knowledge within the domain. Given the nature of knowledge needed for new innovation in an insular domain the puzzle is why do new firms enter these niches? In a longitudinal sample of 128 biotechnology start-ups founded from 1980 to 1999 we explain why start-ups enter insular domains and how the start-ups develop technology capabilities.

INTRODUCTION

Recent studies proffer causal arguments for the curvilinear relationship between entry into a new technological domain and the firm's innovative output. First, extensive experimentation without deep understanding of the causal relationships between technology components may prove counterproductive. When firms enter several domains it would be difficult to simultaneously absorb knowledge from multiple domains (Levinthal & March, 1993). Second, assimilating knowledge is a time-consuming and expensive endeavor (Hitt et al, 1996); further exacerbating the resource constraints faced by young companies. Similarly, excessive experimentation can also hurt output by reducing reliability (March, 1991; Martins and Mitchell, 1998). Therefore, moderate levels of entry into new domains and moderate distance of the domain from a firm's past knowledge are likely to increase both the number and impact of new innovations that a firm can gainfully sustain (George et al., 2006).

A puzzle that remains unresolved by knowledge recombination arguments is the presence of insular technology domains. We refer to insular domains as those technical domains that rely heavily on prior inventions within the same domain for subsequent inventions. Recombination assumes that entry into a new technological domain provides opportunities to synthesize and create knowledge. However, entry into insular domains may be counter to such assumptions as subsequent recombination efforts may draw from within a narrow, self-contained domain rather than spanning across technical boundaries. Furthermore, these entry patterns are likely to have a significant effect in young technology firms. Recent theoretical work by Sapienza, Autio, George and Zahra (2006) posits that entry into new markets is likely to have a significant effect on capability development and survival of young firms, more so than in mature organizations. These authors suggest that new market entry has an 'imprinting' effect (Stinchcombe, 1965) that has lasting consequences for a firm's growth and survival opportunities. Similarly, we argue that the resource-constrained nature of start-ups (George, 2005) is likely to exert a disproportionate influence on entry into new technological niches, wherein entry into insular domains that do not generate significant payoffs could have damaging consequences for the young organizations. Therefore, it becomes important to examine the patterns of innovative output and technological impact of firms that enter into insular domains, which is the focus of this study. By innovative active and technological impact, we refer specifically to the firm's inventive activity (number of patents) and its subsequent technical impact on the field (citations received).

THEORY AND HYPOTHESES

By depth of technological capabilities, we refer to a firm's level of expertise within a technological niche. Whereas some authors have used technological capabilities to broadly include technology integration and commercialization abilities (Zahra & Nielsen, 2002), our focus is on the firm's capacity to innovate within a technical niche (Sampson, 2005; Sorensen & Stuart, 2000). The literature on organizational learning suggests three advantages of deep knowledge of a technical domain. First, depth allows a firm to understand causal linkages within the niche (March, 1991); which allows the firm to select the appropriate technology components to recombine to produce fruitful innovation. The result of this targeted selection is an increased reliability of the output (Ghemawat & Spence, 1985). Second, a firm's depth of technology expertise enables the firm to build absorptive capacity to understand new information generated within and outside firm boundaries (Cohen & Levinthal, 1990; Zahra & George, 2002). Finally, the depth of technological capabilities enables a firm to make new combinations from old components as the firm understands the limitations of existing components from repeated use. Hence, as firms acquire more depth of capabilities in a domain, they are likely to improve their innovative output within these domains.

However, there are upper bound limits to the advantages accrued from building depth of technological capabilities. The first limitation occurs due to the exhaustion of opportunities in a domain. Technology exhaustion sets in when firms have tried feasible combinations of components within a technical domain (Fleming, 2001), and the stock and flow of new opportunities are curtailed (Klevorick et al., 1995). If the stock of opportunities is limited and a firm already possesses high depth in that domain, then the firm may have exploited the freely available opportunities in the domain. Consequently, the quantity of innovative output may decrease after a certain inflection point as a firm's depth of capabilities increases.

Hypothesis 1a: The relationship between depth of technological capabilities and the quantity of a firm's innovative output is curvilinear such that moderate depth yields optimal outcomes.

A second upper bound limitation of depth of technological capabilities arises as a firm faces a trade-off between (a) exploiting existing capabilities within a technical domain to generate incremental new knowledge, and (b) exploring distant technical domains in which the firm has less technical understanding and knowledge. Deep knowledge within a technical domain may lead the firm along the path of incremental innovation because the returns to incremental innovation are more immediate and more certain than the returns to exploring distant knowledge domains (March, 1991). Since the new knowledge being created is incremental in nature, it is less likely to be of influence on other technical domains (Sorensen & Stuart, 2000). Also, the propensity to conduct local search is reinforced by customer pressure to find solutions to existing problems (Christensen & Bower, 1996). Consequently, the innovative output of firms with high depth is likely to be incremental rather than revolutionary in nature. Hence we posit:

Hypothesis 1b: The relationship between depth of technological capabilities and the impact of a firm's innovative output is curvilinear such that moderate depth yields optimal outcomes.

Entry into 'New to the Firm' Insular Domains

Insular domains, by definition, predominantly draw on knowledge within the domain to generate new innovation. Two views prevail on the persistence of insularity in certain technical domains. The first view suggests that the development of a paradigm within a discipline leads to consensus among researchers on the fundamental questions and the appropriate techniques to investigate these questions (Kuhn, 1962); which result in new innovations in the domain drawing heavily on prior work within the same domain. Also, because the questions are clearly defined, only incremental changes to these models are likely to transpire. The model of innovation in an insular domain resembles exploitation of knowledge rather than exploration. Exploitation is used to describe all things that include refinement, choice, production, efficiency, selection, implementation, and execution (March, 1991). Firms in the exploiting mode are

prone to leverage prior knowledge (Katila & Ahuja, 2002), tend to produce incremental innovations (March, 1991), where the impact of the innovative output is lower (Sorensen & Stuart, 2000).

When organizations draw on prior knowledge or knowledge within a domain, the organizations are adept at churning out new innovations in their domain (Sorensen & Stuart, 2000). Since firms with experience of producing innovation in a domain know the uses and limitations of the components, and the best way to recombine them, the firms become more adept at working with prior knowledge components. However, such innovations tend to have a lower impact on the technology domain as they tend to be incremental in nature. Since insular domains draw on knowledge within the domain, the number of possible recombinations is lower than if the firms drew knowledge from disparate domains. In addition, technology exhaustion may set in as the feasible recombinations may have already been explored (Fleming, 2001). The mechanisms that influence depth of capabilities to have a curvilinear effect on innovation may also influence the pattern of innovation within an insular domain. Hence the paradigmatic view of insular domains suggests that there may be a curvilinear relationship between insularity of the technical domain and its impact on firm-level innovation.

The second view on insular domains is that some technology domains are closer to the basic sciences. Basic sciences are clear, distinct bodies of theoretical and empirical investigations that draw on little knowledge that is produced outside the domain of the basic science. Of course, exceptions can be cited: for example the quantitative results in physics lead to Lavoisier's revolution of modern chemistry (Conant & Nash, 1964; Tushman & Anderson, 1986). Predominantly, research in basic sciences draws on previous work within the same science. Breakthroughs in basic science can impact several related disciplines that draw on the basic science. Klevorick, Levin, Nelson and Winter (1995) explain why some industries have larger stock and growth rates in new technological opportunities. The authors posit that industries differ in technology opportunities in three ways: distance to basic sciences, linkages to other industries, and learning that happens within the industry.

Industries closer to the basic sciences are likely to be impacted by discoveries and, consequently, have more opportunities. The new knowledge can be used to solve problems, especially problems that did not have a solution prior to discoveries in the basic sciences. For example, the discovery of gene cloning enabled the development of therapeutic remedies. The usefulness of new knowledge discovered is contingent upon the relationship between the basic science and the technology domains. For instance, the ability to reach lower temperatures using mercury paved the way for the discovery of superconductivity and the closely related high-performance ceramics industry blossomed. Since moderately insular domains are more likely to draw on other domains for innovation, the discoveries in moderately insular domains may be more widely applicable. However, in highly insular domains the applicability of new innovation to other technology domains may need further work as there may be limited applied work done to extend discoveries from basic science to the applied domains. Hence, as the insularity of a domain increases the rate and technological impact of the output may decrease beyond an inflection point.

Hypothesis 2: The relationship between entry into insular domains and (a) the quantity and (b) the impact of a firm's innovative output is curvilinear such that moderate insularity yields the most optimal outcomes.

Insularity and Depth of Technological Capabilities

We suggest two distinct mechanisms by which the depth of technological capabilities positively moderates the relationship between entry into insular domains and the quantity and impact of the firm's innovative output. First, depth of technology capability builds absorptive capacity within an organization to understand and assimilate new innovation discovered outside organizational boundaries (Cohen & Levinthal, 1990; Zahra & George, 2002). Absorptive capacity is built within a firm by investment in research and development and/or by hiring researchers (Kaplan, Murray & Henderson, 2003; Lacetera,

Cockburn & Henderson, 2004). The process through which individual knowledge becomes internalized as organizational knowledge is through the socialization of employees and communication (March, 1991). For new knowledge to flow between employees there needs to be a common ground by which individuals can communicate tacit and idiosyncratic knowledge (March, 1991). The common ground enables the communication of complex information through the use of artifacts. By entering insular domains, the depth of technological capability in another domain provides a common ground by which employee scientists can communicate and integrate knowledge from the new, insular domain.

A second mechanism through which depth of capability positively moderates innovative output after entry into insular domains is by increasing the potential for recombination. Given that niches vary in their stock and growth of technology opportunities (Klevorick et al. 1995), entry into new domains provides the potential to recombine knowledge components with its existing capabilities (Fleming, 2001). Consequently, a firm whose knowledge is located across niches has access to a larger pool of opportunities. Therefore, firms with high depth of technological capabilities that enter a 'new to the firm' insular domain can absorb the new information to increase the quantity of innovative output. In addition, firms can create radical innovation by combining technology elements from the insular domain that have not been previously combined with other domains (Utterback, 1994). Hence, we posit that:

Hypothesis 3: Depth of technological capabilities positively moderates the curvilinear relationship between entry into insular domains and (a) the quantity, and (b) the impact of a firm's innovative output.

METHOD

Sample

To test the hypotheses, we collected longitudinal data on biotechnology startups from the year of their incorporation. Our sample consists of firms founded from 1980 to 1999 in the human diagnostics and therapeutics segment. In the first step, classification through SIC codes yielded 504 firms: 104 firms in Human Diagnostics (SIC #2835), 96 firms in biological products excluding diagnostics (SIC #2836), and 304 in pharmaceutical preparations (SIC #2834). We further refined this sample using the firm's business focus, as provided in *The GEN Guides to Biotechnology Companies*. Only gene therapy, human diagnostics and therapeutics firms were included, yielding 128 firms with an average age of 6.87 years (s.d. = 4.22). This sampling strategy excluded firms in agricultural biotechnology and generic pharmaceuticals that have distinct innovation cycles and regulatory regimes that govern them. Also, this sample includes private and public firms. To provide some descriptive statistics, the sample consists of 622 private firms and 974 public firm observations. The sample includes firms aged less than five years (690 observations), between five and twelve years (720 observations), and above twelve years (186 observations). For the analyses, we include 1491 firm-year observations which allow us to track firm level innovation from its founding year as a start-up, consistent with our theoretical framework.

Dependent Variables

Quantity of Innovative Output is measured as the number of new patents applied for in two subsequent years. Use of patents to study firm-level innovativeness is common in academic research (Ahuja & Lampert, 2001; Rothaermel & Deeds, 2004; Stuart, 2000). The average innovative output per firm in a year was 4.69 and the standard deviation was 12.84.

Technological Impact is measured as the number of citations that a firm's patent has received (Argyres & Silverman, 2004; Sorensen & Stuart, 2000). We used the USPTO records up to the year ending 2005 to count the number of citations received by each patent held by the firms. By extending six years beyond the sample cut-off date, we reduced the impact of right censoring on the dependent variable. We

aggregate the citations by firm patent year, i.e., we sum the number of citations received by all patents granted in a year to a firm. For example, if a firm was granted two patents in 1985 and these patents received 8 and 12 citations by the year ending 2005, then the impact measure for the firm for the year 1985 would be 20. The average citation rate was 25.1 and the standard deviation was 63.43.

Independent Variables

Depth of technological capabilities is measured by calculating the maximum number of patents in any one technical class as defined by the USPTO. This measure captures the depth of technical expertise in one area (Argyres & Silverman, 2004). To assess construct validity, we developed an alternative measure of patent concentration across multiple classes using $\Sigma(p_i)^2$, where p_i is the number of patents in one particular technical class divided by the total number of patents issued. A firm that had a few patents concentrated in a single class may have more depth than firms that have patents spread across several technical classes. For example, if a firm had five patents that fell into five different technological classes, then the value would be $\Sigma (1/5)^2 + (1/5)^2 + (1/5)^2 + (1/5)^2 = 0.2$. This measure was significantly correlated (r = .80, p<.001) with our depth measure of maximum patents in any technical class and bolstered our confidence in our measure for depth of technological capabilities.

Insularity of 'new to the firm' technical domains. The construct captures a firm's entry into an insular technical domain, i.e. the degree to which prior inventions within the same technical domain help generate new innovation. Insularity is measured as the count of citations made to patents within the technology subclass divided by the total number of citations made by the patents in the subclass. We used the USPTO patent records of citations by patents from the years 1975 to 1999. We built a cross citation matrix where the diagonal matrix represents the citation by class i patents of other class i patents. The diagonal vector measures the insularity of the technology class. This is a global measure of insularity of technology classes across all technical classes and not drawn only for our biotechnology sample; improving construct validity and its generalizability. On average the insularity of technology domains in our sample is 47%. This suggests that, new innovation on average draws nearly half of the knowledge from within the domain. This suggests a high entry barrier for firms to enter new technology domains as start-up firms would need to invest time and resources to understand the new knowledge in the new technology domain. However, there is variance among the technology classes on what extent the classes draw on knowledge within the same domain. The insularity ratio for the subclass varies from 20% for data calibration equipment subclass to 76% for radiation and imagery subclass. We further refine the insularity measure to capture the firm's entry into these insular domains. If the firm enters more than one technology class then we take the average insularity of such new to the firm classes. The measure ranges from 0 to 0.71 in our data, with a mean value of 0.12 and standard deviation of 0.21.

Insularity differs from two other often used measures in the innovation literature: originality and importance. Originality and importance are primarily used at the level of the single innovation (patent). Recently these constructs have also been used at the level of a technical domain (Goureev, 2006). Originality implies that for innovation that draws from multiple domains, there is a more need for a synthesis of multiple ideas (Trajtenberg, Henderson, & Jaffe, 1997). Insular domains may score low on originality since they draw their innovation predominantly from within the domain; this, however, does not imply that insularity is a reciprocal of originality. For insularity to be distinct it should be possible that when originality is either low or high. For example consider a technology Domain A, if an innovation in Domain A cites other patents predominantly in Domain A, then the insularity score would be high and the originality score would be low. However, if patents in Domain A cite a number of patents within Domain A and other domains then the technology field A will have a high insularity and a high originality score, showing the insularity is not the inverse of originality.

Insularity of a technology domain is also distinct from the importance of the technology domain. Importance measures the extent to which a patent class stands on broad base of previous innovation that themselves are important (Trajtenberg, Henderson & Jaffe, 1997). Importance counts the number of patents that a technology class cites and, in turn, the number of patents cited by the cited patents. The number of different technology classes to which the citations are made by the patents within a domain has no bearing on the importance of the class, whereas, the number of classes and the number of citations within a technology class is important for the calculation of insularity. Hence, insularity of a technology domain is distinct for what has been studied in prior literature.

Control Variables

The control variables for this study are *Breadth of technological capabilities, Branching, Branching Distance, Firm Age, Patent self-citation, Knowledge Stock, and Achieved IPO all of which are described in greater detail in the Georege et al. (2006).*

RESULTS

Hypothesis 1a posits an inverted U shaped relationship between depth of capabilities and innovative output. We find that the relationship is curvilinear but not inverted U shaped as posited but U shaped. The linear and quadratic terms are significant (b=-.043, p<.001 and b=.001, p<.001 respectively in Table 2, Model 4). The negative main term and positive quadratic term suggests a diminishing returns relationship between depth and output which after a point turns to an increasing relationship. Hypothesis 1a was not supported.

Hypothesis 1b suggests that depth has an inverted "u" shaped relationship with the technological impact. The linear coefficient of depth is positive and the quadratic coefficient is negative (b=.051, p<.001 and b=-.0007, p<.05 respectively in Table 3, Model 4). We find that as depth increases the impact of innovation by the firms (number of citations received) increases up to a point and then diminishes. Hypothesis 1b was supported.

Hypotheses 2a predicts the relationship between the firm's entry into an insular domain on its subsequent innovative output. Here, the linear term is negative but not significant but the quadratic term is positive and significant (b=2.877, p<.05; Table 2, Model 4). Using a plot of the coefficients, we found that as insularity increases; innovative output initially decreases and then subsequently increases after an inflection point of .25 (U-shaped). Given that our hypothesis was for an inverted-U shaped relationship where moderate insularity yields optimal outcomes, we did not find support for hypothesis 2a.

Hypothesis 2b predicts an increasing and then diminishing returns to insularity on technological impact. We find that the linear coefficient is positive and the quadratic term is negative and significant (b=11.33, p<.001 and b= -11.45, p<.001 respectively in Table 3, Model 4). Additionally, we plotted the function to confirm the inverted "U" shaped relationship between entry into insular domains and the technological impact of the firm's patents. Hypothesis 2b was supported.

The moderating effect is complex as both depth and insularity have linear and quadratic terms. To interpret the meaning of the coefficients, we graph the estimates. The figures are shown in Figure 1 (innovative output) and Figure 2 (technological impact). We find support for the positive moderation posited in hypotheses 3a and 3b: the highest output and impact occur when both depth and insularity of the new technology domain are high.

DISCUSSION

The source and growth of technological opportunities has received sporadic attention from scholars. Schumpeter (1942) suggests that opportunities arise from the discovery of new markets and customers.

Drucker (1985) classifies sources of opportunities into two broad classes: within the enterprise and outside the enterprise or industry. We suggest that there are significant differences in the rate of opportunities across technology domains. For example, in the biotechnology industry, human embryonic stem cells research has mushroomed in growth globally in terms of new firm entry and patenting in the specific technical domain during a period when overall biotechnology growth rates have remained stable. Our study adds to this dialog and documents that dispersion across technical domains (but within the same industry) also has significant and valuable outcomes for new opportunities.

It is in this context that knowledge structuration becomes important. If we use a metaphor for a firm's knowledge structure as knowledge held in metaphorical buckets. A young firm may have buckets of knowledge in a single technical domain or across multiple technical domains. If the firm's knowledge is thus *structured* that it has a single deep bucket of knowledge (high depth) in a technical niche and the firm subsequently enters an insular domain, the entry is of critical relevance for innovative activity. The degree of domain insularity, then, influences the nature of growth opportunities available to the startup firm. Alternatively, if the firm's knowledge is structured across multiple domains (breadth of technological capabilities) then the potential for recombination is higher. In this case, the ability of young firms to leverage depth of their technological capabilities to find new solutions within or across domains influences innovative activity. Though we do not explicitly theorize for the effects of breadth of technological capabilities, we empirically control for its effect in the estimations (Tables 2 and 3). The findings of this study endorse our fundamental premise that knowledge structuration is an issue of significant relevance for technology firms.

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REFERENCES

- Ahuja, G, Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. Strategic Management Journal, 22(3): 197-220.
- Ahuja, G, Lampert, CM. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal, 22(6-7): 521-543.
- Argyres, NS, Silverman, BS. 2004. R&D, Organization structure, and the development of corporate technological knowledge. Strategic Management Journal, 25(8-9): 929-958.
- Basalla, G. 1988. The Evolution of Technology. Cambridge University Press: Cambridge, MA.
- Benner, MJ, Tushman, M. 2002. Process management and technological innovation: A longitudinal study of the photography and paint Industries. Administrative Science Quarterly, 47(4): 676-706.
- Christensen, CM, & Bower, JL. 1996. Customer power, strategic investment, and the failure of leading firms. Strategic Management Journal 17(3): 197-218.
- Cohen, J, Cohen, P, West, SG, Aiken, LS. 2003. Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences, 3rd ed. Hillsdale: Erlbaum
- Cohen, WM, Levinthal, DA. 1990. Absorptive-capacity A new perspective on learning and innovation. Administrative Science Quarterly, 35(1): 128-152.
- Conant, JB, Nash, LK. 1964. Harvard case histories in experimental science. Harvard University Press. Cambridge, MA.
- Cyert, RM, March, JG. 1963. A Behavioral Theory of the Firm. Englewood Cliffs, NJ: Prentice-Hall.
- Drucker, PF.1985. Innovation and Entrepreneurship Practice and Principles. New York, Harper & Row.
- Ethiraj, S. & Puranam, P. 2004. The distribution of R&D effort in systemic industries: Implications for competitive advantage, Business Strategy over the Industry Life Cycle, Vol. 21: 225-253.
- Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science,47(1): 117-132.

- George, G. 2005. Slack resources and the performance of privately held firms. Academy of Management Journal, 48(4): 661-676.
- George, G, Zheng, Y, & Kotha, R. 2006. Branching into new niches: The expansion of technology capabilities in start-ups. Working paper, London Business School.
- Ghemawat, P, Spence, AM. 1985. Learning-curve spillovers and market performance. Quarterly Journal of Economics, 100: 839-852.
- Greve, HR. 1998. Performance, aspirations, and risky organizational change. Administrative Science Quarterly 43(1): 58-86.
- Griliches, Z. 1990. Patent statistics as economic indicators A survey. Journal of Economic Literature, 28(4): 1661-1707.
- Hall, BH, Jaffe, A, Trajtenberg, M. 2005. Market value and patent citations. Rand Journal of Economics, 36(1): 16-38.
- Hausman, J, Hall, BH, Griliches, Z. 1984. Econometric-models for count data with an application to the patents R and D relationship. Econometrica, 52(4): 909-938.
- Henderson, R, Cockburn, I. 1994. Measuring competence Exploring firm effects in pharmaceutical research. Strategic Management Journal, 15: 63-84.
- Hitt, MA, Hoskisson, RE, Johnson, RA, Moesel, DD. 1996. The market for corporate control and firm innovation. Academy of Management Journal, 39(5): 1084-1119.
- Jaffe, AB. 1986. Technological opportunity and spillovers of research-and-development evidence from firms patents, profits, and market value. American Economic Review, 76(5): 984-1001.
- Kale, P, Dyer, JH, Singh, H. 2002. Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. Strategic Management Journal, 23(8): 747-767.
- Kaplan, S, Murray, F, Henderson, R. 2003. Discontinuities and senior management: Assessing the role of recognition in pharmaceutical firm response to biotechnology. Industrial and Corporate Change, 12(2): 203-233.
- Katila, R. 2002. New product search overtime: Past ideas in their prime? Academy of Management Journal, 45(5): 995-1010.
- Katila, R, Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal, 45(6): 1183-1194.
- Kogut, B, Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science, 3(3): 383-397.
- Kuhn, T. 1962. The structure of scientific revolutions. Chicago: University of Chicago Press.
- Lacetera, N, Cockburn, IM, Henderson, R.2004. Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. In J. A. Baum and A. M. McGahan (eds) Business Strategy over the Industry Life Cycle Advances in Strategic Management 21: forthcoming. Oxford: Elsevier/JAI Press.
- Lerner, J. 1995. Patenting in the shadow of competitors. Journal of Law & Economics, 38(2): 463-495.
- Levinthal, DA, March, JG. 1993. The myopia of learning. Strategic Management Journal, 14: 95-112.

March, JG. 1991. Exploration and exploitation in organizational learning. Organization Science, 2: 71-87.

- March, JG. & Simon, HA. 1958. Organizations. New York: Wiley.
- Martin, X. Mitchell, W. 1998. The Influence of local search and performance heuristics on new design introduction in a new product market. Research Policy, 26(7-8): 753-771.
- Nelson, RR, Winter, SG. 1982. An Evolutionary Theory of Economic Change. Cambridge, MA: Belknap Press.
- Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. Management Science, 49(2): 211-229.
- Neter, J, Wasserman, W, Kutner, M. 1985. Applied Linear Statistical Models. Homewood, IL: Irwin.
- Pakes, A. Griliches, Z. 1980. Patents and R-and-D at the firm level A 1st Report. Economics Letters, 5(4): 377-381.
- Pisano, GP. 1990. The research-and-development boundaries of the firm An empirical-analysis. Administrative Science Quarterly, 35(1): 153-176.

- Pisano, GP. 1994. Knowledge, integration, and the locus of learning: An empirical analysis of process development. Strategic Management Journal, 15: 85-100.
- Pisano, GP. 2000. In search of dynamic capabilities. In G. Dosi, R. R. Nelson, & S. G. Winter (Eds.), The Nature and Dynamics of Organizational Capabilities. New York: Oxford University Press.
- Powell, WW, Koput, KW, Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. Administrative Science Quarterly, 41(1): 116-145.
- Powell, WW, White, DR, Koput, KW, Owen-Smith, J. 2005. Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. American Journal of Sociology, 110(4): 1132-1205.
- Rosenkopf, L, Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. Strategic Management Journal, 22(4): 287-306.
- Rothaermel, FT, Deeds, DL. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. Strategic Management Journal, 25(3): 201-221.
- Sampson, RC. 2005. Experience Effects and Collaborative Returns in R&D Alliances. Strategic Management Journal. 26(11):1009-1031.
- Sapienza, HJ, Autio, E, George, G, Zahra, SA. 2006. A capabilities perspective on the effects of early internationalization on firm growth and survival. Academy of Management Review, 31(4):913-933.
- Schumpeter, JA. 1939. Business Cycles. McGraw-Hill: New York.
- Shaver, JM. 1998. Accounting for endogeneity when assessing strategy performance: Does entry mode choice affect FDI survival? Management Science, 44(4): 571-585.
- Sorensen, JB, Stuart, TE. 2000. Aging, obsolescence, and organizational innovation. Administrative Science Quarterly, 45(1): 81-112.
- Stinchcombe, A. 1965. Social Structure and Organizations. In J.G. March, (Ed.), Handbook of Organizations. Chicago: Rand McNally & Co.
- Stuart, TE. 2000. Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. Strategic Management Journal, 21(8): 791-811.
- Stuart, TE, Podolny, JM. 1996. Local search and the evolution of technological capabilities. Strategic Management Journal, 17: 21-38.
- Trajtenberg, M, Henderson, R, Jaffe, A, 1997. University versus corporate patents: A window on the basicness of innovation. Economics of Innovation and New Technology, 5(1): 19-50.
- Tushman, ML, Anderson, P. 1986. Technological discontinuities and organizational Environments. Administrative Science Quarterly, 31(3): 439-465.
- Utterback, JM. 1994. Radical innovation and corporate regeneration. Research-Technology Management, 37(4): 10.
- Zahra, SA, George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review, 27(2): 185-203.
- Zahra, SA., Nielsen, A. 2002. Sources of capabilities, integration and technology commercialization. Strategic Management Journal, 23: 377-398.

Table 1: Descriptive Statistics and Correlations

	Variables	Mean	Sd. Dv.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12
1	Innovative Output	4.69	12.84	0	270	1											
2	Technology Impact	25.1	63.43	0	927	.42	1										
3	Age	6.87	4.22	1	18	.07	.1	1									
4	Knowledge Stock	4.8	11.51	0	265.8	.52	.51	.30	1								
5	Patent self-citation (t, t-1, t-2)	0.05	0.11	0	1	.14	.11	.30	.23	1							
6	Number of Alliances (t)	0.57	1.02	0	9	.29	.22	.03	.29	.04	1						
7	Prior Alliances (t-1t-n)	2.92	4.25	0	27	.23	.26	.50	.45	.17	.29	1					
8	Achieved IPO	0.61	0.49	0	1	.13	.13	.63	.24	.24	.10	.40	1				
9	Depth of capabilities	2.41	6.07	0	71	.26	.26	.46	.54	.35	.10	.46	.29	1			
10	Breadth of capabilities	1.4	2.01	0	14	.34	.43	.46	.62	.34	.17	.45	.40	.60	1		
11	Branching	0.36	0.71	0	5	.22	.43	.23	.05	.1	.13	.11	.06	.21	.06	1	
12	Branching Distance	0.26	0.63	0	4.2	.56	.49	.38	.08	.17	.18	.11	.15	.29	.06	.66	1
13	Insularity	0.12	.21	0	.7	.19	.34	.04	.04	.00	.19	.06	.10	.12	.10	.05	.40

Year dummies not reported, Number of observations = 1491, Number of firms = 128. All correlations greater than .06 are significant at .001 level.

	Model 1	Model 2	Model 3	Model 4
Constant	.268	.260	.279	.272
	(.143)	(.148)	(.153)	(.155)
Age	.217***	.292***	.288***	.298***
	(.033)	(.034)	(.034)	(.034)
Age-squared	008***	011***	010***	011***
	(.002)	(.002)	(.002)	(.002)
Knowledge Stock	.004*	.004*	.004*	.004*
-	(.002)	(.002)	(.002)	(.002)
Patent self-citation (t, t-1, t-2)	-1.573***	-1.551***	-1.590***	-1.503***
	(.330)	(.333)	(.334)	(.328)
Number of Alliances (t)	.067***	.058**	.063**	.060**
	(.020)	(.020)	(.020)	(.020)
Prior Alliances (t-1 t-n)	.025*	.027*	.028*	.029**
(*******	(.011)	(.011)	(.011)	(.011)
Achieved IPO	066	- 002	0001	- 001
	(.088)	(.084)	(.084)	(.083)
Breadth of capabilities	090**	073*	088**	070*
	(.033)	(.033)	(.034)	(.034)
Breadth Square	- 005*	- 004	- 005	- 003
	(.003)	(.003)	(.003)	(.003)
Branching (Hazard)	- 245***	251***	220*	190*
2-m.eg (m2m.e)	(.051)	(.050)	(.087)	(.087)
Branching Distance	.625***	.588***	.587***	.670***
	(.111)	(.110)	(.120)	(.124)
Branching Distance Square	108***	094***	090**	102***
0 1	(.027)	(.027)	(.030)	(.031)
Depth		058***	058***	043***
•		(.010)	(.010)	(.012)
Depth Square		.001***	.001***	.001***
		(.00014)	(.00014)	(.00014)
Insularity			-1.195	-1.568
-			(.824)	(.916)
Insularity Square			2.153*	2.877*
			(1.086)	(1.292)
Depth* Insularity				008
_ ~				(.110)
Depth Square* Insularity				008*
				(.004)
Insularity Square* Depth				326

Table 2:	Fixed-Effects	Negative	Binomial	Estimates	of Inno	vative (Jutput

				(.218)
Insularity Square * Depth Square				.019*
				(.008)
Log Likelihood	-2248.1	-2222.2	-2219.0	-2209.7
Wald Chi-square	1401.2***	1474.1***	1483.7***	1554.6***
Change in Chi-square		60.4***	6.4**	18.4***

[†]p<.10 * p<.05; ** p<.01; *** p<.001

Number of observations =1491, number of firms = 128, average observation per firm=11.6

Unstandardized coefficients reported (standard errors in parentheses)

Year dummies included but not reported0

Constant -2.834^{***} -2.855^{***} -3.373^{***} -3.580^{***} (.179)(.183)(.195)(.202)Age.102*.100*.039.089(.046)(.049)(.048)(.047)Age-squared 007^{**} 007^* 002 005^* (.002)(.003)(.003)(.003)Knowledge Stock $.010^{***}$ $.010^{***}$.003.003
(.179) $(.183)$ $(.195)$ $(.202)$ Age $.102*$ $.100*$ $.039$ $.089$ $(.046)$ $(.049)$ $(.048)$ $(.047)$ Age-squared $007**$ $007*$ 002 $005*$ $(.002)$ $(.003)$ $(.003)$ $(.003)$ Knowledge Stock $.010***$ $.010***$ $.003$ $.003$
Age $.102^*$ $.100^*$ $.039$ $.089$ $(.046)$ $(.049)$ $(.048)$ $(.047)$ Age-squared 007^{**} 007^* 002 005^* $(.002)$ $(.003)$ $(.003)$ $(.003)$ Knowledge Stock $.010^{***}$ $.010^{***}$ $.003$ $.003$
(.046) (.049) (.048) (.047) Age-squared 007** 007* 002 005* (.002) (.003) (.003) (.003) Knowledge Stock .010*** .010*** .003 .003 (.002) (.002) (.002) (.002) (.002)
Age-squared 007** 007* 002 005* (.002) (.003) (.003) (.003) Knowledge Stock .010*** .010*** .003 .003 (.002) (.002) (.002) (.002) (.002)
(.002) (.003) (.003) (.003) Knowledge Stock .010*** .010*** .003 .003 (.002) (.002) (.002) (.002) (.002)
Knowledge Stock .010*** .010*** .003 .003 (002) (002) (002) (002) (002) (002)
(002) (002) (002) (002)
(.002) $(.002)$ $(.002)$ $(.002)$
Patent self-citation (t, t-1, t-2) .252* .424 .629 .632
(.389) (.395) (.391) (.383)
Number of Alliances (t) .056 .050 .039 .026
(.029) (.029) (.027) (.026)
Prior Alliances (t-1,t-n) .011 .016 .005 .010
(.011) (.012) (.012) (.012)
Achieved IPO .252 .241 .218 .182
(.128) (.126) (.121) (.118)
Breadth of capabilities .759*** .778*** .681*** .562***
(.051) (.050) (.051) (.051)
Breadth Square047***047***042***032***
(.005) (.005) (.005) (.004)
Branching Hazard .505*** .499***612***544***
(.070) (.070) (.103) (.103)
Branching Distance .129 .111 499** 357*
(.169) (.168) (.167) (.169)
Branching Distance Square073066 .093* .093*
(.046) (.046) (.043) (.044)
Depth034**014 .051***
(.011) (.011) (.015)
Depth Square .0004* .000180007*
(.00018) (.00012) (.0003)
Insularity 9.640*** 11.337***
(1.065) (1.180)
Insularity Square -9.169*** -11.451***
(1.449) (1.710)
Depth* Insularity555***
(.158)
Depth Square* Insularity .003
Insularity Square* Depth 572*

 Table 3: Fixed-Effects Negative Binomial Estimates of Technological Impact

				(.303)
Insularity Square * Depth Square				.002
				(.009)
Log Likelihood	-3135.5	-3130.3	-3069.6	-3035.9
Wald Chi-square	1317.3***	1327.5***	1420.7***	1452.4***
Change in Chi-square		10.0**	151.0***	64.8***

[†]p<.10 * p<.05; ** p<.01; *** p<.001

Number of observations =1491, number of firms = 128, average observation per firm=11.6

Unstandardized coefficients reported (standard errors in parentheses)

Year dummies included but not reported

Figure 1: Interaction of Depth and Insularity of the New Domain on Innovative Output



Figure 2: Interaction of Depth and Insularity of the New Domain on Technological Impact

