



HAL
open science

Do Firms Benefit from Being Present in Multiple Technology Clusters? An Assessment of the Technological Performance of Biopharmaceutical Firms.

Catherine Lecocq, Bart Leten, Jeroen Kusters, Bart van Looy

► To cite this version:

Catherine Lecocq, Bart Leten, Jeroen Kusters, Bart van Looy. Do Firms Benefit from Being Present in Multiple Technology Clusters? An Assessment of the Technological Performance of Biopharmaceutical Firms.. *Regional Studies*, 2011, pp.1. 10.1080/00343404.2011.552494 . hal-00680011

HAL Id: hal-00680011

<https://hal.science/hal-00680011>

Submitted on 17 Mar 2012

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



**Do Firms Benefit from Being Present in Multiple Technology Clusters?
An Assessment of the Technological Performance of Biopharmaceutical Firms.**

Journal:	<i>Regional Studies</i>
Manuscript ID:	CRES-2009-0211.R2
Manuscript Type:	Main Section
JEL codes:	O30 - General < O3 - Technological Change Research and Development < O - Economic Development, Technological Change, and Growth, R12 - Size and Spatial Distributions of Regional Economic Activity < R1 - General Regional Economics < R - Urban, Rural, and Regional Economics, R30 - General < R3 - Production Analysis and Firm Location < R - Urban, Rural, and Regional Economics
Keywords:	Cluster, Biotechnology, Innovation

SCHOLARONE™
Manuscripts

1
2
3 Do Firms Benefit from Being Present in Multiple Technology Clusters?
4
5

6 An Assessment of the Technological Performance of Biopharmaceutical Firms.
7
8
9

10 Catherine Lecocq^{1,2}

11 Bart Leten^{1,3}

12 Jeroen Kusters⁴

13 Bart Van Looy^{1,5,6}
14
15
16
17

18 ¹Department of Managerial Economics, Strategy and Innovation. Faculty of Business and
19 Economics, K.U. Leuven (Belgium). Naamsestraat 69, B-3000 Leuven (Belgium).
20
21

22 ²Steunpunt Ondernemen en Internationaal Ondernemen (Belgium)
23

24 ³Vlerick Leuven-Gent Management School (Belgium).
25

26 ⁴Deloitte Consulting (Belgium). Berkenlaan 8c, B-1831 Diegem (Belgium).
27

28 ⁵Expertisecentrum O&O Monitoring (ECOOM) (Belgium)
29

30 ⁶School of Management and Governance, University of Twente (Netherlands)
31
32

33 E-mails: Catherine.Lecocq@econ.kuleuven.be; Bart.Leten@econ.kuleuven.be;
34

35 jkusters@deloitte.com; Bart.VanLooy@econ.kuleuven.be
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

(Received July 2009; in revised form December 2010)

1
2
3
4
5
6 ABSTRACT
7

8 Firms active in knowledge-intensive fields are increasingly organizing their R&D
9 activities on an international scale. This paper investigates whether firms active in
10 biotechnology can improve their technological performance by developing R&D
11 activities in multiple technology clusters. Regions in the Europe, Japan and US,
12 characterized by a critical mass in terms of technological activity within
13 biotechnology, are identified as clusters. Fixed-effect panel data analyses with 59
14 biopharmaceutical firms (period 1995-2002) provides evidence for a positive, albeit
15 diminishing (inverted-U shape) relationship between the number of technology
16 clusters in which a firm is present and its overall technological performance. This
17 effect is distinct from a mere multi-location effect.
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33

34 Keywords: Cluster; Innovation; Biotechnology.
35

36 JEL classification: O30, R12 and R30.
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

INTRODUCTION

Corporate activities, especially in knowledge-intensive industries, display a tendency to cluster geographically (AUDRETSCH and FELDMAN, 1996; FELDMAN and FLORIDA, 1994). According to MARSHALL (1920), presence in clusters enhances the innovative capacity of firms through the presence of localized knowledge spillovers, and the access to a pool of highly-skilled labor and specialized suppliers that agglomerate in such regions. Innovation dynamics in clusters are further stimulated by the presence of local competition and peer pressure among firms (PORTER, 1990). Empirical studies stemming from the economic geography literature indeed provide evidence that firms located in clusters are more innovative than counterparts located elsewhere (BAPTISTA and SWANN, 1998; BATEN et al., 2007; BEAUDRY and BRESCHI, 2003; DEEDS, DECAROLIS and COOMBS, 1999; VAN GEENHUIZEN and REYER-GONZALES, 2007). At the same time, little is known about the relationship between presence in *multiple* clusters and the overall technological performance of firms. Exploring this relationship is relevant because firms increasingly organize R&D activities on an international scale whereby knowledge from different regions is being accessed. (GASSMAN AND VON ZEDTWITZ, 1999; KUEMMERLE, 1997; GRANSTRAND, 1999). In this paper, we engage in such an analysis by means of a panel dataset of 59 biopharmaceutical firms (period 1995-2002). The focus of the paper is on the relationship between the technological performance of consolidated firms (i.e. the parent firm and its subsidiaries) and the number of technology clusters in which they engage in technological activities. Clusters are identified as regions within the United States, Europe and Japan with a critical mass of technological activities in the field of biotechnology. Whereas previous economic geography studies controlled only to a

1
2
3 limited extent¹ for the heterogeneity of firms in terms of innovative efforts and
4 capabilities, this study uses fixed effect panel data techniques and includes controls
5 for time-varying firm differences in R&D expenditures and past experience. This
6 allows to distinguish cluster presence from other firm-specific characteristics
7 (BEUGELSDIJK, 2007). The analyses provide evidence of an inverted-U shape
8 relationship between the number of technology clusters in which a firm is present and
9 its overall technological performance. This effect is distinct from a mere multi-
10 location effect.
11
12
13
14
15
16
17
18
19
20
21

22 The remainder of the paper is organized as follows. First, an overview of prior
23 research on clusters and firm performance is provided, resulting in hypotheses on the
24 relationship between cluster presence and firm's technological performance. Next, the
25 data sources and variables used in this study are presented, followed by the empirical
26 results. Conclusions, limitations and directions for further research are discussed in
27 the final section.
28
29
30
31
32
33
34
35
36
37
38
39

40 INDUSTRY AND TECHNOLOGY CLUSTERS

41
42 The clustering of industrial activity in well-defined and relatively small geographic
43 areas has been observed for a long time by economic geographers and regional
44 scholars (e.g. MARSHALL 1920; KRUGMAN 1991; PORTER 1990). Famous examples of
45 industrial clusters include Detroit's car manufacturing industry, the entertainment
46 industry of Hollywood and the fashion industry in northern Italy. Clustering remains a
47 striking feature of national and regional economies, despite the availability of better
48 transportation and communication infrastructure and the presence of global markets
49 from which capital, talent and technology can be sourced (PORTER, 1998; 2000).
50 Following the success of Silicon Valley in California and Route 128 in Boston
51
52
53
54
55
56
57
58
59
60

1
2
3 (SAXENIAN, 1994), there has been a wide interest of researchers and policy makers in
4
5 the innovative and economic potential of technology clusters. Unlike industry-focused
6
7 clusters, where inter-firm connections are predominantly vertical, technology clusters
8
9 exhibit a more lateral structure consisting of direct and indirect competitors
10
11 developing diversified applications of the same core technology within different
12
13 markets or industries (ST. JOHN and POWDER, 2006). Value dynamics in technology
14
15 clusters or “technology districts” build on unique technological resources - the
16
17 technological infrastructure - which supports firms’ innovation activities (FELDMAN
18
19 and FLORIDA, 1994; STORPER, 1992). Sources of knowledge in technology clusters are
20
21 diverse, ranging from universities and public research institutes to firms, suppliers and
22
23 customers.
24
25
26
27
28
29

30 MARSHALL (1920) highlighted three incentives for firms to cluster
31
32 geographically: (i) broader access to specialized, highly-skilled labor; (ii) access to
33
34 specialized suppliers; and (iii) the presence of inter-organizational knowledge
35
36 spillovers among similar firms². The broad concept of knowledge spillovers is
37
38 probably the most frequently invoked source of agglomeration economies (HEAD et
39
40 al, 1995) and has been widely investigated in the literature (e.g. DÖRING and
41
42 SCHNELLENBACH, 2006; BRESCHI and LISSONI, 2001). Knowledge spillovers arise
43
44 through labor mobility (ALMEIDA and KOGUT, 1999) and exchange processes
45
46 involving competitors, suppliers, customers and providers of professional services
47
48 (VON HIPPEL, 1988; ROSENKOPF and ALMEIDA, 2003). They allow firms to achieve
49
50 similar R&D results faster and/or with fewer resources. Empirical work has shown the
51
52 existence and geographically bounded nature of knowledge spillovers (JAFJE et al.,
53
54 1993; ALMEIDA and KOGUT, 1999; VARGA, 2000; RODRÍGUEZ-POSE and CRESCENZI,
55
56 2008). Spillovers are more local to the extent that the relevant knowledge base is tacit
57
58
59
60

1
2
3 (POLANYI, 1966; NONAKA, 1994; VON HIPPEL, 1994). This is particularly true for
4
5 emerging, complex technologies like biotechnology. PORTER (1990; 1998) provided
6
7 two additional reasons why firms located in clusters are more innovative than firms
8
9 located outside clusters. First, opportunities for innovation (both new buyer needs and
10
11 new technological opportunities) are more visible in clusters. Next, competitive
12
13 and/or peer pressure among local firms stimulates firms to be more innovative and
14
15 increases the efficiency of their operations.
16
17
18

19
20 While clusters are often associated with positive effects on firm performance,
21
22 potential disadvantages can be noticed as well. First, resources (e.g. labor, real estate,
23
24 professional services) might be significantly more expensive in clusters due to
25
26 congestion effects (BEAUDRY and BRESCHI, 2003). Second, cluster membership might
27
28 lead to an inward orientation whereby relevant developments situated outside the
29
30 cluster are neglected (PORTER, 1998). Firms located in clusters might also be
31
32 confronted with higher levels of unintended (outward) knowledge spillovers, affecting
33
34 the firm's competitive advantage in a negative way (SHAVER and FLYER, 2000).
35
36 While such disadvantages might occur, they are not directly relevant for the research
37
38 questions addressed in this paper as the focus is on the firm's technological
39
40 performance (as opposed to the overall competitive position of the firm or the
41
42 efficiency implications of being present in clusters).
43
44
45
46
47
48
49
50
51
52

53 CLUSTERS AND FIRM PERFORMANCE

54
55 The capacity of firms to innovate is not limited to the boundaries of the firm but
56
57 increasingly depends on external resources that agglomerate in specific places
58
59 (FELDMAN and FLORIDA, 1994; STORPER, 1992). If knowledge spillovers are an
60

1
2
3 essential characteristic of clusters, the beneficial effects from being present in a
4 cluster should manifest themselves in the first place on the innovative output of firms
5 rather than on the firm's financial or growth performance (BAPTISTA and SWANN,
6 1998). Studies in the economic geography literature have investigated whether firms
7 (plant level) located in an industrial or technology cluster are more innovative than
8 firms outside clusters³. These studies can be classified in two groups based on the
9 methodologies used to measure clusters.
10
11
12
13
14
15
16
17
18

19
20 A first set of studies investigated whether firms located in industrial clusters
21 are more innovative. The concentration of industrial activity in a region is measured
22 by sector level employment data. BAPTISTA and SWANN (1998) found a positive effect
23 of own sector employment in the region, on the likelihood of manufacturing firms in
24 the United Kingdom to innovate. In contrast, BEAUDRY and BRESCHI (2003) found no
25 effect of own sector employment on firms' innovative performance for a sample of
26 UK and Italian firms. Only the concentration of innovative firms (and the size of their
27 accumulated knowledge base) in the own industry had a positive impact on the
28 technological performance of firms. Similar results were found in the study of BATEN
29 et al. (2007) for firms trading in the state of Baden (Germany) around 1900. These
30 findings suggest that for firms' innovative performance, the presence of critical mass
31 in terms of knowledge creation activities in a region is more important than the
32 overall industrial activity per se.
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49

50
51 A second set of studies classified regions in clusters and non-clusters based on
52 the amount of technological activity observed in the region, and examined whether
53 firms located in technology clusters are more innovative than firms located elsewhere.
54 DEEDS et al. (1999) classified eight regions in the United States (MSA level) that host
55 the largest number of biotechnology firms, as clusters and found that biotechnology
56
57
58
59
60

1
2
3 firms located in clusters are more innovative than firms located outside the clusters.
4
5 For the Netherlands, VAN GEENHUIZEN and REYER-GONZALES (2007) defined clusters
6
7 as regions with at least one knowledge institute and 10 young entrepreneurial
8
9 biotechnology firms. Their analyses showed no significant effect from cluster location
10
11 on the innovativeness of biotechnology firms. However, when only the largest and
12
13 oldest biotechnology cluster in the Netherlands - the Leiden region - is considered,
14
15 cluster presence had a significant positive effect on firm performance. These results,
16
17 again, suggest that a critical mass of technological activity is needed before positive
18
19 cluster effects can be observed at level of the firm.
20
21
22
23
24

25 Aforementioned economic geography studies use cross-sectional data at the
26
27 level of single plants to investigate whether clusters are supportive to firms'
28
29 innovation activities. While the results indicate that firms in clusters are more
30
31 innovative than firms located elsewhere, they do not provide evidence whether firms
32
33 can improve their technological performance by extending their presence within
34
35 multiple clusters. This research question is addressed in this paper. More specifically,
36
37 the relationship between the number of technology clusters in which a firm is present
38
39 and its overall technological performance is studied. Exploring this relationship is
40
41 relevant because firms increasingly organize R&D activities within multiple units -
42
43 located in different regions - to benefit from agglomeration externalities (GASSMAN
44
45 and VON ZEDTWITZ, 1999; KUEMMERLE, 1997; GRANSTRAND, 1999; CANTWELL and
46
47 PISCITELLO, 2005). In so doing, R&D location choices are not confined to national
48
49 borders, but increasingly take place on a global scale. As such, empirical analyses
50
51 assessing the impact of cluster presence should not be limited to one particular
52
53 country or region, but should consider technology clusters on a more global scale.
54
55
56
57
58
59
60

1
2
3 Likewise, on the firm level, studying the impact of cluster presence requires taking
4
5 into account the location of all firms' R&D facilities (headquarters and subsidiaries).
6
7

8 In this paper, such an analysis is performed by means of a panel dataset
9
10 consisting of the technological activities of 59 biopharmaceutical firms (1995-2002).
11
12 In line with economic geography studies, locations of firms' R&D activities
13
14 (including cluster presence) are analyzed at the regional level. Technology clusters are
15
16 defined as worldwide leading regions in technology development. The models in this
17
18 study control for firm-level heterogeneity in innovative efforts and capabilities by
19
20 employing fixed effects panel data techniques and including time-varying, firm-level
21
22 control variables (R&D expenditures and innovation experience). This allows to
23
24 clearly distinguish between cluster presence and other, firm-specific, characteristics
25
26 (BEUGELSDIJK, 2007).
27
28
29
30

31 A positive effect on a firm's overall technological performance is expected
32
33 from being present in multiple clusters, as this coincides with an increased access to
34
35 state-of-the-art knowledge available within each of these regions. At the same time,
36
37 the more one is already involved in different clusters, the smaller the additional
38
39 effects in terms of access to new, relevant knowledge might become. In addition, the
40
41 costs of coordinating multiple R&D units and leveraging and integrating knowledge
42
43 from multiple locations will increase with the number of locations in which a firm is
44
45 present. Building on the aforementioned research, it is expected that location benefits
46
47 will principally stem from being present in technology clusters with a critical mass of
48
49 relevant knowledge. Therefore, the effects of cluster membership on the overall
50
51 technological performance of firms should be distinctive from a mere multiple
52
53 location effect. Taken together, these arguments lead to the following set of
54
55 hypotheses:
56
57
58
59
60

1
2
3 Hypothesis 1: Firms improve their technological performance when extending their
4
5
6 presence in technology clusters.

7
8 Hypothesis 2: Firms extending their presence in technology clusters will gain
9
10 additional benefits in terms of technological performance, albeit of a
11
12 diminishing nature (inverted U-shape relationship).

13
14
15 Hypothesis 3: The relationship between cluster membership and overall technological
16
17 performance is distinct from a mere multi-location effect.
18
19
20
21
22

23 DATA AND METHODOLOGY

24
25
26 Panel data on the technological activities of 59 biopharmaceutical firms with parent
27
28 firms located in the United States, Europe and Japan, have been collected to study the
29
30 relationship between the location of R&D activities in multiple clusters and regions
31
32 and the overall technological performance of firms. Patent data are used to create
33
34 indicators of firms' technological activities (location and performance) and to identify
35
36 biotechnology clusters within the United States, Europe and Japan . The use of patent
37
38 data has several advantages (PAVITT, 1985; GRILICHES, 1990). They are easy to
39
40 access, cover long time series and contain detailed information on the technological
41
42 content, owners and inventors of patented inventions. This allows to mark out
43
44 biotechnology patents, construct indicators of the technological performance of firms
45
46 and regions, and identify the locations where inventions took place. At the same time,
47
48 patent indicators also have some deficits: not all inventions are patented, patent
49
50 propensities vary across industries and firms, and patented inventions vary in
51
52 technical and economic value (MANSFIELD, 1986; GAMBARDELLA et al, 2008). One
53
54 can lessen these problems by restricting patent analyses to technologies with high
55
56 propensities to patent such as biotechnology (ARUNDEL and KABLA, 1998), and by
57
58
59
60

1
2
3 weighting patent counts (technological performance indicator) by the number of
4 forward citations received (HALL et al, 2005; TRAJTENBERG, 1990; HARHOFF et al.,
5 1999). Despite their shortcomings, there is simply no other indicator that provides the
6 same level of detail on firms' technological activities as patents do (GRILICHES,
7 1990). Further, studies have found a strong correlation between patent counts and
8 other technology indicators (e.g. new product announcements and expert opinions) on
9 the level of firms (HAGEDOORN and CLOODT, 2003; NARIN and NOMA, 1987) and
10 regions (ACS et al, 2002), establishing patents as a valid indicator of novel
11 technological activity.
12
13
14
15
16
17
18
19
20
21
22
23

24
25 In this study, patent indicators are based on data from the European Patent
26 Office (EPO). Patent application data rather than patent grants are used because of the
27 extensive time periods observed between application and granting decisions at the
28 European Patent Office (especially for biotech)⁴. The geographic location of
29 inventions is identified via inventor address information (LECOCQ et al., 2008).
30 Allocation based on inventor addresses is the most commonly used approach in patent
31 studies since – especially for large firms - allocation based on assignee addresses
32 might signal the location of corporate headquarters rather than the research laboratory
33 where the invention took place (DEYLE and GRUPP, 2005; KHAN and DERNIS, 2006).
34 The use of inventor addresses may however also introduce some bias since inventors
35 may not live in the same region as they work. LANDONI et al. (2008) performed a
36 validation exercise where both allocation methods (inventor and applicant addresses)
37 are compared with the real R&D locations of inventions. This work confirmed the
38 superiority of the inventor's address criterion, for patent statistics at a fine-grained
39 geographical level.
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Sample of Biopharmaceutical Firms

Parent firms with a large biotech patent portfolio are identified from a dataset with all EPO patent applications in the field of biotechnology (time period 1978-2001). This dataset is the result of a study by GLÄNZEL et al. (2004) that delineates technological activity in the field of biotechnology⁵. The selected firms are active in different sectors: mostly in biotechnology, the pharmaceutical or chemical industry, but the list of parent firms also includes producers of consumer products, energy concerns and breweries. For consistency of the sample, only the biopharmaceutical firms (75 largest patenting firms) were retained. Due to missing data on firm R&D expenditures or incomplete information on the group structure of parent firms, the list of firms was further reduced to 59 biopharmaceutical firms. All these firms have headquarters in the United States, Japan or Europe (EU-15 and Switzerland). Appendix 1 contains a complete list of the firms under study.

For this sample of 59 biopharmaceutical firms, patent data were collected at the consolidated parent level, i.e. comprising headquarters and all majority-owned (share > 50%) subsidiaries of the parent firm. This consolidation process implied the mapping of all changes in the group structure of the parent firms due to acquisitions, mergers, green-field investments and spin-offs during the period 1995 to 2002. For this purpose, yearly lists of subsidiaries included in annual reports were used, as well as yearly 10-K reports filed with the SEC in the United States and, for Japanese firms, information on foreign subsidiaries published by Toyo Keizai in the yearly Directories of Japanese Overseas Investments. Using consolidated patent data is important to get a complete picture of firms' technological activities as a significant part of large firms' patents are not filed under the parent firm name (LETEN et al,

1
2
3 2007). Firm financial data are also collected at the consolidated firm level via
4
5 corporate annual reports, Worldscope and Compustat financial databases.
6
7

8 9 Biotechnology Clusters

10
11 Biotechnology is a knowledge-intensive technology field, which from its origin has
12 developed within a limited number of regions, such as California and the Boston area
13 in the United States, and Cambridge in the United Kingdom. To identify
14 biotechnology clusters worldwide, the aforementioned dataset with all EPO patent
15 applications in the field of biotechnology is used (Glänzel et al., 2004). The dataset
16 shows that, for the period 1990-1999, almost all patenting activity in the domain of
17 biotechnology (94%) takes place in the United States, Europe (EU-15 and
18 Switzerland) and Japan. No other region has sufficient patent applications to qualify
19 as a cluster.
20
21
22
23
24
25
26
27
28
29
30
31
32

33 In this study, the focus is on regions in the United States, Europe and Japan. It
34 is important to select a spatial level of analysis which is comparable across continents
35 in terms of size (population). Regions are therefore defined at the level of the
36 following national subdivisions: European NUTS 1 regions (n=73), US states (n=50),
37 and Japanese prefectures (n=47)⁶. Cluster boundaries do not necessarily coincide with
38 the boundaries of such administrative regions. Clusters may well spread over more
39 than one region (e.g. the tri-state cluster in the states of New York, New Jersey and
40 Pennsylvania and the cluster covering the prefectures of Tokyo and Kanagawa).
41 Alternatively, regions may enclose more than one cluster (e.g. the triangle San
42 Francisco - San Jose - Sacramento, better known as Silicon Valley, and the region
43 between Los Angeles and San Diego in the state of California). Despite these
44 concerns, an analysis of regions coinciding with the boundaries of the administrative
45 subdivisions was chosen, as they provide comparable regional units of analysis.
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

The amount of biotechnological R&D activities in a region is measured by the number of EPO patents in that region during the period 1990-1999. Patent applications are allocated to regions based on inventor addresses. When a patent contains multiple inventors in different regions, the patent is fully counted in each region. Table 1 shows the 50 regions with the highest technological performance in the field of biotechnology. A region is defined as a biotechnology cluster if it contains at least 2.5% of the total number of EPO patent applications in the field of biotechnology. Twelve regions satisfy this condition. Together they account for 50% of biotechnology patents worldwide. Most biotechnology clusters are located in the United States, with a clear supremacy of the state of California which accounts for almost 15% of all biotechnology patents. Other US regions with a substantial amount of activity in biotechnology are Massachusetts, Maryland, Pennsylvania, New York and New Jersey. Europe has three top regions: the region of Paris (France) , the region of Cambridge, Bedfordshire, Hertfordshire and Essex (East Anglia. United Kingdom) and the region of Munich (Bayern, Germany). With Tokyo, Kanagawa and Osaka, Japan counts three top regions in biotechnology.

Insert Table 1 about here

Firm Variables and Model

Dependent Variable

The dependent variable in the study is the technological performance of firms in biotechnology. This is measured by the number of biotech patent applications of a firm in a certain year, weighted by the number of forward patent citations received over a fixed four year time window⁷. The ‘weighting’ is done to account for variation in the technological and economic importance of patented inventions (ALBERT et al., 1991, HARHOFF et al., 1999; TRAJTENBERG, 1990; HALL et al, 2005)⁸.

The dependent variable is a count variable with only non-negative integer values. In this case, non-linear count data models are preferred to standard linear regression models as the former explicitly take into account the non-negativity and discreteness of the dependent variable (CAMERON and TRIVEDI, 1998). Negative binomial models used in the study allow for overdispersion in the dependent variable. To control for the presence of unobserved firm-specific effects (which may correlate with, and bias the effect of explanatory variables in the models, if not controlled for), fixed effects panel data estimators are used. This estimation technique removes (time constant) unobserved firm-specific factors by time-demeaning all variables (dependent and explanatory) before performing regressions (WOOLDRIDGE, 2001).

Presence in Technology Clusters

To identify the regions in which firms are present, inventor address information on the biotechnology patents of the firms is used. More specifically, a firm is considered to engage in biotechnology R&D activities in a region if the firm owns patents with at least two inventors residing in that region during the last two years. Given the fact that

1
2
3 R&D collaboration is quite widespread in the field of biotechnology (LECOCQ and
4 VAN LOOY, 2009)⁹, it was decided to consider presence in a region only on the firm's
5
6 fully owned patents, thus reflecting the number of regions (clusters and other regions)
7
8 in which a firm is present through its fully owned or single parent patents. For co-
9
10 owned patents, i.e. patents with multiple assignees from different parent
11
12 organizations, it is not possible to identify to which assignee an inventor belongs.
13
14 Therefore using inventor address information on such patents may not only pick up a
15
16 firm's own R&D locations, but also the R&D locations of co-assignees. It should be
17
18 noted that our R&D location variable, even after correcting for co-assigneeship, might
19
20 contain additional locations through the location of co-inventors not belonging to the
21
22 firm. This is for instance the case when a firm engages in collaboration with a
23
24 university or other organization, while retaining full ownership of the IP. The location
25
26 variable will then be overestimated, however, only to the extent that the firm is
27
28 collaborating with at least two inventors that are located outside the firm's own
29
30 region. Despite this shortcoming, patent data are the best available public source to
31
32 systematically map the biotech R&D locations of global firms. Other sources of
33
34 information such as corporate annual reports also show some limitations: they often
35
36 do not specify the exact location (region) of firm facilities and the type of activities
37
38 (e.g. research, production, administration, sales) undertaken at different locations.
39
40 Corporate annual reports also do not provide information on the type of research
41
42 activities (biotechnology versus other research fields) in R&D establishments. This is
43
44 however important information, as we study the locations where firms engage in
45
46 biotech R&D activities.
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3
4 Three indicators related to the location of the biotechnology R&D activities of
5 a firm are created: (i) “clusters”, reflecting the number of R&D biotechnology clusters
6 in which a firm is present, (ii) “other regions”, reflecting the number of other regions,
7 not defined as clusters, in which a firm undertakes R&D activities, and (iii)
8 “countries”, the number of countries in which a firm is present¹⁰. To test for non-
9 linear relationships between the R&D location variables and the firm’s overall
10 technological performance, both linear and squared terms of the location variables are
11 included in the empirical models. Applying fixed effect panel data models require that
12 there is enough within-firm variation in the number of R&D locations over time. This
13 is the case for the sample firms, as they all engaged in M&A activities, opened new
14 laboratories and/or closed down existing ones over the time period 1995-2002.
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31

32 Control Variables

33
34 Several (time varying) variables that might affect the technological performance of
35 firms are included as control variables in the analyses. First, an indicator for the size
36 of a firm’s existing technology portfolio in biotech is included, measured by the
37 number of biotech patents applied for by the firm in the last 5 years. In analogy to the
38 dependent variable, this variable is weighted by the number of forward patent
39 citations received over a fixed four year time window to account for differences in
40 patent quality. Firms with large technology portfolios are more experienced in
41 innovation, and may be better positioned to develop new technological competences
42 (NESTA and SAVIOTTI, 2005). In previous studies, a time period of 5 years has been
43 considered as appropriate for assessing the validity of knowledge bases in a given
44 technology (STUART and PODOLNY, 1996; AHUJA and LAMPERT, 2001; LETEN et al.,
45 2007). Second, differences in the size of firms’ R&D effort are included, measured by
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 one-year lagged R&D expenditures¹¹. Firms that have more R&D resources, are
4
5 expected to have a higher technological performance. Third, year dummies are
6
7 included in the models to control for changes over time in the propensity of firms to
8
9 patent.
10

11
12 Descriptive statistics and correlation coefficients for the dependent and
13
14 explanatory variables are reported in table 2. The mean (yearly) number of citation-
15
16 weighted patents for the firms in the sample is 21, and firms' average R&D
17
18 expenditures amount to 452 million US dollars a year. The sample firms are, on
19
20 average, present in 1.8 biotechnology clusters and 2.4 other regions, spread over 2
21
22 countries. None of the reported correlations are excessively high.
23
24
25
26
27
28
29

30
31 -----
32 Insert Table 2 about here
33
34 -----
35
36

37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402 403 404 405 406 407 408 409 410 411 412 413 414 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 447 448 449 450 451 452 453 454 455 456 457 458 459 460 461 462 463 464 465 466 467 468 469 470 471 472 473 474 475 476 477 478 479 480 481 482 483 484 485 486 487 488 489 490 491 492 493 494 495 496 497 498 499 500 501 502 503 504 505 506 507 508 509 510 511 512 513 514 515 516 517 518 519 520 521 522 523 524 525 526 527 528 529 530 531 532 533 534 535 536 537 538 539 540 541 542 543 544 545 546 547 548 549 550 551 552 553 554 555 556 557 558 559 560 561 562 563 564 565 566 567 568 569 570 571 572 573 574 575 576 577 578 579 580 581 582 583 584 585 586 587 588 589 590 591 592 593 594 595 596 597 598 599 600 601 602 603 604 605 606 607 608 609 610 611 612 613 614 615 616 617 618 619 620 621 622 623 624 625 626 627 628 629 630 631 632 633 634 635 636 637 638 639 640 641 642 643 644 645 646 647 648 649 650 651 652 653 654 655 656 657 658 659 660 661 662 663 664 665 666 667 668 669 670 671 672 673 674 675 676 677 678 679 680 681 682 683 684 685 686 687 688 689 690 691 692 693 694 695 696 697 698 699 700 701 702 703 704 705 706 707 708 709 710 711 712 713 714 715 716 717 718 719 720 721 722 723 724 725 726 727 728 729 730 731 732 733 734 735 736 737 738 739 740 741 742 743 744 745 746 747 748 749 750 751 752 753 754 755 756 757 758 759 760 761 762 763 764 765 766 767 768 769 770 771 772 773 774 775 776 777 778 779 780 781 782 783 784 785 786 787 788 789 790 791 792 793 794 795 796 797 798 799 800 801 802 803 804 805 806 807 808 809 810 811 812 813 814 815 816 817 818 819 820 821 822 823 824 825 826 827 828 829 830 831 832 833 834 835 836 837 838 839 840 841 842 843 844 845 846 847 848 849 850 851 852 853 854 855 856 857 858 859 860 861 862 863 864 865 866 867 868 869 870 871 872 873 874 875 876 877 878 879 880 881 882 883 884 885 886 887 888 889 890 891 892 893 894 895 896 897 898 899 900 901 902 903 904 905 906 907 908 909 910 911 912 913 914 915 916 917 918 919 920 921 922 923 924 925 926 927 928 929 930 931 932 933 934 935 936 937 938 939 940 941 942 943 944 945 946 947 948 949 950 951 952 953 954 955 956 957 958 959 960 961 962 963 964 965 966 967 968 969 970 971 972 973 974 975 976 977 978 979 980 981 982 983 984 985 986 987 988 989 990 991 992 993 994 995 996 997 998 999 1000

40 The results of the fixed effects negative binomial models on the relation between
41
42 cluster membership and firms' overall technological performance are presented in
43
44 Table 3. Model 1 includes only the control variables. Both the lagged biotech patent
45
46 portfolio and the R&D expenditure variable are positive and significant. In model 2,
47
48 the "clusters" variable is introduced, which indicates the number of clusters in which
49
50 a firm is involved when developing R&D activities. The cluster variable is positive
51
52 and significant, indicating that firms can enhance their technological performance by
53
54 extending their R&D activities in multiple technology clusters (confirming hypothesis
55
56 1). In model 3, the "other regions" variable is added to the set of control variables,
57
58 reflecting the number of regions, outside clusters, in which a firm develops R&D
59
60

1
2
3 activities. This variable is not significant. The log likelihood ratio test reveals that
4 including the other regions variable does not add significantly to the explanatory
5 power of the model (Chi^2 LR test = 1.89, $p=0.17$). Model 4 includes both the
6 “clusters” and “other regions” variables. A positive and significant coefficient is
7 found for the “clusters” variable, while the coefficient for the “other regions” variable
8 remains insignificant. Together, the findings from models 2 to 4 suggest that it is the
9 presence in technology clusters, and not in other regions, that influences the
10 technological performance of firms.
11
12
13
14
15
16
17
18
19
20
21

22 -----
23
24 Insert Table 3 about here
25
26 -----
27
28

29 Model 5 is the most complete model and includes, besides the linear terms,
30 also the quadratic terms of the “clusters” and the “other regions” variables. Including
31 quadratic terms allows to check for non-linear relationships between the location
32 variables and firm performance. The log likelihood ratio test indicates that model 5
33 significantly adds to model 4 in terms of explanatory power (Chi^2 LR test = 7.43,
34 $p=0.02$). The “clusters” variable has a positive and significant linear term, and a
35 negative and significant quadratic term. This confirms hypothesis 2: there is an
36 inverted U-shape relationship between the number of technology clusters in which a
37 firm engages in R&D activities and the firm’s total technological performance. The
38 coefficients of the “clusters” variables in model 5 further indicate that
39 biopharmaceutical firms should – ideally – be present in 4 biotechnology clusters.
40 Since the average biopharmaceutical firm in the sample is present in less than 2
41 biotech clusters, most firms can still improve their technological performance by
42 setting up R&D activities in additional biotechnology clusters¹². In line with previous
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 models, no significant effects are found for the “other regions” variables in model 5
4
5
6 (confirming hypothesis 3).
7
8
9

10
11 In model 6, an additional regression is performed to verify whether the cluster
12 effect is distinctive from a mere R&D internationalization effect. Therefore, the linear
13 and quadratic term of the countries variable, reflecting the number of countries in
14 which a firm is present, are added to the initial model. The “countries” variables are
15 not significant, and the model does not significantly improve compared to the model
16 containing only the control variables (Chi^2 LR test = 1.57, $p=0.46$). This again
17 confirms that presence in multiple technology clusters and not the mere presence in
18 multiple locations, is contributing to the firms’ overall technological performance.
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

CONCLUSIONS

Firms active in knowledge-intensive fields such as biotechnology, are increasingly developing global R&D activities with location choices for an important degree being determined by the presence of local technological capabilities. Studies in the economic geography literature have shown that firms located in regions where technological activities agglomerate (technology clusters), are more innovative than firms located elsewhere (BAPTISTA and SWANN, 1998; BEAUDRY and BRESCHI, 2003; DEEDS, DECAROLIS and COOMBS, 1999; VAN GEENHUIZEN and REYER-GONZALES, 2007; BATEN et al., 2007). However, so far, little is known about the impact of presence in multiple clusters and regions on the technological performance of multi-location firms.

In this study, such an analysis is performed, based on a panel dataset of the largest biopharmaceutical firms - in terms of technological output - in biotechnology. The companies have headquarters in the United States, Europe or Japan, and engage in biotech R&D activities in different locations worldwide. Clusters are defined as worldwide leading regions in terms of technology development in the field of biotechnology. Over the time period under study (period 1995-2002), most of the firms in our sample extended and/or contracted their presence in technology clusters and other regions. In the analyses, firm-fixed effect regression techniques and controls on time-varying changes in R&D efforts and past innovation experience of firms are used to account for firm-level differences in size and innovative capabilities. The findings suggest that biopharmaceutical firms can enhance their technological performance by developing R&D activities in multiple technology clusters. The results also reveal that boundaries exist in terms of the net beneficial effects of

1
2
3 spreading R&D activities over multiple locations. When the number of clusters in
4
5 which a firm is engaged becomes too large, increasing costs in terms of coordinating
6
7 and integrating geographically dispersed R&D units might start to prevail over the
8
9 marginal benefits from getting access to new, relevant knowledge. At the same time,
10
11 the observed diminishing effects might also be caused by insufficient critical mass in
12
13 terms of technological activity (economies of scale and scope) when R&D activities
14
15 become dispersed.
16
17
18

19
20 The analyses provide evidence that the cluster effect is distinctive from a mere
21
22 multi-location effect: the presence in technology clusters, and not the presence in
23
24 multiple regions and countries, is contributing to a better technological performance
25
26 of firms. As such, the study provides interesting insights for the R&D
27
28 internationalisation literature. Recently, this stream of literature started to investigate
29
30 the relationship between the geographical dispersion of firms' R&D activities and
31
32 firm performance. Some studies (SINGH, 2008; FURMAN et al, 2005) found negative
33
34 effects, while other studies (CRISCUOLO and AUTIO, 2008; IWASA and ODAGIRI, 2004;
35
36 PENNER-HAHN and SHAVER, 2005; TODO and SHIMIZUTANI, 2008) reported positive
37
38 effects of geographical dispersion on firms' performance. These studies did not take
39
40 into account the technological characteristics of regions in which R&D activities are
41
42 deployed (clusters or non-cluster regions). This may be one factor explaining the
43
44 mixed results reported so far.
45
46
47
48
49

50
51 At the same time, the observed findings imply limitations as well. First, our
52
53 sample consists of firms with large biotech patent portfolio's and, consequently, the
54
55 results apply to this type of technology-active biopharmaceutical firms only. Further
56
57 research could investigate whether smaller firms in terms of biotech technology
58
59 development activities - e.g. entrepreneurial ventures -, also benefit from being
60

1
2
3 present in (multiple) technology clusters. Next, to retrieve the locations in which firms
4 develop biotechnology research activities, inventor addresses on the firms' fully
5 owned patents are used. While we corrected for co-assigneeship, the derived R&D
6 location variables might still reflect locations of co-inventors not belonging to the
7 firm. This is notably the case when a firm engages in collaboration with a university
8 or other organization, while retaining full ownership of the resulting inventions.
9 Ideally, the locations where firms have R&D establishments (R&D labs) should be
10 distinguished from locations where firms are present through other collaboration
11 modes, such as R&D collaborations or sponsoring of research at universities and
12 public labs. This requires conducting a firm survey since corporate annual reports do
13 not provide sufficiently detailed information on the type and exact location of the
14 research activities (biotechnology versus other fields) performed by firms.
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31

32 Within this study, the focus was on regional technological capabilities within
33 the same field (biotechnology); as such, a natural extension of the research reported
34 here implies an examination of 'Jacobs' externalities as well. Regions do not only
35 differ in terms of biotechnology capabilities but also with respect to the presence of
36 technological activities within other, related and unrelated, fields. Studying the impact
37 of technological variety in regions on the technological performance of firms, as well
38 as the number of regions needed to access such variety, is an interesting avenue for
39 further research. Closely related, one could study the relative importance of field-
40 specific regional capabilities (MAR externalities) and technological variety (Jacobs
41 externalities) in regions for the technological performance of firms. A final suggestion
42 for further research implies the micro-dynamics underlying the observed positive
43 performance effects from presence in multiple technology clusters. While the findings
44 are interesting within the framework of R&D location decisions, identifying the most
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 effective mechanisms (e.g. collaboration with local firms and/or research institutes,
4 technology acquisition, researcher mobility, establishment of fully owned research
5 labs) through which firms can benefit from agglomeration externalities in technology
6 clusters might be highly relevant to ensure that firms yield results once location
7 decisions have been made. We do hope that our analyses and findings inspire
8 colleagues in the fields of economic geography and R&D internationalisation to
9 engage in such endeavours.
10
11
12
13
14
15
16
17
18
19
20
21
22
23

24 Acknowledgments: The authors acknowledge the “Steunpunt Ondernemen en
25 Internationaal Ondernemen” and the “Fonds voor Wetenschappelijk Onderzoek”
26 (G.0468.09) for the financial support. We also want to express our gratitude for the
27 comments received from the participants at the Academy of Management Conference
28 (Anaheim, 2008) and the Regional Studies Association Conference (Leuven, 2009).
29 We thank the editor and especially the anonymous referees for their valuable and
30 usefull comments.
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Appendix 1: List of biopharmaceutical firms

Abbott Laboratories	Innogenetics
Affymetrix Inc.	Invitrogen
Ajinomoto	Isis Pharmaceuticals Inc
Amgen	Johnson Johnson
Applera	Kyowa Hakko Kogyo
Astrazeneca	Lonza Ag
Aventis	Martek Biosciences
Beckman Coulter	Maxygen Inc
Becton Dickinson And Company	Merck Co
Biogen Idec	Merck Kgaa
Boehringer Ingelheim	Millennium Pharmaceuticals
Bristol Myers Squibb	Mochida Pharmaceutical
Cell Genesys Inc	Myriad Genetics Inc
Chiron	Nanogen Inc
Diversa Corp	Novartis
Eli Lilly	Novo Nordisk As
Fujisawa Pharmaceutical	Pfizer
Gen Probe Inc	Regeneron Pharmaceuticals
Genelabs	Ribozyme Pharmaceuticals
Genencor	Schering
Genentech Inc	Schering Plough
Genzyme	Scios Inc
Geron Corp	Seikagaku

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Gilead Sciences	Sequenom Inc
Heska Ag	Shionogi
Human Genome Sciences	Solexa
Hybridon	Tanox Inc
Icos Corporation	Transgene
Idexx Laboratories	Wyeth
Incyte Corporation	

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

¹ Prior studies used cross-sectional data analysis techniques, and did not control for differences in firms' innovation efforts (absolute level of R&D expenses) when studying the impact of cluster membership on firms' technological performance.

² MARSHALL (1920), ARROW (1962) and ROMER (1986) (henceforth M-A-R) suggest that knowledge spillovers mainly arise among firms in the same industry. On the contrary, JACOBS (1969) believes that the most important knowledge spillovers occur across industries. Empirical results on the relative importance of both types of knowledge externalities are mixed (see for example GLAESER et al, 1992; FELDMAN and AUDRETSCH, 1999; HENDERSON et al, 1995; BEAUDRY and SCHIFFAUEROVA, 2009; FRENKEN et al, 2007).

³ Other studies (ex. HILL and NAROFF, 1984; SWANN and PREVEZER, 1996 and HENDRY and BROWN, 2006) have studied the impact of cluster location on the financial performance and growth of firms.

⁴ We calculated that for EPO biotechnology patents applied for in 1995 and granted by 2006, only 40% of the patents were granted within 6 years after application.

⁵ GLÄNZEL et al. (2004) defined and validated a search key to retrieve all EPO patents in the biotechnology domain in the period 1978-2001.

⁶ The NUTS (Nomenclature of Territorial Units for Statistics) classification, established by Eurostat, provides a breakdown of European countries into regions, primarily based on institutional divisions currently in force in the country. The average population size for NUTS 1 regions in Europe (n=73) is 5.3 million. The United States of America consist of 50 sub-national entities called states, having their own state government with substantial state responsibilities. The average population

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

in the US states is 5.5 million. The prefectures of Japan consists of 47 sub-national jurisdictions with an own governor and parliament. The average size of prefectures is 2.7 million inhabitants.

⁷ Forward patent citations are calculated on the EPO patent citation database described in Webb et al. (2005). They are calculated for all citing EPO patents and national patents with EPO patent equivalents.

⁸ In addition to citation-weighted patent counts, we have also used the number of triadic patents as an alternative measure to control for differences in the quality of patents. Triadic patents are patents simultaneously applied at the patent offices of the US, Europe and Japan. Analyses with triadic patents lead to similar results as the analyses presented in table 3.

⁹ In Europe, 12% of biotech patents have multiple assignees (LECOCQ and VAN LOOY, 2009).

¹⁰ Analogous to the cluster and other regions variables, we only count countries from Europe (EU-15 and Switzerland), US and Japan.

¹¹ Firm level R&D expenses specifically related to biotechnology activities are not available.

¹² Only in 7.35% of the observations (firm-year), firms develop biotech activities in more than 4 technology clusters.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60



For Peer Review Only

References

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

ACS, Z. J., ANSELIN, L., and VARGA, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, 31 (7); pp. 1069-1085.

AHUJA, G. and LAMPERT, C.M. (2001). Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough innovations. *Strategic Management Journal* 22 (6-7), pp.521-543.

ALBERT, MB, AVERY, D. and NARIN, F. (1991). Direct validation of citation counts as indicators of industrially important patents. *Research Policy* 20(3), pp. 251-259.

ALMEIDA, P. and KOGUT, B. (1999). Localization of Knowledge and the Mobility of Engineers in Regional Networks. *Management Science* 45 (7), pp. 905-917.

ARROW, K.J. (1962). The implications of Learning by Doing. *Review of Economic Studies* 29; pp 155-173.

ARUNDEL, A. and KABLA, I. (1998). What percentage of innovations are patented? Empirical estimates for European firms. *Research Policy* 27 (2), pp. 127-141.

AUDRETSCH, D. and FELDMAN, M. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review* 86(3), pp.630-640.

BAPTISTA, R. and SWANN, P. (1998). Do Firms in Clusters Innovate More? *Research Policy* 27 (5), pp.522-540.

BATEN, J., SPADAVECCHIA A., STREB J. and YIN, S. (2007). What made southwest German firms innovative around 1900? Assessing the importance of intra- and inter-industry externalities. *Oxford Economic Papers* 59, i105-i106.

1
2 BEAUDRY, C. and BRESCHI, S. (2003). Are Firms in Clusters Really more Innovative?
3
4 *Economics of Innovation and New Technology* 124, pp.325-342.

6
7
8 BEAUDRY, C. and SCHIFFAUEROVA, A. (2009). Who's right, Marshall or Jacobs? The
9
10 localization versus urbanization debate. *Research Policy* 38 (2), pp. 318-337.

12
13
14 BEUGELSDIJK, S. (2007). The regional environment and a firm's innovative
15
16 performance: A plea for a multilevel interactionist approach. *Economic Geography* 83
17
18 (2), pp. 181-199.

20
21
22 BRESCHI, S. and LISSONI, F. (2001). Knowledge spillovers and local innovation
23
24 systems: a critical survey. *Industrial and Corporate Change* 10 (4), pp.975-1005.

26
27
28 CANTWELL, J. and PISCITELLO, L. (2005). Recent location of foreign-owned research
29
30 and development activities by large multinational corporations in the European
31
32 regions: The role of spillovers and externalities. *Regional Studies* 39 (1), pp.1-16.

34
35
36 CAMERON, A. and TRIVEDI, P. (1998). *Regression analysis of count data*. Cambridge
37
38 University Press, Cambridge.

40
41
42 CRISCUOLO, P. and AUTIO, E. (2008). The impact of internationalization of research
43
44 on firm market value. Working paper.

46
47
48 DEEDS, D.L.; DECAROLIS, D. and COOMBS, J. (1999). Dynamic capabilities and new
49
50 product development in high technology ventures: an empirical analysis of new
51
52 biotechnology firms. *Journal of Business Venturing* 15, pp 211–229.

54
55
56 DEYLE, H. and GRUPP, H. (2005). Commuters and the regional assignment of
57
58 innovative activities: A methodological patent study of German districts. *Research*
59
60 *Policy* 34 (2), pp.221-234.

1
2 DÖRING, T. and SCHNELLENBACH, J. (2006). What do we know about geographical
3
4 knowledge spillovers and regional growth?: A survey of the literature. *Regional*
5
6 *Studies* 40 (3), pp.375-395.
7
8

9
10 FELDMAN, MP. and AUDRETSCH, DB. (1999). Innovation in cities: Science-based
11
12 diversity, specialization and localized competition. *European Economic Review* 43(2),
13
14 pp. 409-429.
15
16

17
18 FELDMAN, M. and FLORIDA, R. (1994). The geographic sources of innovation:
19
20 Technological infrastructure and product innovation in the United States. *Annals of*
21
22 *the Association of American Geographers* 84(2), pp.210-229.
23
24

25
26 FRENKEN, K., VAN OORT, F. and VERBURG, T. (2007). Relate variety, unrelated
27
28 variety and regional economic growth. *Regional Studies* 41(5), pp. 685-697.
29
30

31
32 FURMAN, J., KYLE, M., COCKBURN, I. and HENDERSON, R. (2005). Public and private
33
34 spillovers, location and the productivity of pharmaceutical research. *Annales*
35
36 *d'Economie et de Statistique* 79/80, pp.167-190.
37
38

39
40 GAMBARDELLA, A., HARHOFF, D. and VERSPAGEN, B. (2008). The value of European
41
42 patents. CEPR discussion paper no 6848.
43
44

45
46 GASSMANN, O. and VON ZEDTWITZ, M. (1999). New concepts and trends in
47
48 international R&D organization. *Research Policy* 28 (2-3), pp. 231–250.
49
50

51
52 GLAESER, E. L., KALLAL, H. D., SCHEINKMAN, J. A., and SHLEIFER, A. (1992). Growth
53
54 in Cities. *Journal of Political Economy* 100, pp. 1126-1152.
55

56
57 GLÄNZEL W., MEYER M., SCHLEMMER B., DU PLESSIS M., THIJIS B., MAGERMAN T.
58
59 and DEBACKERE K. (2004). Domain study “Biotechnology” – An analysis based on
60

1
2 publications and patents. Report published by Steunpunt O&O indicators (now
3 Expertise centrum O&O Monitoring); <http://www.ecoom.be>.

4
5
6
7
8 GRANSTRAND, O. (1999). Internationalisation of corporate R&D: A study of Japanese
9 and Swedish corporations. *Research Policy*, 28 (2-3), pp. 275-302.

10
11
12
13 GRILICHES, Z. (1990). Patent statistics as economic indicators – a survey. *Journal of*
14
15 *Economic Literature*, 28(4): pp.1661-1707.

16
17
18
19 HAGEDOORN, J. and CLOODT, M. (2003). Measuring innovative performance: is there
20
21 an advantage in using multiple indicators? *Research Policy* 32 (8), pp. 1365-1379.

22
23
24
25 HALL, B., JAFFE, A. and TRAJTENBERG, M. (2005). Market value and patent citations.
26
27 *Rand Journal of Economics* 36(1), pp16-38.

28
29
30
31 HARHOFF, D., NARIN, F., SCHERER, F. and VOGEL, K.(1999). Citation frequency and
32
33 the value of patented inventions. *Review of Economics and Statistics* 81 (3), pp. 511-
34
35 515.

36
37
38
39 HEAD K., RIES, J., and SWENSON, D. (1995). Agglomeration benefits and location
40
41 choice: Evidence from Japanese manufacturing investments in the United States.
42
43 *Journal of International Economics*. 38, pp. 223-247.

44
45
46
47 HENDERSON, V., KUNCORO, A., and TURNER, M. (1995). Industrial-Development in
48
49 Cities. *Journal of Political Economy* 103, pp.1067-1090.

50
51
52
53 HENDRY, C. and BROWN, J. (2005). Dynamics of clustering and performance in the
54
55 UK opto-electronics industry. *Regional Studies* 40 (7), pp. 707-725.

56
57
58
59 HILL J. and NAROFF J. (1984). The Effect of Location on the Performance of High
60
Technology Firms. *Financial Management*, pp. 27-36.

1
2 IWASA, T. and ODAGIRI, H. (2004). Overseas R&D, knowledge sourcing and
3
4 patenting: an empirical study of Japanese R&D investments in the US. *Research*
5
6 *Policy* 33(5), pp. 807-829.
7
8

9
10 JACOBS, J. (1969). *The economies of cities*. New York: Vintage.
11
12

13
14 JAFFE, A., TRAJTENBERG, M. and HENDERSON, R. (1993). Geographic localization of
15
16 knowledge spillovers as evidenced by patent citations. *Quarterly Journal of*
17
18 *Economics* 108, pp.577–598.
19
20

21
22 KHAN, M and DERNIS, H. (2006). Global overview of innovative activities from patent
23
24 indicators perspective. OECD Science, Technology and Industry working papers
25
26 2006/3, OECD Publishing.
27
28

29
30 KRUGMAN, P. (1991). Increasing returns and economic geography. *Journal of*
31
32 *Political Economy* 99 (3), pp.483-499.
33
34

35
36 KUEMMERLE, W. (1999). Foreign direct investment in industrial research in the
37
38 pharmaceutical and electronics industries—results from a survey of multinational
39
40 firm. *Research Policy* 28 (2-3), pp. 179–193.
41
42

43
44 LANDONI P., LETEN, B. and VAN LOOY, B. (2008). Localization of innovative
45
46 activities: Myths and facts of methodologies to assign patents to spatial areas. Paper
47
48 presented at the 10th International Conference on Science and Technology Indicators
49
50 (Vienna, September 2008).
51
52

53
54 LECOCQ, C., SONG, X., DU PLESSIS, M. AND VAN LOOY, B. (2008). Data Production
55
56 Methods For Harmonized Patent Statistics. Regionalizing Patent Data – EU-27:
57
58 Methodological outline. Eurostat Working Paper.
59
60

1
2 LECOCQ, C. and VAN LOOY, B. (2009). The impact of collaboration on the
3
4 technological performance of regions: time invariant or driven by life cycle
5
6 dynamics? An explorative investigation of European regions in the field of
7
8 Biotechnology. *Scientometrics* 80(3), pp. 847–867.
9

10
11
12 LETEN, B., BELDERBOS, R. and VAN LOOY, B. (2007). Technological diversification,
13
14 coherence and performance of firms. *The Journal of Product Innovation Management*
15
16 24(6), pp. 567-579.
17

18
19
20 MARSHALL, A. (1920). *Principles of economics*; London, Macmillan.
21

22
23
24 MANSFIELD, E. (1986). Patents and innovation: an empirical study. *Management*
25
26 *Science* 32(2), pp173-181.
27

28
29
30 NARIN F. and NOMA E. (1987). Patents as indicators of corporate technological
31
32 strenght. *Research Policy* 16 (2-4), pp.143-155.
33

34
35
36 NESTA, L. and SAVIOTTI, P.P. (2005). Coherence of the knowledge base and the
37
38 firm's innovative performance: Evidence from the US pharmaceutical industry.
39
40 *Journal of Industrial Economics* 53(1), pp.123-142.
41

42
43
44 NONAKA I., (1994). A dynamic theory of organizational knowledge creation.
45
46 *Organization Science* 5(1),pp. 14-37.
47

48
49
50 PAVITT, K. (1985). Patent statistics as indicators of innovative activities. Possibilities
51
52 and problems. *Scientometrics* 7(1), pp. 77-99.
53

54
55
56 PENNER-HAHN, J. and SHAVER, M. (2005). Does international research and
57
58 development increase patent output? An analysis of Japanese pharmaceutical firms.
59
60 *Strategic Management Journal* 26, pp. 121-140.

- 1
2 POLANYI, M. (1966). *The tacit dimension*. New York, Doubleday Anchor..
3
4
5 PORTER, M. (1998). Clusters and the new Economics of Competition. *Harvard*
6
7 *Business Review*, November - December, pp. 77-90.
8
9
10 PORTER, M. (1990). *The Competitive Advantage of Nations*. London, Macmillan.,
11
12
13 PORTER, M. (2000). Location, Competition, and Economic Development: Local
14
15 Clusters in a Global Economy. *Economic Development Quarterly* 14(1), pp 15-34.
16
17
18 RODRÍGUEZ-POSE, A. and CRESCENZI, R. (2008). Research and Development,
19
20 Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe.
21
22 *Regional Studies* 421, pp. 51-67.
23
24
25
26
27 ROMER, P.M. (1986). Increasing returns and long-run growth. *Journal of Political*
28
29 *Economy* 94 (5), pp. 1002-1037.
30
31
32
33 ROSENKOPF, L. and ALMEIDA, P. (2003). Overcoming Local Search through Alliances
34
35 and Mobility. *Management Science* 49 (6), pp. 751-766.
36
37
38
39 SAXENIAN, A. (1994). *Regional advantage – Culture and Competition in Silicon*
40
41 *Valley and Route 128*. Boston: Harvard Business School Press.
42
43
44
45 SHAVER, J.M. and FLYER, F. (2000). Agglomeration economies, firm heterogeneity,
46
47 and foreign direct investment in the United States. *Strategic Management Journal*
48
49 21(12), pp. 1175-1193.
50
51
52
53 SINGH, J. (2008). Distributed R&D, cross-regional knowledge integration and quality
54
55 of innovative output. *Research Policy* 37 (1), pp. 77–96.
56
57
58
59
60

- 1
2 ST. JOHN, C. and POWDER, R.W. (2006). Technology Clusters versus Industry Clusters:
3
4 Resources, Networks, and Regional Advantages. *Growth and Change* 37 (2), pp. 141–
5
6 171.
7
8
9
10 STORPER, M. (1992). The Limits to Globalization: Technology Districts and
11
12 International Trade. *Economic Geography* 68(1), pp. 60-93.
13
14
15
16 STUART, T. and PODOLNY, J. (1996). Local search and the evolution of technological
17
18 capabilities. *Strategic Management Journal* 17, pp. 21-38.
19
20
21
22 SWANN, P. and PREVEZER, M. (1996). A comparison of the dynamics of industrial
23
24 clustering in computing and biotechnology. *Research Policy* 25 (7), pp.1139-1157.
25
26
27
28 TODO, Y. and SHIMIZUTANI, S. (2008). Overseas R&D activities and home
29
30 productivity growth: evidence from Japanese firm level data. *Journal of Industrial*
31
32 *Economics* 56(4), pp. 752-777.
33
34
35
36 TRAJTENBERG, M. (1990). A penny for your quotes: Patent citations and the value of
37
38 innovations. *Rand Journal of Economics* 21, pp.172-187.
39
40
41
42 VAN GEENHUIZEN, M. and REYER-GONZALES, L. (2007). Does a clustered location
43
44 matter for high-technology companies' performance? The case of biotechnology in
45
46 the Netherlands. *Technological Forecasting & Social Change* 74, pp.1681-1696.
47
48
49
50 VARGA A. (2000). Local academic knowledge spillovers and the concentration of
51
52 economic activity. *Journal of Regional Science*, 40, pp. 289-309.
53
54
55
56 VON HIPPEL, E. (1994). Sticky information and the locus of problem solving:
57
58 Implications for innovations. *Management Science* 40(3), pp. 429-439.
59
60

1
2 VON HIPPEL, E. (1988). *The Sources of Innovation*. New York, Oxford University
3
4 Press.
5

6
7
8 WEBB, C., DERNIS, H. and HOISL, K. (2005). Analyzing European and international
9
10 patent citations: a set of EPO patent database building blocks. OECD Science,
11
12 Technology and Industry working papers 2005/9. OECD Publishing.
13
14

15
16 WOOLDRIDGE J. (2001). *Econometric Analysis of Cross Section and Panel Data*. MIT
17
18 Press, Cambridge, Massachusetts (USA).
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Table 1 Top Biotechnology regions (period 1990-1999)

Region	Country	Patents	%	Cum %
1 California	United States	4,162	15.4%	15.4%
2 Massachusetts	United States	1,853	6.8%	21.6%
3 Maryland	United States	1,285	4.7%	25.5%
4 Pennsylvania	United States	1,264	4.7%	29.6%
5 New York	United States	1,072	4.0%	32.8%
6 New Jersey	United States	1,005	3.7%	34.9%
7 Tokyo	Japan	916	3.4%	38.2%
8 Île De France	France	873	3.2%	41.1%
9 East Of England	United Kingdom	766	2.8%	43.5%
10 Kanagawa	Japan	724	2.7%	45.2%
11 Bayern	Germany	716	2.6%	47.6%
12 Osaka	Japan	672	2.5%	49.7%
13 Baden-Württemberg	Germany	654	2.4%	51.7%
14 Danmark	Danmark	643	2.4%	53.7%
15 Switzerland	Switzerland	626	2.3%	55.4%
16 Washington	United States	619	2.3%	57.1%
17 South East	United Kingdom	614	2.3%	58.8%
18 Hessen	Germany	607	2.2%	60.3%
19 West-Nederland	Netherlands	601	2.2%	62.1%
20 Nordrhein-Westfalen	Germany	534	2.0%	63.4%
21 Illinois	United States	473	1.7%	64.7%
22 Texas	United States	446	1.6%	65.8%
23 London	United Kingdom	444	1.6%	66.6%
24 North Carolina	United States	416	1.5%	67.5%
25 Indiana	United States	406	1.5%	68.7%
26 Ibaraki	Japan	394	1.5%	69.6%
27 Hyogo	Japan	394	1.5%	70.1%
28 Vlaams Gewest	Belgium	389	1.4%	71.2%
29 Connecticut	United States	385	1.4%	71.9%

1					
2	30	Kyoto	Japan	377	1.4% 72.5%
3					
4	31	Sverige	Sweden	376	1.4% 73.5%
5					
6	32	Centre-Est	France	373	1.4% 74.4%
7					
8	33	Wisconsin	United States	320	1.2% 75.1%
9					
10	34	Saitama	Japan	317	1.2% 75.5%
11					
12	35	Ohio	United States	308	1.1% 76.2%
13					
14	36	Niedersachsen	Germany	283	1.0% 76.8%
15					
16	37	Missouri	United States	280	1.0% 77.4%
17					
18	38	Chiba	Japan	276	1.0% 77.7%
19					
20	39	Michigan	United States	265	1.0% 78.3%
21					
22	40	Iowa	United States	261	1.0% 79.0%
23					
24	41	Berlin	Germany	258	1.0% 79.6%
25					
26	42	Colorado	United States	251	0.9% 80.2%
27					
28	43	Shizuoka	Japan	245	0.9% 80.6%
29					
30	44	Scotland	United Kingdom	237	0.9% 81.1%
31					
32	45	Delaware	United States	232	0.9% 81.4%
33					
34	46	Nord-Ovest	Italy	220	0.8% 82.1%
35					
36	47	Minnesota	United States	213	0.8% 82.6%
37					
38	48	Est	France	213	0.8% 82.9%
39					
40	49	Virginia	United States	211	0.8% 83.1%
41					
42	50	Rheinland-Pfalz	Germany	210	0.8% 83.4%

¹ Cumulative % excludes double counts due to co-patenting in multiple regions

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47

Table 2 Descriptive statistics

	Obs	Mean	Std. Dev.	Biotech patents	Biotech portfolio	R&D	Clusters	Other regions	Countries
Weighted number of Biotech patents	422	21.1	36.2	1					
Size of Biotech Patent Portfolio (5year, weighted)	422	106.1	131.1	0.5673	1				
R&D Expenditures (in thousands USD)	422	452.4	760.3	0.0681	0.2164	1			
Number of clusters	422	1.8	1.6	0.3082	0.5024	0.4427	1		
Number of other regions	422	2.4	2.7	0.1471	0.3253	0.5401	0.4453	1	
Number of countries	422	2.0	1.5	0.0930	0.2435	0.5579	0.4348	0.7685	1

Table 3 Fixed Effect Negative Binomial Regressions:

Weighted Number of Biotech Patents Acting as Dependent Variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Biotech portfolio	0.0014***	0.0011***	0.0012***	0.0011***	0.0012***	0.0013***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
R&D expenditures	0.0005***	0.0004***	0.0005***	0.0004***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Clusters		0.0948**		0.0864**	0.2945***	
		(0.0402)		(0.0440)	(0.0924)	
Clusters ²					-0.0339**	
					(0.0132)	
Other regions			0.0325	0.0123	-0.0634	
			(0.0231)	(0.0256)	(0.0540)	
Other regions ²					0.0066	
					(0.0042)	
Countries						-0.0095
						(0.0974)
Countries ²						0.0075
						(0.0113)
Time dummies	yes	yes	yes	yes	yes	yes
Constant	0.2229	0.0954	0.1566	0.0802	0.0052	0.207
	(0.1541)	(0.1641)	(0.1620)	(0.1675)	(0.1879)	(0.2100)
Number Obs	422	422	422	422	422	422
Wald Chi ²	122.00***	131.01***	127.15***	132.13***	141.03***	127.85***

Standard errors are reported between parentheses; *, **, *** indicate significance at the 10% 5% and 1% levels