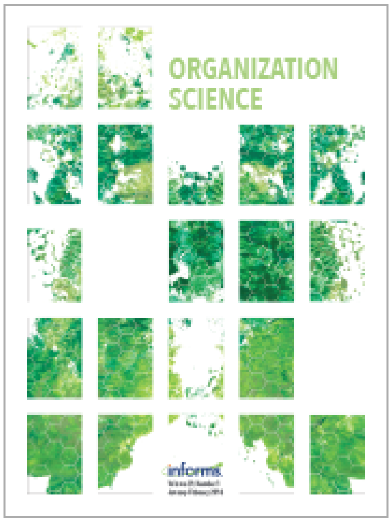

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Location, Decentralization, and Knowledge Sources for Innovation

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When firms seek to innovate, they must decide where to locate their innovation activity. This location choice requires firms to make a simultaneous choice about the organizational structure of innovation activity: almost by definition, multiple locations per firm imply some degree of decentralization. We compare predictions of the knowledge-based view with the predictions of organizational economics regarding the location and decentralization of R&D. Using firm-level data on R&D locations in Finland, we examine the conditions under which firms with multiple R&D locations also have greater innovation output. Our results indicate that multilocation of R&D activity is positively associated with imitative innovation output and is strongly correlated with greater external knowledge sourcing. We also find that the positive association between multiple R&D locations and innovative output does not apply to new-to-the-market innovations. The results are consistent with the interpretation that multilocation of R&D enables firms to access a broad set of external sources of knowledge in pursuit of imitative rather than new-to the market innovation. Moreover, these findings imply heterogeneity in R&D strategies between firms pursuing new-to-the-market innovation and firms pursuing imitative innovation. It is thus important to distinguish between new-to-the-market and imitative innovations, because their determinants may differ.

Key words: decentralization; research and development; imitative innovation; new-to-the-market innovation
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1. Introduction

When firms seek to innovate, they must decide where to locate their innovation activity. This location choice requires firms to make a simultaneous choice about the organizational structure of innovation activity: almost by definition, multiple locations per firm imply some degree of decentralization. We study the conditions under which multilocation of R&D is associated with greater innovation output using a survey data set of Finnish manufacturing firms' innovation activities and domestic R&D locations.

Two different schools of thought have somewhat conflicting implications for multilocation of R&D. The knowledge-based view (e.g., Grant 1996, Kogut and Zander 1993) has argued that multiple R&D locations enable firms to adapt existing technological knowledge to new markets and to access new sources of knowledge that improve the ability to innovate. Although these arguments are often applied to foreign expansion of innovation activity, they also apply within countries (Kuemmerle 1999, Furman et al. 2006). In contrast, organizational economics research on decentralization versus centralization of R&D (e.g., Argyres and Silverman 2004) has argued that centralization improves innovation output, because it economizes on costs of communication and coordination when there are economies of scope in R&D. Researchers have started to bring these literatures together, noting that although decentralization of R&D through multilocation may improve external knowledge sourcing, it raises costs of communication and coordination (e.g., Chacar and Lieberman 2003, Singh 2008, Zhao and Islam 2006). This literature, however, has yet to account for the possibility that the type of R&D that firms perform may affect the extent to which multilocation of R&D improves innovation output through external knowledge sourcing. Using unique firm-level data on location of R&D activity and innovation output, we find that multilocation of R&D activity is positively associated with imitative rather than new-to-the-market innovation output, and is strongly correlated with greater external knowledge sourcing.[1] Thus, we observe heterogeneity in R&D strategies between firms pursuing new-to-the-market innovation and firms pursuing imitative innovation.

Our analysis makes a number of contributions. First, we bring together two relatively separate perspectives on the relationship between multilocation of R&D and innovation output, and identify conditions under which each view holds. Second, we examine R&D location choices within a single country, and test the theoretical predictions in this setting. Because the data contain information only for domestic R&D locations, the analysis controls for foreign R&D locations insofar as possible, and includes a robustness test using a subsample of firms that are less likely to have foreign R&D labs. Third, we provide the first test of whether any positive association of innovation output with R&D in multiple locations reflects an accompanying breadth of search for new knowledge through multilocation of R&D. We find a strong statistical association between the two. Fourth, we compare new-to-the-market versus imitative innovation output in the context of R&D location choice. Although studies of innovation often focus on patents, which reflect new-to-the-market innovations, a great deal of business R&D is directed toward imitative innovation. Finally, we can overcome some well-known problems of using patent data. Patents are meaningful measures only of intermediate innovation output and in a relatively small number of industries (Griliches 1990). In contrast, our data include commercialized innovations, and the sample is close to representative of the manufacturing sector as a whole.

In what follows, we first compare and contrast the relevant literatures and develop testable hypotheses. Then we describe our data, empirical methodology, and results.

2. Location and Innovation Activity

As noted above, prior literature contains two distinct perspectives regarding the location of innovation activity. One perspective emphasizes the benefits of multiple R&D locations and derives from the knowledge-based view of the firm. The other perspective emphasizes the costs of decentralized innovation activity and derives from organizational economics. We focus on the *net benefits* of multilocation of R&D and ask under what conditions the benefits net of costs are likely to be positive or negative. We first examine implications of the two literatures separately, because they differ in important ways. Then we compare and contrast the literatures to develop hypotheses.

2.1. Benefits of Multiple Locations

Firms may utilize multiple locations for their technological innovation activity for two reasons. First, firms may set up additional R&D facilities to adapt preexisting technological knowledge to local markets, which Kuemmerle (1999) termed "home-base-exploiting" R&D. Second, firms may seek to acquire spillovers of new location-specific technological knowledge (Kogut 1991, Chung and Alcácer 2002), termed "home-base-augmenting" R&D (Kuemmerle 1999). Although the issue of location and knowledge transfer arose in the literature on foreign direct investment (e.g., Teece 1977), it applies within countries as well (see Furman et al. 2006, Kuemmerle 1999, Chacar and Lieberman 2003). If local markets differ sufficiently, firms may set up regional R&D facilities within countries in order to adapt preexisting technological knowledge. Kuemmerle (1999), for example, found that most of the firms in his survey had a network of R&D sites in their home countries. Thus, the general issues regarding location of R&D activity, summarized next, apply within countries as well as between them.

A great deal of technological knowledge is tacit or not well codified, and even the use of codified knowledge requires an understanding of the context in which the knowledge is employed (Kogut and Zander 1993). Because organizations consist of communities of practice that are more likely to have shared languages and understandings, firms are superior to markets in transferring knowledge (Kogut and Zander 1992, Grant 1996). Therefore, firms that seek to exploit their preexisting knowledge in local markets often use internal organization to do so.

When firms seek to acquire knowledge specific to other locales, they also may need to establish facilities in those locales (Kogut 1991, Kuemmerle 1999, Tripsas 1997). Specialized local knowledge useful in innovation may come from many different sources, including universities, research institutes, suppliers, customers, and competitors. For example, in "user-based" innovation (Von Hippel 1998), companies receive valuable ideas for innovation from their customers. Fabrizio and Thomas (2007) have further argued that knowledge of customer demand has tacit, geographically localized aspects. Moreover, if researchers in a particular locale possess relevant tacit knowledge and are unwilling or unable to relocate, or if research activity stands to benefit from local knowledge sharing among researchers, firms may locate their R&D where the researchers reside. As a result, firms that use multiple R&D locations in pursuit of knowledge spillovers will be able to access a greater number of knowledge sources than firms confined to a single location. This in turn improves the likelihood of innovation success. Additionally, if having multiple locations yields a wider range of knowledge on which to build and recombine, the resulting set of innovations should span a wider range of applications as well (e.g., product and process innovations, rather than just one or the other).

2.2. Costs of Multiple Locations

Many large, diversified firms utilize a decentralized multidivisional (M-form) structure organized according to product markets (Chandler 1962) because it minimizes coordination costs by allocating decision-making authority to product lines and enables top managers to focus on strategic issues for the company as a whole (Williamson 1975). An M-form structure further enables top management to reward division managers based on business unit performance (Williamson 1991). This ensures that division managers, who are closer to customers and markets, have responsibility for product R&D directed towards those customers and markets (Argyres and Silverman 2004).

These arguments do not account for potential economies of scope in R&D (e.g., Henderson and Cockburn 1994, 1996), which require information transfer. This leaves firms in a quandary. If they seek to transfer knowledge between disparate organizational units, this may conflict with the incentive efficiencies of the M-form firm. In particular, if firms tie the compensation of R&D managers to the performance of their divisions, these managers may have little incentive to transfer knowledge across divisions (Kay 1988). One alternative is to centralize R&D in order to facilitate knowledge transfer. Centralization also enables firms to provide R&D personnel with appropriate corporate-level incentives to perform research that spans a range of businesses (Kay 1988, Lerner and Wulf 2007).

To reconcile the foregoing arguments regarding decentralization versus centralization of R&D, it is important to consider the type of R&D in question and the extent of decentralization. If a firm is highly decentralized with many R&D locations and seeks coordination and communication among its facilities, coordination costs are likely to be high. However, the need for coordination is likely to vary with the type of R&D. If a firm undertakes more applied, market- and customer-oriented R&D, the lower potential for economies of scope implies less need for coordination between R&D locations.[2] In contrast, research that is not tied to a particular product or business is likely to generate more general and fundamental knowledge that can underpin a range of innovations (Nelson 1990), it therefore is subject to economies of scope (Kay 1988). Argyres and Silverman (2004) argue that this greater potential for economies of scope from "non-specific" R&D requires greater communication and coordination. To minimize coordination costs, firms should centralize such R&D, utilizing a single location (Chacar and Lieberman 2003).

Argyres and Silverman (2004) draw two further implications from the observation that centralized R&D is best directed toward innovations with broad applicability. First, firms with more centralized R&D activity will search more widely, including outside of their organizational boundaries, for information relevant to innovation. Second, the resulting innovations will have a wider range of applications. These arguments imply that firms with more decentralized R&D, including through multiple locations, will search less widely and obtain innovations with a narrower range of applications.

2.3. Benefits vs. Costs of Multiple Locations for Innovation Activity

By comparing and contrasting the foregoing literatures, we can better understand the conditions under which multilocation of R&D activity is likely to lead to a greater amount and broader range of innovation output. First, the literature on centralization versus decentralization suggests that a decentralized R&D organization will focus more on product- and market-specific innovations than a centralized organization. Relative to nonspecific innovation activity, R&D directed toward product- and market-specific innovation is likely to include a greater emphasis on incremental and imitative innovations, in order to satisfy customer demand for new products and product enhancements that competitors may already have successfully introduced. Decentralized R&D, therefore, will tend to result in relatively more imitative innovation and less new-to-the-market innovation than in centralized R&D.[3]

The knowledge-based view does not provide a clear prediction regarding the type of innovation output associated with multilocation of R&D. When firms use home-base-exploiting R&D to adapt products and processes to local customers and manufacturing, this may result in a greater emphasis on imitative innovation. In contrast, home-base-augmenting R&D is often viewed as oriented toward new-to- the-market innovations, because such R&D involves search for new knowledge. This presumption, however, neglects the possibility that firms also may use home-base-augmenting R&D for imitative innovation, because imitation may require access to knowledge sources outside the firm. Because the knowledge-based arguments do not provide a clear prediction regarding the type of innovation associated with multiple R&D locations, the following hypothesis reflects the organizational arguments.

Hypothesis 1 (H1). *Multiple locations of R&D activity are associated with greater innovation output for imitative innovations than for new-to-the-market innovations.*

We test this hypothesis in a single-country setting, using data on the number of R&D labs per company within Finland. Conditional on finding support for this hypothesis, we also assess whether the data show a limit to the number of R&D locations per firm. The literature on centralization versus decentralization suggests that if firms seek to share knowledge between R&D locations, costs of coordination may offset the benefits. In addition, holding the R&D budget constant, the "minimum efficient scale" for a stand-alone R&D unit may limit the number of locations per firm.

The knowledge-based view posits an important mechanism through which multilocation of R&D may lead to greater innovation output: multiple locations enable the firm to access a larger number of different knowledge sources outside of the organization. That is, access to external knowledge sources mediates the relationship between multiple R&D locations and innovation output (Baron and Kenny 1986). The following hypothesis reflects this argument, and is conditional on a positive association between multiple locations of R&D and innovation output. Rejection of the hypothesis would be consistent with the organizational economics arguments that when firms decentralize R&D, they will search less broadly outside of their organizational boundaries for information relevant to innovation. Rejection of the hypothesis also would be consistent with the use of multiple R&D locations for knowledge exploitation in local markets (home-base-exploiting R&D), rather than to obtain spillovers of localized external knowledge (home-base-augmenting R&D).

Hypothesis 2 (H2). *A positive association between multiple locations of R&D and the amount of innovation output is mediated by the extent of external knowledge sourcing that firms utilize in their innovation activities.*

Finally, if firms use multilocation of R&D to access a wider range of knowledge, then, as argued earlier, the resulting innovations should span a wider range of applications. This conflicts with organizational economics arguments that decentralization of R&D will result in innovations that have a narrower range of applications. We test these competing arguments against one another, as follows.

Hypothesis 3A (H3A). *Firms that have multiple R&D locations generate a wider range of innovation output than firms that have a single R&D unit.*

Hypothesis 3B (H3B). *Firms that have multiple R&D locations generate a narrower range of innovation output than firms that have a single R&D unit.*

3. Prior Evidence on Multilocation of R&D and Innovation Output

A limited number of prior studies have provided valuable initial findings regarding the association between firm innovation output and R&D location/decentralization, but have been hampered by the difficulty of obtaining appropriate data. Researchers have had to hand-collect data on firm R&D locations (e.g., Penner-Hahn and Shaver 2005, Chacar and Lieberman 2003), resulting in small samples. Key studies (e.g., Argyres and Silverman 2004, Chacar and Lieberman 2003, Furman et al. 2006, Penner-Hahn and Shaver 2005) have focused on the research-intensive pharmaceutical industry, but have relatively small samples of firms (between 9 and 71 in the studies just cited).

Lack of data has also made it difficult to assess whether knowledge sourcing mediates the relationship between multilocation of R&D and innovation output. Although Kuemmerle (1999) and Furman (2003) found a correlation between R&D location and access to scientific knowledge, both studies lacked data on innovation output. On the other hand, the study by Argyres and Silverman (2004) on R&D decentralization in the pharmaceutical industry is the only one that has analyzed breadth rather than just the amount of innovation output, but the study did not have information on R&D locations. In addition, we are not aware of any evidence regarding the relationship between multiple locations of R&D and imitative versus new-to-the-market innovation output, and whether home-base-augmenting R&D extends to imitative innovation. In part, this lack of evidence regarding imitative innovation reflects the difficulty of obtaining data on innovation output other than patents.

Prior empirical results do not present a consistent relationship between innovation output and R&D location or decentralization, even though most of these results come from the same industry. Two studies suggest that pharmaceutical R&D, which is subject to economies of scope (Henderson and Cockburn 1996), benefits from fewer locations and more centralization (Chacar and Lieberman 2003, Argyres and Silverman 2004). In contrast, Penner-Hahn and Shaver (2005) found that pharmaceutical companies benefit from foreign R&D activities if they have relevant complementary assets. In addition, Furman et al. (2006) found that pharmaceutical companies benefit from local sources of scientific knowledge. In these studies, the small sample sizes, single-industry focus, and differing results limit the conclusions that can be drawn. A large sample multi-industry study (Singh 2008) found a negative relationship between patent output and geographically dispersed patent inventors. However, the indirect measures of R&D location and lack of data on external knowledge sourcing and imitative innovations suggest the need for additional research.

Our data make it possible to address several issues that prior studies could not. Our data contain detailed information on the locations of domestic R&D facilities, knowledge sources utilized in innovation activity, and commercial success of innovation, including both the amount and breadth of innovation output. Our data also distinguish between new-to-the-market and imitative innovations, encompass a broad range of manufacturing industries, and contain a large sample of firms.

Our data have three primary limitations. First, they include only firms from a single country, namely, Finland. Although the arguments regarding R&D location and decentralization apply within, as well as between, countries, our findings may not generalize to firms in countries with different characteristics. Second, the lack of multiple observations over time for many firms, combined with relatively low variation in R&D locations within firms over time, makes it difficult to construct a longitudinal data set. Third, although most of the data reflect firm-level activity and innovation output of Finnish firms both within Finland and abroad, data are only available for R&D locations within Finland. Because some firms may have R&D locations outside of Finland that we cannot observe, we take several steps to address this empirically. First, the regressions include a control variable for the number of foreign subsidiaries, which provides information about the potential number of foreign R&D locations per firm. In addition, the analysis includes controls for firm size as well as innovation output in the previous period, which reflects the impact of preexisting foreign R&D locations. Finally, we conduct a robustness test using a subsample of firms that do not report any foreign subsidiaries, and are therefore less likely to have foreign R&D labs.

4. Data, Modeling Approach, and Variables

The empirical setting for our study is the manufacturing sector in Finland. Like several other European Union countries, the national statistical agency in Finland conducts surveys on innovation activity. Although Finland is relatively small in surface area (similar to the state of California) and population (5.2 million), it is physically dispersed and diverse. The Helsinki metropolitan area is the most important commercial, industrial, and intellectual center, but the regional centers of Turku and Tampere also provide significant markets and high-quality universities. Moreover, there are geographically dispersed technological concentrations, such as electronics around Oulu University in the North, the forest sector around Lappeenranta University of Technology in the Southeast, and medical research around University of Turku and Åbo Akademi in the city of Turku. Firms thus may consider locating R&D activities in major markets, near major universities, or close to peers in technology "hot spots."

To illustrate the range of R&D locations in our sample, Figure 1 displays locales where R&D activity occurred in 1998. Each county on the map has at least three R&D units included in our sample. Fifty-six different counties have three or more R&D units in our sample, 91 counties have two or more units, and 167 counties have at least one R&D unit. Thus, innovation activity occurs in many different geographic locations, which suggests that firms have many options for where to locate their R&D activity. Nevertheless, the fact that Finland is a relatively small country may limit the number of geographic locations that an individual firm might find attractive for its R&D activity.

The data used to test the hypotheses come from the biannual Finnish R&D Survey and the Finnish Community Innovation Survey (CIS) conducted every four years. Statistics Finland, the national statistical agency, administered both surveys.[4] The statistical agency of the European Union, Eurostat, coordinated the initial development of the CIS survey instrument and the data collection techniques with several EU member countries. The R&D survey collected detailed information about investments in R&D, including the locations of R&D activities. The Community Innovation Survey included questions about innovation output, R&D activity, and knowledge sources related to innovation. As the CIS data have become available in several European countries, scholars have begun to use them to measure innovation output as a complement to more traditional measures such as patents (e.g., Leiponen 2000, 2005; Mairesse and Mohnen 2002; Cassiman and Veugelers 2002). The CEO or the R&D manager of each firm filled out the survey; the response rate was 50%.

We combined data from the CIS survey administered in 2001 with data on R&D location from the R&D survey administered two years earlier to obtain a sample of firms that had data in both surveys. The R&D survey reflects data as of 1998 and the CIS survey covers the period 1998–2000. The sample includes 469 manufacturing firms that had activity directed toward innovation, regardless of whether the firms succeeded in innovating, and encompasses all of the manufacturing industries in Finland. Some Finnish industrial companies are organized as so-called business groups. For example, the basic metals company Outokumpu Inc. is a business group that has two divisions, Outokumpu Stainless Steel and Outokumpu Technology, which are wholly owned subsidiaries of the parent company. Survey respondents were independent (not part of a business group), a subsidiary of a business group, or, in a few instances, the parent company itself (the business group). As a result, the firms in the sample were not widely diversified. Because the data are confidential, firms in the data set are not identified by name.

Table 1 compares the industry distribution of firms in our sample with the industry distribution of the Finnish manufacturing sector as a whole. Relative to the manufacturing sector as a whole, the forest sector (wood, pulp, paper, printing, and publishing) is underrepresented in our sample, whereas the chemical sector is overrepresented. This may occur because our sample only includes firms with some activity directed toward technological innovation, and innovation activities are relatively less frequent in the forest-related sector and relatively more frequent in chemicals. Otherwise, the sample used here is similar to the actual distribution of Finnish manufacturing industries. Importantly, unlike in many analyses of innovation, the majority of the firms in the sample are not in science-based industries.

Compared with firms active in R&D in the manufacturing sector as a whole, firms in our cross-sectional sample are larger and slightly more R&D intensive (R&D expenditures equal to 4.3% versus 2.9% of sales). However, surprisingly, the firms in our sample are less innovative than R&D-active firms in the manufacturing sector as a whole (67% are successful product innovators in our sample versus an average of 75% in the entire

Figure 1 Geographic Distribution of R&D Activity Within Finland in 1998

Notes. Each county indicated on the map has at least three R&D units included in our sample. There are 56 unique counties in the sample with three or more R&D units (not all of them are shown on the map, because they are close together in the southern part or the country). Ninety one counties have 2 or more units, and 167 counties in the sample have at least one R&D unit.

manufacturing sector). Thus, the sample does not appear to be consistently or strongly biased towards firms with greater innovation success.

Surveys can pose issues related to nonresponse bias and common method variance. Controlling for firm size in the regressions alleviates the concern that average firm size for respondents to the innovation survey and the R&D surveys was twice that of the firms that received the surveys. In addition, because respondents had less innovation success than the targeted population as a whole, this suggests that any nonresponse bias does not inflate the survey measures of innovation success.

Both the innovation and R&D surveys had a single respondent per firm, suggesting the need to check for common method variance. Because the variables come from two different surveys, and the same person may not have filled out both forms, this reduces the potential for common method variance. Nevertheless, we conducted a standard check for common method variance, using Harmon's one-factor test (see Podsakoff and Organ 1986). The results of this analysis, described in the footnote below, indicate that our regressions are not subject to an inherent common method bias.[5]

4.1. Modeling Approach and Variables

Our empirical analysis employs a production function approach used in prior studies of the relationship between R&D location and innovation output. The

Table 1 Industry Representation

NACE class	Industry	Number of firms	Percentage in sample	Percentage in manufacturing sector as a whole
15–16	Food products, beverages, and tobacco	35	7.5	10.2
17–19	Textiles, textile products, leather, and leather products	16	3.4	7.6
20–22	Wood, wood products, pulp, paper, paper products, printing, publishing	47	10.0	19.6
23–25	Coke, refined petroleum products, nuclear fuel, chemicals, chemical products, manmade fiber, rubber, plastics	77	16.4	8.7
26	Nonmetallic mineral products	23	4.9	4.4
27	Basic metals	10	2.1	2.4
28	Fabricated metal products	49	10.5	9.6
29	Machinery and equipment	86	18.3	14.2
30–32	Office machinery, computers, TV, radio, communication equipment, and other electrical machinery	52	11.1	9.4
33	Medical, optical, precision instruments; watches and clocks	26	5.5	3.3
34–35	Transport equipment	20	4.3	5.2
36	Furniture, other manufacturing not included elsewhere	28	6.0	5.4
	Total manufacturing	469	100.0	100.0

dependent variables measure innovation output per firm. Our sample includes successful innovators as well as firms that attempted, but failed, to innovate. The primary explanatory variables reflect the number of R&D locations within Finland per firm and the external sources of knowledge that firms utilized in their innovation activities. We control for other factors that may affect innovation output, such as R&D expenditures. In addition, we control for factors that might affect the propensity of firms to use multiple R&D locations, including firm size. The models include a lagged dependent variable to control for potential reverse causality such that past innovation output might lead to multiple locations rather than the reverse.[6] The lagged dependent variable reflects factors that affected innovation output in the period immediately preceding that of our analysis, such as innovation capability. One alternative to this approach would be to use a two-stage model to first predict the number of R&D locations and then use this predicted value in the innovation output equations. We attempted to do this, but were unable to construct valid and statistically significant instruments from the available data.

We test Hypothesis 1 using a set of dependent variables that measure the combined imitative and new-to-the-market innovation output per firm, and compare these results with those for new-to-the-market innovation output only. The right-hand-side variables include the number of R&D locations within Finland, and control variables. To test Hypothesis 2, we add a variable that captures the extent of external knowledge sourcing. Additionally, to assess whether any individual types of knowledge have a particularly strong association with innovation output, we replace the summary variable for external knowledge sourcing with dummy variables for individual knowledge sources. As a supplementary test of Hypothesis 2, we estimate a mediating regression where the extent of external knowledge sourcing is a function of the number of R&D locations. Then we test Hypotheses 3A and 3B using dependent variables that measure the breadth of innovation output. We also assess the relationship between external knowledge sourcing and breadth of innovation output. Finally, we investigate the robustness of these results in two subsamples of firms: smaller firms and firms that do not report any foreign subsidiaries.

4.1.1. Dependent Variables. The data used to construct the dependent variables for innovation output worldwide come from the CIS survey, which provided a detailed explanation to respondents of what constituted a technological innovation.[7] To measure innovation output, we utilized binary variables as well as sales revenue data. Our binary $(0, 1)$ variables indicate whether a firm introduced any technological innovations during the 1998–2000 period. The first binary variable indicates whether a firm introduced any innovations, and the second binary variable indicates whether a firm introduced any product innovations. The third binary variable indicates whether the firm had any new-to-the-market product innovations. Sixty-seven percent of the firms in the sample introduced product innovations. More than three-quarters of these firms (and 55% of all firms in the sample) introduced new-to-the-market product innovations, often in addition to imitative innovations; the remaining firms introduced only imitative product innovations (13% of all firms). Fewer firms introduced process innovations (46% of all firms). Of the firms that innovated, approximately 90% introduced product innovations. Fifty-eight percent of these firms also had process innovations, indicating that product sales do not fully reflect innovation success.

The second type of dependent variable measures total firm sales revenues from innovative products in 2000 that derived from technologically new products introduced during the period 1998–2000. We also constructed a variable that measures innovative sales revenues from new-to-the-market product innovations. Both product sales variables are expressed in natural logarithmic terms. These variables measure the extent of commercial success. By using both binary and product sales variables, we obtain a fuller picture of the dimensions of innovation output.

In addition to the binary and sales variables that measure the amount of innovation output, we created two dependent variables reflecting the range of applicability of each firm's innovations, in order to test Hypotheses 3A and 3B. A binary $(0, 1)$ variable indicates whether the firm had both product and process innovations, as opposed to only one or neither type of innovation. Three-quarters of the firms introduced some type of innovation. Of this group, about half introduced *both* product and process innovations. The innovation survey also asked firms to assess the impact of their innovations in nine categories: expanding product range, improving product quality, extending market share or opening up new markets, improving production flexibility, expanding production capacity, reducing labor costs, reducing materials costs, reducing environmental effects, and fulfilling government regulations and standards. Survey respondents evaluated each of these effects on a four-point scale from zero (not applicable or no impact) to three (a very substantial impact). To measure the range of innovation impact, we constructed a variable that reflects the number of different effects that firms viewed as important or very important, using the same procedure as that described below for knowledge sources. We assigned a binary value of 1 if an individual innovation effect received a value of two (substantial impact) or three (a very substantial impact), and a zero otherwise. We then summed the binary values for the nine possible innovation effects.

4.1.2. Explanatory Variables. Our key explanatory variables relate to: (1) the number of locations where firms carried out R&D activities within Finland, and (2) the external sources of knowledge that firms reported were important in their innovation activities. The location variables derive from the R&D survey and reflect 1998 data. R&D locations are identified as separate counties where R&D activity took place within Finland.

As indicated in Table 2, most firms centralized their R&D activities. Only 7.5% of the firms had two R&D locations and 5.3% had three or more locations; a mere 1% of firms had six or more locations. Given this clustering of the data, we formed two binary indicators, one indicating whether a firm had two locations and another indicating whether a firm had three or more locations. The reference case (and omitted variable) is

Table 2 Number of R&D Locations per Firm Within Finland

Number of geographically distinct units per firm	Number of firms
1	409
2	35
3	11
4	6
5	3
6	1
8	1
9	2
13	1
Total	469

one location. Firms with one location include 57 companies that did not report formal R&D units, but conducted innovation activities. Because these companies conducted innovation activity at a single location, we coded them as having one location. Sensitivity tests excluding these companies do not change the substance of the results reported below.

The innovation survey asked respondents to identify the importance of seven external sources of information for innovation activity: customers, suppliers, competitors, universities, nonprofit research institutes, professional meetings and publications, and trade fairs/exhibitions. Location may affect utilization of all of these knowledge sources, including publicly available ones. For example, personnel may be more likely to attend nearby meetings and trade fairs. Furman et al. (2006) also found that firms obtained greater benefit from publications of university researchers located near their R&D labs.

For each knowledge source listed in the survey questionnaire, each firm was asked to "evaluate the importance of the following sources of information for the innovation activities of your firm" on a four-point scale from zero (not important at all/not used) to three (very important). We used this information to test Hypothesis 2, which rests on the proposition that multiple R&D locations enable firms to obtain information from a larger number of different knowledge sources than they could from a single location. We therefore constructed a summary variable that reflects the extent of external knowledge sourcing per firm. Other research, such as that of Laursen and Salter (2004, 2006) and Mol and Birkenshaw (2009), has utilized a very similar variable using UK CIS data.

To account for the varying importance of different knowledge sources, we adopted an approach introduced by Cohen and Malerba (2001) for industry-level innovation activity and subsequently used by Leiponen and Helfat (2010) for firm-level analysis. For each of the seven knowledge sources, we first assigned a binary value based on whether the survey response indicated that the item was important to the firm. A survey response of either two (important) or three (very important) received a binary value of one; a survey response of zero (not important at all/not used) or one (some importance) received a binary value of zero. The use of binary values helps to alleviate potential measurement error from use of a Likert scale in the survey questions (Cohen and Malerba 2001).

To construct a variable indicating the extent of external knowledge sourcing, we summed the binary values for the seven knowledge sources. On average, the most important external sources in the sample are customers and suppliers, followed by professional and trade meetings. Additionally, in order to assess the relationship between innovation success and particular types of external knowledge sources, we utilized (0, 1) dummy variables for each of the external knowledge sources, where a binary value of 1 indicates that the knowledge source was important or very important to the firm.

4.1.3. Control Variables. We include the number of employees, because larger firms have access to greater financial and human resources, these firms may have a greater ability to achieve at least a single innovation and may derive more sales from a single innovation because they have a larger base of customers. Additionally, firm size helps to control for potential nonresponse bias, because the firms that responded to the innovation survey were larger than those in the target population. Finally, because larger firms are more likely to be able to afford the costs of setting up and operating multiple R&D locations, it is important to control for firm size. We use the natural logarithmic transformation of the raw data.

R&D expenditures may increase the probability of achieving at least one innovation, as well as potential sales revenues from successful innovation. In addition, because the number of R&D locations may be correlated with the amount of R&D spending, it is important to control for the scale of R&D. R&D expenditures are measured in natural logarithmic form.

Lagged dependent variable directly controls for the possibility that past innovation success could lead firms to have more R&D locations. Because a lagged dependent variable reflects factors associated with innovation success in the preceding period, this variable also helps to control for firm-level factors such as innovation capability and preexisting foreign R&D locations. The lagged dependent variable reflects data for 1998 for product innovation sales revenue and data for 1996–1998 for the binary innovation output indicators.

Number of foreign subsidiaries is a proxy for the extent to which firms have R&D labs outside of Finland. Firms that have operations in other countries may be more likely to establish R&D labs in those countries. These data originate from the Bank of Finland register of Foreign Direct Investment flows from Finland, which includes units with over 5 million euros on the balance sheet.

Business group subsidiary and business group parent are binary (0, 1) variables that come from the innovation survey and measure whether a firm was either a subsidiary of a larger firm or a business group parent company, rather than an independent firm. These variables control for whether the firm was part of a diversified company, which can affect innovation output as well as the propensity to have multiple R&D locations. For example, firms in a business group might have access to internal knowledge sources of other firms in the group, which can affect innovation output. The propensity of firms in business groups to set up multiple R&D labs also might be affected by corporate parent decisions. In addition, the business group parent variable controls for the possibility that these firms might report a larger number of R&D locations due to the inclusion of subsidiaries in their responses.

Export revenues may affect innovation outcomes, because the potential for greater sales outside of Finland may increase the incentive to innovate. Additionally, if firms with a high volume of exports face more intense international competition, they may have stronger motivation to introduce new innovations. Export revenues are measured in natural logarithmic form.

Sales growth due to mergers and acquisitions and sales reduction due to divestitures are binary (0, 1) variables that come from the innovation survey. The first variable measures whether mergers or acquisitions increased firm sales revenues by 10% or more during the 1998–2000 period. The second variable measures whether divestitures decreased firm sales revenues by 10% or more during the same period. These variables control for the possibility that both innovation output and R&D locations could reflect recent large acquisitions or divestitures.

We include a (0, 1) dummy variable for each two-digit-level NACE industry in the sample (the excluded industry is manufacture of furniture).[8] Industry-level factors such as technological opportunity, appropriability of the returns to innovation, and customer demand for new products may affect the incentives of firms to innovate as well as the likelihood and extent of innovation success.

Table 3 presents summary statistics describing the sample. The last two columns in Table 3 report descriptive statistics for firms with multiple R&D locations and firms with only a single location. Multiple R&D locations correlate positively with firm size, R&D expenditures, export revenues, number of foreign subsidiaries, business group membership, sales growth due to mergers or acquisitions, and sales reductions due to divestitures. Firms with multiple R&D locations, however, do not have greater R&D intensity (expenditures relative to size) than their single-location counterparts. Nevertheless, firms with multiple locations have a higher probability of innovation, greater sales from innovative

Table 3 Descriptive Statistics ($N = 469$)

Variable	Mean	Standard deviation	Min	Max	Mean for firms with one R&D location	Mean for firms with multiple R&D locations
Number of employees	354.122	1,553.888	5	22,000	209.086	1,342.783
Export revenues	212,637.400	1,129,475.000	0	20,300,000	105,858.800	940,511.500
Sales growth due to mergers or acquisitions (M&A)	0.102	0.303	0	1	0.090	0.183
Sales reduction due to divestitures	0.038	0.192	0	1	0.034	0.067
Business group subsidiary	0.510	0.500	0	1	0.482	0.700
Business group parent	0.051	0.221	0	1	0.037	0.150
Number of foreign subsidiaries	2.053	14.720	0	221	1.039	8.967
R&D expenditures	5,800.192	20,733.340	0	311,149	3,206.785	23,478.580
R&D intensity (expenditures/sales)	0.043	0.095	0	0.933	0.043	0.045
Product innovation 2000	0.674	0.469	0	1	0.648	0.850
Product innovation 1998	0.729	0.445	0	1	0.711	0.850
Process innovation 2000	0.458	0.499	0	1	0.425	0.683
Process innovation 1998	0.542	0.499	0	1	0.518	0.700
New-to-the-market innovation 2000	0.546	0.498	0	1	0.521	0.717
New-to-the-market innovation 1998	0.431	0.496	0	1	0.418	0.517
Any innovation 2000	0.742	0.438	0	1	0.719	0.900
Any innovation 1998	0.844	0.363	0	1	0.839	0.883
Both product and process innovation 2000	0.390	0.488	0	1	0.355	0.633
Both product and process innovation 1998	0.426	0.495	0	1	0.391	0.667
Sales revenue from newly introduced product innovations 2000	60,714.690	225,251.500	0	2,730,268	37,162.470	221,262.300
Sales revenue from new-to-the-market product innovations 2000	40,923.960	187,693.500	0	2,730,268	25,730.010	144,496.000
Number of R&D locations per firm within Finland	1.2708	1.026	1	13	1	3.117
Firms with two R&D locations	0.075	0.263	0	1	0	0.583
Firms with three or more R&D locations	0.053	0.225	0	1	0	0.417
Innovation effects	3.188	2.730	0	9	3.046	4.150
External knowledge sourcing	2.525	2.015	0	7	2.320	3.900
• Knowledge from suppliers of equipment, material, components, or software	0.469	0.500	0	1	0.443	0.650
• Knowledge from customers	0.616	0.487	0	1	0.592	0.783
• Knowledge from competitors	0.303	0.460	0	1	0.286	0.417
• Knowledge from universities	0.275	0.447	0	1	0.227	0.600
• Knowledge from nonprofit research institutes	0.205	0.404	0	1	0.176	0.400
• Knowledge from conferences, professional meetings, literature	0.309	0.463	0	1	0.264	0.617
• Knowledge from trade fairs, exhibitions	0.348	0.477	0	1	0.335	0.433

Note. All the monetary variables are measured in thousands of Finnish markka.

products, a wider range of innovation effects, and seek external information from a larger number of sources.

5. Results and Discussion

5.1. Imitative vs. New-to-the-Market Innovation Output

Table 4 contains the results relevant to Hypothesis 1, which posits that multiple R&D locations are associated with greater success for imitative innovation than for new-to-the-market innovation. The table reports probit estimates for binary indicators of innovation output and tobit estimates for sales revenues from new product innovations.

In the first two models in Table 4, probit estimates show that having two R&D locations within Finland is positively and statistically significantly associated with the probability that firms introduced any innovations at all, as well as with the probability that firms introduced product innovations of any type. The marginal effect for two locations in both models is substantial, indicating that an increase in the number of R&D locations in Finland from one to two is associated with an increase in the probability of innovation by approximately 20%.[9] In the third model in Table 4, a continuous dependent variable measures sales from innovative products of any type. The coefficient estimate for two R&D locations

Table 4 Results for Binary Innovation Indicators and Sales Revenue from Product Innovations

Dependent variable:	(1) Product innovation			(2) Any innovation			(3) Log(Product innovation sales revenue)			(4) New-to-the-market innovation			(5) Log(New-to-the-market innovation sales)		
Explanatory variables	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.
Constant	−0.985**	0.410		−0.596	0.431		−3.146*	1.690	−2.585	−0.870**	0.381		−4.216*	2.285	−2.575
Log(Employees)	0.049	0.080	0.017	0.084	0.082	0.025	0.448	0.347	0.360	−0.024	0.078	−0.010	0.100	0.474	0.055
Log(R&D)	0.085***	0.027	0.029	0.112***	0.027	0.034	0.353***	0.127	0.287	0.094***	0.028	0.037	0.555***	0.179	0.336
Log(Exports)	0.008	0.043	0.003	−0.030	0.044	−0.009	0.088	0.193	0.077	0.024	0.042	0.010	0.089	0.262	0.059
Business group subsidiary	0.153	0.151	0.053	0.088	0.154	0.026	0.578	0.656	0.471	0.176	0.145	0.069	1.082	0.900	0.656
Business group parent	−0.456	0.355	0.140	−0.102	0.372	0.119	−1.528	1.431	−1.250	−0.064	0.335	0.133	−0.914	1.922	−0.557
M&A	0.095	0.239	0.032	0.207	0.256	0.058	1.101	0.940	0.897	−0.123	0.222	−0.049	0.105	1.292	0.063
Divest	−0.716**	0.327	−0.273	−0.635*	0.334	−0.225	−3.052**	1.538	−2.494	−0.244	0.322	−0.097	−1.260	2.063	−0.768
Log(Number of foreign subsidiaries)	0.308**	0.156	0.106	0.167	0.155	0.050	0.984**	0.465	0.801	0.248*	0.132	0.098	0.954	0.619	0.578
Lagged dependent variable	0.651***	0.147	0.237	0.475***	0.178	0.158	0.371***	0.071	0.302	0.526***	0.132	0.204	0.442***	0.091	0.268
Two locations	0.754**	0.335	0.206	0.939**	0.405	0.195	2.164**	1.076	1.762	0.345	0.256	0.131	1.887	1.450	1.141
Three or more locations	−0.204	0.348	−0.073	−0.248	0.361	−0.080	−0.285	1.380	−0.228	−0.066	0.319	−0.026	−0.095	1.842	−0.054
Log likelihood	−248.270			−237.000			−1,127.440			−279.740			−993.090		

Notes. S.E., standard error. M.E., marginal effect. Observations = 469. The models were estimated using probit ML for the binary indicators of product innovation and any innovation, and tobit ML for log(Innovation sales). ***Indicates significance at the 1% level, **indicates significance at the 5% level, and *indicates significance at the 10% level. Two-digit industry dummies are included in all models.

is again positive and statistically significant. Having two R&D locations rather than one, holding other variables at their means, is associated with over five times ($\exp(1.762) = 5.824$) greater innovation sales revenues. Although the magnitude of the marginal effect of two R&D locations differs for the probability of innovation and sales from innovation, it is substantial for both types of variables. In all three models, the coefficient for three or more R&D locations is insignificant. These results suggest that multiple R&D locations, up to a point, are associated with substantially greater innovation output. This result is limited to two R&D locations, which could reflect diminishing returns to the number of locations due to coordination costs, or the need for minimum efficient scale to support additional R&D locations, or the fact that Finland has fewer location choices than a larger country.

In contrast to the first three models, the coefficient estimates for two (and three) R&D locations are insignificant in the last two models in Table 4. The dependent variables in these models reflect new-to-the-market innovation. In model 4, a binary variable indicates firms that introduced new-to-the-market product innovations; in model 5, the dependent variable measures product innovation sales revenues for these firms. When combined with the first three models, these results support Hypothesis 1: multiple locations of R&D activity are associated with imitative, but not new-to-the-market, innovation output.

Of the control variables in Table 4, R&D expenditures and lagged innovation output are positive and statistically significant in all models. The number of foreign subsidiaries has a significant and positive coefficient in only three of the models. The only other significant variables are two industry dummy variables (coke/petroleum in four models and metal products in one model) and the divestment variable in the first three models. Although the divestment variable has a negative coefficient, indicating that divestment is associated with less innovative output, it reflects a relatively small number of firms, making it difficult to draw strong conclusions.

5.2. External Knowledge Sourcing

Next we examined the role of external knowledge sourcing in order to test Hypothesis 2, that the extent of knowledge sourcing mediates the association between R&D location and innovation success. Table 5 reports the earlier specifications in Table 4 with the summary external knowledge-sourcing variable added as a mediating explanatory variable. Table 6 reports the results when $(0, 1)$ dummy variables for each of the external knowledge sources are included in the models rather than the summary variable for external knowledge sourcing.

The models in Table 5 demonstrate a strong correlation between the extent of knowledge sourcing and multiple locations of R&D: adding the knowledge-sourcing variable to the regressions makes the previously significant positive relationship between two R&D locations and innovation output insignificant, suggestive of mediation.[10] The coefficient on the external

Table 5 External Knowledge Sourcing as a Mediating Explanatory Variable

	(1) Product innovation			(2) Any innovation			(3) Log(Product innovation sales)			(4) New-to-the-market innovation			(5) Log(New-to-the-market innovation sales)		
	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.
Constant	−1.004**	0.442		−0.703	0.506		−3.494**	1.562	−2.942	−1.073***	0.384		−4.925**	2.186	−3.035
Log(Employees)	−0.007	0.085	−0.002	0.031	0.093	0.007	0.237	0.321	0.192	−0.054	0.079	−0.021	−0.132	0.453	−0.087
Log(R&D)	0.043	0.030	0.014	0.064**	0.031	0.015	0.173	0.119	0.144	0.063**	0.029	0.025	0.352**	0.172	0.215
Log(Exports)	0.002	0.045	0.001	−0.049	0.049	−0.012	0.098	0.178	0.088	0.014	0.043	0.006	0.089	0.251	0.060
Business group subsidiary	0.194	0.163	0.064	0.084	0.178	0.020	0.654	0.606	0.547	0.153	0.148	0.060	0.089	0.251	0.060
Business group parent	−0.357	0.379	0.144	0.110	0.442	0.096	−0.919	1.321	−0.772	−0.028	0.343	0.136	−0.475	1.832	−0.294
M&A	0.001	0.253	0.000	0.192	0.295	0.043	0.776	0.866	0.648	−0.208	0.226	−0.083	−0.202	1.229	−0.125
Divest	−0.583*	0.336	−0.216	−0.464	0.362	−0.135	−1.724	1.418	−1.447	−0.074	0.324	−0.029	0.076	1.958	0.043
Log(Number of foreign subsidiaries)	0.237	0.163	0.078	0.028	0.174	0.007	0.664	0.428	0.554	0.173	0.131	0.068	0.637	0.588	0.389
Lagged dependent variable	0.520***	0.156	0.181	0.464**	0.201	0.129	0.253***	0.067	0.212	0.419***	0.136	0.163	0.358***	0.087	0.219
Two locations	0.499	0.351	0.140	0.688	0.462	0.120	1.035	0.994	0.862	0.118	0.257	0.046	0.630	1.382	0.383
Three or more locations	−0.437	0.362	−0.158	−0.773*	0.402	−0.245	−0.467	1.265	−0.386	−0.093	0.325	−0.037	−0.423	1.745	−0.255
External knowledge sourcing	0.328***	0.042	0.108	0.474***	0.052	0.114	1.284***	0.149	1.074	0.211***	0.036	0.083	1.368***	0.210	0.838
Log likelihood	−214.290			−182.190			−1090.930			−264.500			−971.540		

Notes. S.E., standard error. M.E., marginal effect. Observations = 469. The models were estimated using probit ML for the binary indicators of product innovation and any innovation, and tobit ML for log(Innovation sales). ***Indicates significance at the 1% level, **indicates significance at the 5% level, and *indicates significance at the 10% level. Two-digit industry dummies are included in all models.

knowledge-sourcing variable is positive and statistically significant in all of the models. In the three probit models, the marginal effects indicate that an increase in the number of external knowledge sources is associated with an increase of approximately 8%–11% in the probability of innovating. In the tobit models, an increase of one important external knowledge source is associated with an almost threefold increase in all product innovation sales ($\exp(1.074) = 2.927$) and a twofold increase in new-to-the-market innovation sales ($\exp(0.838) = 2.312$). Thus, new-to-the-market innovation is also positively and significantly associated with the extent of external knowledge sourcing. However, considering the earlier results in Table 4, new-to-the-market innovation does not appear to reflect the use of multiple R&D locations to access external knowledge sources.

These results have implications for the argument in prior literature that multilocation of R&D directed toward imitative innovation is home base exploiting. Our results suggest that imitative innovation may involve home-base-augmenting R&D, wherein firms seek knowledge from external sources. We find that multiple R&D locations are positively and statistically significantly associated with imitative innovation, and this multilocation of R&D is correlated with external knowledge sourcing, consistent with the pursuit of knowledge spillovers through home-base-augmenting R&D.

The results in Table 6 provide additional information regarding external knowledge sourcing. The coefficient estimates for knowledge from suppliers and customers are positive and significant in all five models. The coefficients for knowledge from universities and competitors are positive but at lower significance levels and in fewer models. The other knowledge sources are not significant, except trade fairs in one model. Obtaining knowledge from customers has particularly large marginal effects, and is associated with an increase in the probability of innovation of between 26% and 40% in the probit regressions and at least a ninefold increase ($\exp(2.264) = 9.6$) in innovation sales in the tobit regressions. These results suggest that companies in this sample that do not obtain information from customers may be at a severe disadvantage. These results also provide additional evidence of mediation by external knowledge sourcing. However, the coefficient for two R&D locations remains statistically significant at a lower level in two of the five models, suggesting that individual knowledge dummy variables may not capture external knowledge sourcing as fully as the summary variable.

The knowledge-sourcing variables in Tables 5 and 6 derive from the same survey as the innovation output variables and reflect knowledge sources for 1998–2000. Thus, multiple locations in 1998 might have enabled firms to access a greater number of knowledge sources during 1998–2000, consistent with the literature that motivated Hypothesis 2. As a supplementary test of Hypothesis 2, we estimate a mediating regression where the extent of knowledge sourcing is the dependent variable, and the R&D location variables, along with control variables, are on the right-hand side.[11] The results, reported in Table 7, show that the coefficient on two R&D locations is positive and statistically significant;

Table 6 Individual Knowledge Sources as Mediating Explanatory Variables

	(1) Product innovation			(2) Any innovation			(3) Log(Product innovation sales)			(4) New-to-the-market innovation			(5) Log(New-to-the-market innovation sales)		
	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.
Constant	−1.249***	0.473		−0.720	0.535		−4.946***	1.537	−4.236	−1.304***	0.402		−6.363***	2.241	−3.921
Log(Employees)	−0.011	0.090	−0.004	0.017	0.099	0.004	0.305	0.306	0.250	−0.056	0.081	−0.022	−0.083	0.449	−0.058
Log(R&D)	0.049	0.031	0.016	0.074**	0.033	0.017	0.180	0.115	0.152	0.071**	0.030	0.028	0.391**	0.173	0.238
Log(Exports)	0.013	0.048	0.004	−0.055	0.054	−0.013	0.128	0.171	0.118	0.017	0.045	0.007	0.098	0.250	0.067
Business group subsidiary	0.174	0.173	0.057	0.102	0.191	0.024	0.523	0.587	0.444	0.180	0.155	0.071	1.112	0.864	0.680
Business group parent	−0.428	0.388	−0.154	0.002	0.473	0.000	−1.306	1.258	−1.114	0.011	0.349	0.004	−0.615	1.816	−0.380
M&A	−0.031	0.270	−0.010	0.178	0.321	0.039	0.587	0.829	0.496	−0.251	0.232	−0.100	−0.273	1.225	−0.169
Divest	−0.582*	0.347	−0.215	−0.434	0.377	−0.123	−1.589	1.347	−1.357	−0.049	0.327	−0.019	0.270	1.930	0.160
Log(Number of foreign subsidiaries)	0.216	0.164	0.071	0.005	0.173	0.001	0.644	0.408	0.545	0.172	0.131	0.068	0.622	0.584	0.379
Lagged dependent variable	0.506***	0.164	0.175	0.406*	0.211	0.109	0.236***	0.064	0.201	0.415***	0.138	0.162	0.347***	0.086	0.212
Two locations	0.608*	0.361	0.162	0.805*	0.475	0.129	1.478	0.955	1.251	0.159	0.260	0.062	1.010	1.385	0.614
Three or more locations	−0.431	0.372	−0.155	−0.679*	0.412	−0.206	−0.511	1.204	−0.429	−0.091	0.326	−0.036	−0.310	1.727	−0.186
External knowledge sources:															
Suppliers	0.325*	0.167	0.105	0.607***	0.190	0.140	1.162**	0.548	0.985	0.395***	0.146	0.155	1.847**	0.803	1.129
Customers	1.170***	0.172	0.395	1.308***	0.189	0.350	5.182***	0.623	4.407	0.671***	0.157	0.262	3.695***	0.912	2.264
Competitors	0.192	0.205	0.061	0.441*	0.259	0.095	0.966	0.600	0.819	0.151	0.166	0.060	1.498*	0.865	0.916
Universities	0.388*	0.215	0.119	0.535**	0.253	0.111	1.372**	0.660	1.171	0.314*	0.180	0.122	1.566	0.964	0.962
Research institutes	0.009	0.231	0.003	−0.165	0.271	−0.041	−0.313	0.713	−0.267	−0.167	0.195	−0.066	−0.090	1.039	−0.055
Professional meetings	−0.297	0.213	−0.100	−0.174	0.243	−0.042	−0.870	0.671	−0.742	−0.205	0.183	−0.081	−0.998	0.974	−0.613
Trade fairs, exhibitions	0.229	0.190	0.073	0.325	0.220	0.073	0.891	0.586	0.758	0.196	0.161	0.077	1.639*	0.853	1.005
Log likelihood	−196.580			−164.400			−1063.600			−254.340			−963.570		

Notes. S.E., standard error. M.E., marginal effect. Observations = 469. The models were estimated using probit ML for the binary indicators of product innovation and any innovation, and tobit ML for log(innovation sales). ***Indicates significance at the 1% level, **indicates significance at the 5% level, and *indicates significance at the 10% level. Two-digit industry dummies are included in all models.

the marginal effect of having two R&D locations rather than one is associated with an increase in knowledge sourcing of close to 80%. The coefficient for three R&D locations is not significant. Although these results are only suggestive due to the potential for correlation between the error terms in the mediating regression and the innovation output regressions (Shaver 2005), they provide additional evidence that multiple R&D locations may enable firms to access external knowledge sources.

To further probe the foregoing results, we investigated mechanisms through which multiple locations of R&D might facilitate knowledge acquisition, such as through outsourcing or R&D collaboration (Cassiman and Veugelers 2002) (results available on request). First, we added two outsourcing variables to the regressions in Table 4: expenditures on contract R&D and expenditures on purchases of technological knowledge (including patents, licenses, copyrights, and software), both measured in logarithmic form. Next we assessed whether R&D collaboration in Finland with suppliers, customers, competitors, or universities might account for the location effects. We also constructed a summary collaboration variable similar to that for knowledge sources, where we summed the binary variables for each type of collaboration. Finally, we included the two outsourcing variables and the summary collaboration variable together in the regressions. Most of the outsourcing and collaboration variables were highly significant. In many of these models, the coefficient on two R&D locations remained significant, but at a lower level of significance than in the base regressions in Table 4. This suggests that outsourcing and R&D collaboration do not entirely mediate the association between R&D location and innovation output. Thus, although multilocation of R&D may facilitate R&D collaboration and outsourcing, these forms of knowledge acquisition do not appear to capture all external knowledge sourcing by firms.

Overall, these results suggest that multiple R&D locations and external knowledge sourcing are strongly related. In line with Hypothesis 2, the positive association between the number of R&D locations and innovation output is strongly correlated with external knowledge sourcing by firms. These results are consistent with arguments of the knowledge-based view regarding pursuit of localized knowledge spillovers through multilocation of R&D. The results are not aligned with organizational arguments regarding the general benefits of centralized innovation activity or with the

Table 7 Estimation Results with External Knowledge Sourcing as the Dependent Variable

	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.
Constant	−0.131	0.225		−0.218	0.245	
Log(Employees)	0.053	0.046	0.124	0.062	0.046	0.145
Log(R&D)	0.080***	0.020	0.184	0.094***	0.020	0.219
Log(Exports)	−0.002	0.026	−0.004	0.004	0.026	0.009
Business group subsidiary	−0.049	0.088	−0.114	−0.033	0.089	−0.077
Business group parent	−0.195	0.171	−0.415	−0.170	0.172	−0.366
M&A	0.113	0.112	0.274	0.122	0.113	0.299
Divest	−0.451*	0.238	−0.855	−0.419*	0.239	−0.810
Log(Number of foreign subsidiaries)	0.049	0.049	0.113	0.058	0.050	0.134
Log(Innovation sales in 1998)	0.034***	0.010	0.079			
Any innovation 1998				0.154	0.107	0.340
Two locations	0.291**	0.118	0.766	0.299**	0.120	0.795
Three or more locations	0.039	0.150	0.092	0.073	0.151	0.177
Log likelihood	−895.370			−900.950		

Notes. This specification was estimated using the negative binomial method with constant dispersion. Observations = 469. S.E., standard error. M.E., marginal effect. ***Indicates significance at the 1% level, **indicates significance at the 5% level, and *indicates significance at the 10% level. Two-digit industry dummies are included in all models. The lagged dependent variable is not observed, thus log(innovation sales in 1998) or any innovation in 1998 is used instead.

argument that firms use multilocation of R&D primarily for knowledge exploitation.

5.3. Range of Innovation Effects

To test Hypotheses 3A and 3B, we next assessed whether multiple R&D locations are associated with a wider or a narrower range of innovation output. Table 8 reports the results for two dependent variables that reflect the range of innovation output: a binary variable indicating whether the firm made both product and process innovations (as opposed to one or the other or neither), and a variable reflecting the range of important innovation effects per firm. For the second dependent variable, because our data do not contain information on innovation effects in the prior period, we utilize the lagged binary dependent variable as well as lagged product innovation sales revenues.

In Table 8, the coefficient for two R&D locations is positive and statistically significant in both of the models for the range of important innovation effects, but not for the binary innovation indicator. The coefficient on three R&D locations is not significant in any models in Table 8. Marginal effects in the negative binomial models for the range of important innovation effects indicate that an increase from one to two R&D locations is associated with an increase of almost 1.00 in the range of important innovation effects. In a sensitivity analysis (available on request), we added the summary knowledge-sourcing variable to the models and the coefficient for two R&D locations became insignificant.

These results provide some evidence in favor of H3A relative to H3B. In particular, the models for the range of innovation effects suggest that multiple locations of innovation activity (up to a point) are positively associated with wider applicability of innovation output, consistent with the knowledge-based view. The sensitivity analysis also points to an association with knowledge sourcing in these results. The coefficients on the R&D

Table 8 Range of Innovation Output

	(1) Product and process innovation			(2) Range of important innovation effects			(3) Range of important innovation effects		
	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.	Coeff.	S.E.	M.E.
Constant	−1.409***	0.377		0.245	0.273		0.171	0.274	
Log(Employees)	0.139*	0.079	0.053	−0.006	0.053	−0.018	−0.004	0.053	−0.013
Log(R&D)	0.021	0.028	0.008	0.091***	0.024	0.269	0.084***	0.024	0.245
Log(Exports)	0.004	0.043	0.002	0.019	0.031	0.055	0.007	0.032	0.020
Business group	−0.112	0.148	−0.043	−0.122	0.103	−0.360	−0.167	0.103	−0.493
Business group subsidiary	−0.245	0.336	−0.089	−0.183	0.204	−0.500	−0.260	0.205	−0.681
M&A	0.302	0.215	0.118	0.323**	0.128	1.091	0.321**	0.129	1.073
Divest	−0.027	0.325	−0.010	−0.388	0.282	−0.966	−0.395	0.281	−0.973
Log(Number of foreign subsidiaries)	0.179	0.115	0.068	0.046	0.061	0.136	0.043	0.061	0.126
Product and process innovation in 1998	0.650***	0.129	0.246	0.312***	0.089	0.947			
Log(Sales revenue from product innovation) in 1998							0.050***	0.012	0.148
Two locations	0.373	0.246	0.146	0.269*	0.140	0.892	0.289**	0.139	0.964
Three or more locations	0.099	0.320	0.038	−0.182	0.197	−0.497	−0.235	0.197	−0.621
Log likelihood	−273.120			−1,037.600			−1033.670		

Notes. Estimation methods include probit ML for product and process innovation and negative binomial with constant dispersion for sum of innovation effects. Observations = 469. S.E., standard error. M.E., marginal effect. ***Indicates significance at the 1% level, **indicates significance at the 5% level, and *indicates significance at the 10% level. Two-digit industry dummies are included in all models.

location variables in the model for the binary innovation indicator are insignificant, and therefore do not provide support for either hypothesis.

5.4. Robustness Tests Using Subsample Analyses

Our sample contains many small firms, reflecting the nature of the Finnish economy. To further investigate the role of firm size, we reran the models in Table 4 for a subsample of relatively small firms having fewer than 300 employees. Because small firms generally operate in fewer countries and industries than large firms, this analysis enabled us to control even further for the extent of foreign operations and firm diversification. For this subsample, we again found that the coefficient on two R&D locations was positive and statistically significant, and the coefficient for three locations was insignificant (detailed results available on request). Adding the summary knowledge-sourcing variable to the regressions again fully mediated the association between two R&D locations and innovation output. Thus, even for small firms, we find an association between multilocation of R&D and innovation output, with evidence of mediation by external knowledge sourcing.

Finally, we reran the models in Table 4 only for companies that did not report any foreign subsidiaries, and therefore were less likely to have foreign R&D operations (detailed results available on request). The results are very similar to those for the full sample of firms. The variable for two R&D locations is positively and significantly associated with innovation output, and the coefficient estimates are very similar to those obtained for the full sample. The coefficient in the tobit model has a slightly lower level of significance than for the full sample, primarily caused by a larger standard error when using the smaller sample. The variable for three R&D locations is insignificant in all three models, as before. These findings support the earlier results regarding multilocation of R&D labs.

6. Conclusion

This study analyzes uniquely detailed data to examine the relationship between multilocation of R&D and innovation output. We compare predictions of the knowledge-based view of the firm with predictions from organizational economics regarding the location and decentralization of R&D, and obtain several novel results. We find that having two R&D locations within Finland is associated with greater output of imitative but not new-to-the-market, innovations. We also find that multilocation of R&D has a positive, although less strong, association with breadth of innovation output. In addition, we provide the first evidence that a positive association of multiple R&D locations with imitative innovative output is strongly correlated with knowledge sourcing. In contrast to prior literature, this result suggests that firms pursuing imitative innovation may use home-base-augmenting R&D, rather than using only home-base-exploiting R&D that adapts preexisting knowledge to local markets. Locating near relevant knowledge sources such as customers and suppliers may reflect pursuit of knowledge spillovers, even for imitative innovation. Overall, the results are consistent with the interpretation that multilocation of R&D enables firms to access a broad set of external sources of knowledge in pursuit of imitative innovation. Moreover, we observe heterogeneity in R&D strategies between firms pursuing new-to-the-market innovation and firms pursuing imitative innovation. We find that new-to-the-market innovation output is not positively correlated with multilocation of R&D, consistent with the benefits of centralized R&D for this type of innovation.

Our findings also are consistent with two recent studies on patenting, which represents new-to-the-world technologies. Singh (2008) found that international dispersion of patenting within firms (a proxy for location of R&D) did not have a positive correlation with forward patent citations (a measure of innovation output). Similarly, Argyres and Silverman (2004) found that organizational centralization of R&D was positively associated with the extent and breadth of firm patenting activity. We also find no statistically significant effect of R&D multilocation on new-to-the-market innovation. Thus, it appears important to distinguish between new-to-the-market and imitative innovations.

Because these results are limited to a single country and relatively small, generally non-science-based firms, more analysis is needed to assess their applicability elsewhere. Other data sources also are necessary to assess whether multilocation of R&D is welfare improving, but our results suggest that it may be profitimproving for many firms, because multiple locations are associated with greater sales from innovative products–which in many markets is crucial for sustaining a competitive edge.

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Endnotes

[1]We do not investigate other aspects of organizational structure, such as which units have budgetary control over R&D

decisions. Although our data contain detailed information about R&D locations within firms, we do not have additional information regarding the structure of command and control inside organizations.

[2]Patel (1995) suggests that this may explain the finding that international dispersion of R&D for large firms in the 1980s often involved non-high-tech industries that tend to emphasize incremental, adaptive innovations.

[3]Dahlin and Behrens (2005) note that new-to-the-world innovations vary in their "novelty," and distinguish between a high level of novelty (low similarity with past technology) and more limited novelty (greater similarity with past technology). For purposes of our analysis, new-to-the-market innovations include all types of novel innovations.

[4]Within the manufacturing sector, all firms with more than 100 employees received the R&D Survey, as did a stratified random sample of firms with 10–99 employees. The sample for firms with fewer than 10 employees is not random; it only includes firms known to perform R&D, based on earlier surveys or firms' public R&D funding applications. For the Finnish CIS, Statistics Finland surveyed all Finnish manufacturing firms with more than 100 employees, as well as a random sample stratified by size and industry of the remainder of the population of Finnish manufacturing companies.

[5]We performed a principal component analysis that included the dependent product innovation sales variable and all of the explanatory and control variables in Table 5. We used the sales dependent variable, because principal component analyses tend not to work as well for binary variables. The analysis retained 12 factors with eigenvalues greater than 1.00, and no factor explained more than 16% of the variance. Moreover, the dependent variable did not load most strongly on the same component as did number of R&D locations. Excluding the industry dummy variables, the principal component analysis still retained four components with eigenvalues above 1.00, and the first component explained 30% of the variance. R&D location variables loaded most strongly on different components than the dependent variable.

[6]Least-squares regressions with lagged dependent variables produce consistent estimates if the error terms are uncorrelated over time (Greene 1997). Under autocorrelation, linear models using a lagged dependent variable produce downward-biased coefficient estimates of (other) explanatory variables. Nevertheless, Keele and and Kelly (2006) find that if the model truly is dynamic, it is better to include a lagged dependent variable than to omit it—more severe biases are caused by omitting it. Standard errors may also be deflated in lagged dependent variable models with autocorrelation, although in Monte Carlo simulations, this "overconfidence" is found to be less severe for binary than for linear dependent variable models (Beck and Katz 1997). In other words, probit models are less sensitive to ignored serial correlation (ibid., p. 8). For our sample, when the models are estimated without the lagged dependent variable, the results are substantively the same as those reported here regarding R&D locations and knowledge sourcing, but the coefficient and marginal effect estimates reported here are slightly lower. However, the standard errors are almost identical in models with and without the lagged dependent variable. We are thus convinced that overconfidence (too small standard errors) is not driving our results. However, the coefficient and marginal effect estimates presented here may be viewed as a lower bound for the economic importance of our key explanatory variables.

[7]The survey defines a product innovation as either a technologically new product or a technologically significant product improvement. A technologically new product is one whose purpose or technological characteristics are clearly distinct from those of the existing products of the firm. The new product can be based on a new technology, a new application of existing technologies, or application of new knowledge. A technologically significant product improvement significantly improves on the characteristics or performance of an existing product of the firm, and it may include improvements in components, materials, or subsystems. The survey defines a process innovation as one that is technologically new or that contains a fundamentally improved method of production or product distribution. A process innovation may include (but is not limited to) improvements based on changes in equipment, instruments, organization of production, or new knowledge.

[8]NACE (Nomenclature Actuariel dans la Communauté Européenne) is the European standardized industry classification system that is similar to the North American Standard Industrial Classification (SIC) system. The data make it difficult to utilize a more fine-grained classification of industry affiliation, which would result in some industries with just one or a few firms. Further disaggregation of the industries also has no effect on the reported reports (details are available on request).

[9]Marginal effects are reported at the mean values of the right-hand side variables. Per Greene (1997, p. 963), in the tobit regressions, the marginal effects reported in the tables reflect an adjustment to the coefficient estimates that account for the effects of the explanatory variables on the censored observations. For a dummy right-hand-side variable in a probit regression, the marginal effect shown in the tables represents the change in the probability that the binary dependent variable has a value of 1 when the dummy variable switches from 0 to 1 (Greene 1997). For a dummy right-hand-side variable in regressions where the dependent variable is in natural logarithmic form, as in the tobit regressions here, we are interested in the marginal effect of the dummy variable on the underlying value of the dependent variable in nonlog form. This marginal effect is calculated by computing the exponentiated (exp) value of the marginal effect that is reported in the table for the dummy variable. This calculation also applies to nondummy right-hand-side variables that are not in log form. In addition, in the tobit regressions, when both the dependent and right-hand-side variables are in logarithmic form, each marginal effect reported in the table represents an elasticity. This means that a marginal effect of 0.3 in the table indicates that a 1% increase in the nonlog value of the right-hand-side variable has a marginal effect of 0.3% on the nonlog value of the dependent variable. In the probit regressions, when a right-hand-side variable is in logarithmic form, a transformation of the marginal effect in the tables is required to obtain the marginal effect of the underlying variable in nonlog form. The marginal effect of a 1% increase in the nonlog value of the variable is calculated by multiplying the marginal effect in the tables by the natural logarithm of 1.01. (See UCLA Academic Technology Services 2009 for a very clear discussion of the foregoing mathematical calculations.)

[10]In one of the models, the coefficient on three R&D locations is negative and significant, and is negative and insignificant in the other models in Tables 4 and 5. The negative coefficients may reflect some degree of multicollinearity. Additionally, the coefficients may reflect a disequilibrium phenomenon, because reducing the number of R&D locations may involve lumpy divestment decisions. If firms do not adjust the number of R&D locations unless they are convinced that this makes sense in the long run, they may temporarily experience negative returns from too large a number of R&D locations.

[11]Because our data do not contain information on knowledge sourcing in the prior period, we could not utilize a lagged dependent variable. Instead, we included two alternative lagged innovation measures in the models, which control for aspects of prior knowledge sourcing that are related to lagged innovation outcomes, including firm innovation capability.

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