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# Localized Knowledge Spillovers and Organizational Capabilities: Evidence from the Canadian Manufacturing Sector

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## Abstract

***Purpose*** – This study empirically investigates how the effects of localized knowledge spillovers on technology adoption are conditional on the organizational capabilities of potential adopters.

***Design/methodology*** – The empirical model utilized in this study examines how the presence of prior adopters of advanced manufacturing technologies affects a plant's technology adoption decision differently based on its organizational capabilities, measured by plant size and plant status (single-plant firm vs. multi-plant firm). Moreover, this study investigates how the scope of knowledge spillovers from prior adopters, both in terms of geographical and functional proximities, differ for plants with different organizational capabilities.

***Findings*** – The main findings of this study are as follows: 1. Although plants with lower organizational capabilities are less likely to adopt advanced technologies, such plants receive greater marginal benefits from knowledge spillovers from prior adopters in their region. 2. Plants with greater organizational capabilities can benefit from knowledge spillovers from a wider set of prior adopters. In other words, while plants with lower organizational capabilities tend to benefit from knowledge spillovers from "similar" and "local" adopters, plants with greater organizational capabilities can also benefit from knowledge spillovers from "not-too-similar" or are geographically distant prior adopters.

***Originality/value*** – While existing studies mainly focus on the effects of the various kinds of regional agglomeration, few studies investigate localized knowledge spillovers in technology adoption. Moreover, no prior studies have explored how the effects of knowledge spillovers on technology adoption depend on a plant's organizational capabilities and how the scope of knowledge spillovers differs for plants with different organizational capabilities. This study is the first to empirically investigate this topic.

**Keywords**: Technology adoption, Agglomeration, Organizational Capabilities, Knowledge spillovers, Micro-data
**JEL Classifications**: O3, R3

## 1. Introduction

The impacts of geographical agglomeration on knowledge spillovers and technology adoption have received significant attention in previous literature (Marshall 1920; Krugman 1991a, 1991b; Porter 1998; Fujita, Krugman, and Venables 1999). Although the effects of localized knowledge spillovers on technology adoption are considered to be important in most discussions about agglomeration, related literature on this topic is scarce. Due to the untraceable nature of knowledge spillovers, few studies empirically trace localized, learning-based knowledge spillovers (Case 1992; Jaffe, Trajtenberg, and Henderson 1993; Powell and Brantley 1992; von Hippel 1988; No 2005). Some attempt to trace knowledge spillovers using

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patent citations (Jaffe, Trajtenberg, and Henderson 1993), while others examine the effects of location characteristics on the adoption of some specific technologies (Harrison, Kelley, and Gant 1996; Kelley and Helper 1997). In most empirical studies on knowledge spillovers, the concept is either measured using patent citations or indirectly inferred. In one exception (No 2005), the localized knowledge spillovers are separately identified and estimated by analyzing the effects of the presence of prior technology adopters on potential adopters' technology adoption decisions. No (2005) finds that there are positive localized knowledge spillovers from prior adopters to potential adopters that are bounded functionally and geographically.

Regarding how organizational characteristics are related to technology adoption, there is extensive research on the effects of organizational characteristics on technology adoption (Clohessy and Acton 2019; Salaheldin 2007; Hameed, Counsell, and Swift 2012; No 2005; Laik and Guynes 1997). According to most studies in this research area, organization size, among others factors, is positively related to technology adoption. Large plants or those that are subsidiaries of multi-plant firms have a higher propensity to adopt technologies (No 2005). Empirical findings in this previous literature are consistent with the theory that organizational capabilities and resources are among the most critical factors influencing technology adoption. Empirical findings of previous research on the effects of organizational characteristics on technology adoption are consistent and clear without much controversy.

Although (1) the types of organizations that are more likely to adopt technologies and (2) the channel of knowledge spillovers from prior adopters to potential adopters are well understood, little is known about how knowledge spillovers from prior adopters are conditional on the organizational capabilities of potential adopters. The investigation of whether the effects of knowledge spillovers are similar for plants of all kinds or differ for different types of plants remains unexplored. For example, while it is well-founded that large firms are more likely to adopt technologies, it is unknown whether they benefit more from localized knowledge spillovers than do smaller firms. Therefore, this study attempts to fill this gap in the literature by investigating whether the effects of the knowledge spillovers from prior adopters to potential adopters are independent of potential adopters' organizational capabilities. Furthermore, if this is not the case, then how do these effects differ for different types of plants.

This paper presents an empirical analysis of how the effects of the localized knowledge spillovers of prior adopters on potential adopters' decisions are dependent on the internal resources and capabilities of potential adopters. This study identifies knowledge spillovers from prior adopters to potential adopters using the dataset on the adoption of 22 advanced manufacturing technologies by Canadian plants, utilizing the same framework used by No (2005). The objectives of this paper are two-fold: First, it aims to estimate how the marginal effects of knowledge spillovers from prior adopters depend on the organizational capabilities of potential adopters. Second, it aims to investigate how the geographical- and functional scope of knowledge spillovers from prior adopters differ for potential adopters with different organizational capabilities. This study explores the organizational capabilities of a plant along two dimensions: plant size (measured by number of employees in a plant) and plant status (single-plant firm vs. multi-plant firm). Since plant size is closely related with various organizational capabilities, such as financial constraints and know-how, and plant status is closely related to better access to information and resources through the intra-firm network, both plant size and plant status are appropriate measures of organizational capabilities.

This study's main findings are as follows. First, although plants with low organizational capabilities (measured by plant size and plant status) are less likely to adopt advanced technologies, such plants tend to receive greater marginal benefits from knowledge spillovers from prior adopters located in the same geographical region than plants with greater organizational capabilities. Second, plants with greater organizational capabilities can benefit from wider sources of knowledge spillovers from prior adopters. In other words, while plants with lower organizational capabilities tend to benefit from knowledge spillovers from prior adopters that are "*similar*" and "*local*," plants with greater organizational capabilities can also benefit from knowledge spillovers from prior adopters that are "*not-too-similar*" or are geographically distant. This study's main findings suggest that regional agglomeration and local economic environments are more important for plants with lower organizational capabilities than for plants with greater organizational capabilities. These findings make an important contribution to the nearly non-existent literature on the relationship between organizational capabilities and the effects of knowledge spillovers on technology adoption.

The rest of this paper is organized as follows. Section 2 presents the background and conceptual framework of this study. Section 3 explains the data and the estimation method, while Section 4 presents the results. Finally, Section 5 discusses the conclusions of this study.

## 2. Background and Conceptual Framework

There has been an increasing emphasis on the role of the agglomeration of economic activities in previous literature (Ellison and Glaeser 1997; Fujita, Krugman, and Venables 1999; Feldman and Audretsch 1999). The high concentrations of economic activities are believed to be driven by the advantages offered by regional agglomeration economies. Knowledge spillovers, specialized skilled labor, and input sharing are the three most widely acknowledged advantages of regional agglomeration (Marshall 1920). While the effects of specialized skilled labor or input sharing can be relatively easily measured with accuracy, estimating the effects of knowledge spillovers has resisted econometric scrutiny mainly because of its unobservable nature in most cases.

While implementing new technologies, plants face various uncertainties associated with issues such as the costs and benefits of technologies, adaptation difficulties, employee training. More information on these would thus reduce uncertainties associated with adopting new technologies and enable plants to assess the risks and expectations better. However, because certain information associated with technology implementations is tacit (e.g., detailed engineering characteristics or particular organizational changes to fully exploit technology capabilities), learning this type of knowledge will depend on the direct observation of early adopters, demonstrations, word-of-mouth, and other informal mechanisms. The easier the access to explicit knowledge, the more critical the role of tacit knowledge in sustaining and enhancing the firm's competitive position (Maskell and Malmberg 1999). Therefore, the local presence of prior adopters can facilitate inter-plant knowledge spillovers in a region (No 2005; Case 1992; Jaffe, Trajtenberg, and Henderson 1993; Powell and Brantley 1992; von Hippel 1988).

### 2.1. Effects of Technology Spillovers Conditional on Organizational Capabilities

While plants of any type can benefit from the localized knowledge spillovers of prior technology adopters, the marginal benefit obtained from localized knowledge spillovers may differ for different kinds of plants. On the one hand, plants with limited organizational capabilities would have less internal resources and access to information or knowledge. Hence, they would rely more to the local economic environment for information and knowledge. On the other hand, plants with greater internal resources can access a greater pool of knowledge and resources that are unavailable to plants with lesser internal resources. Moreover, they have better access to resources that are not available locally. In this case, the local environment of a plant plays a greater role for plants with low organizational capabilities. Therefore, the marginal effect of localized knowledge spillovers is expected to be greater for plants with low organizational capabilities.

***Hypothesis 1a****: The effects of knowledge spillovers from prior adopters are greater for plants with limited internal resources.*

Additionally, plants that are part of a multi-plant firm tend to be constrained and influenced by their corporation regarding their decision-making processes. Moreover, when it comes to obtaining information, their interactions may heavily involve their own corporations rather than their local neighbors. Furthermore, plants that are part of a multi-plant firm have easier access to information and knowledge that are not locally available via intra-firm communications. In contrast, single-plant firms lack the diverse information channels available to multi-plant firms; as such, their interactions with their local neighbors play a greater role in single-plant firms' decision-making.

***Hypothesis 1b****: The effects of knowledge spillovers from prior adopters are greater for single-plant firms than for plants belonging to multi-plant firms.*

## 2.2. Functional Scope of Localized Knowledge Spillovers Conditional on Organizational Characteristics

Additional findings from No's (2005) study reveals that the spillover effects from prior adopters to potential adopters exhibit a clear decaying pattern as the similarities in terms of input usage between these two groups decrease. Thus, technology spillovers from prior technology adopters are bounded by functional similarities, and the mere geographical proximity of prior adopters of the same technology does not guarantee the provision of technology spillovers. This study aims to investigate whether this functional scope of technology spillovers, identified in No (2005), differs for plants with different organizational capabilities. If plants with greater organizational capabilities possess a greater absorptive capacity that enables them to extract meaningful information or knowledge from *not-so-similar* prior adopters, then these plants would have a broader functional scope of knowledge spillovers. Thus, the following hypothesis is proposed.

***Hypothesis 2****: Plants with a greater absorptive capacity can benefit from knowledge spillovers originating from a wider set of prior adopters, including those that are "not-so-similar," whereas plants with a lower absorptive capacity can only benefit from knowledge spillovers originating from a narrower set of prior adopters that are like them.*

### 2.3. Geographical Scope of Knowledge Spillovers Conditional on Organizational Capabilities

When discussing the effects of localized knowledge spillovers, it is pertinent to investigate the geographical extent to which spillover effects originate from prior adopter of the technology. In the case of the adoption of advanced manufacturing technologies by plants, No (2005) found that the spillover effects of prior technology adopters are strongest with geographical proximity and decrease with distance. This indicates that the localization of knowledge spillovers from prior adopters of technologies is dependent on geographical proximity and decays with distance.

If plants with greater organizational capabilities indeed have access to a wider range of information channels that enable them to access knowledge and information that are not necessarily local, then geographical proximity to the sources of knowledge is less important for such plants. In contrast, plants with limited internal resources and capabilities lack the ability to obtain information from distant knowledge sources, and consequently, they rely more on sources that are geographically closer. Plants with greater organizational capabilities can benefit from knowledge spillovers originating from geographically distant adopters. In contrast, plants with limited organizational capabilities can solely benefit from knowledge spillovers that originate from geographically nearby adopters and not geographically distant adopters.

However, studies on how the geographical scope of knowledge spillovers varies for plants with different organizational capabilities are non-existent. Therefore, this study posits the following hypothesis.

***Hypothesis 3***: *Plants with greater organizational capabilities can benefit from knowledge spillovers from more geographically distant prior adopters, whereas plants with lesser organizational capabilities can only benefit from knowledge spillovers from prior adopters that are geographically closer.*

## 3. Data and Estimation Method

### 3.1. Data Sources

The data used in this study come from numerous sources. The main data source is the *1993 Survey of Innovation and Advanced Technology* (SIAT), which is a unique, confidential, and proprietary dataset that surveys approximately 2,500 plants covering the entire manufacturing sector across Canada. This database contains information on the adoption of 22 advanced manufacturing technologies at the plant level. These advanced technologies are categorized into six different technology groups, as listed in Table 1. These technologies are "general-purpose technologies" in that they are not specific to any particular industry but can be used in the production process of any industry.[1] A panel dataset comprising three periods, namely 1984–1986, 1987–1989, and 1990–1992, is constructed using information on the time of adoption of each of the 22 technologies at the plant level.[2]

[1] The concept of general-purpose technology (GPT) used here is not as broad as the one used by Bresnahan and Trajtenberg (1995).

[2] For more detailed construction of a panel dataset, see No (2005).

**Table 1.** List of Advanced Manufacturing Technologies and Incidence of Technology Use by Plants

| Name of Advanced Manufacturing Technologies | 1993 | 1984 |
|---|---|---|
| ***Design and Engineering*** | | |
| Computer aided design (CAD) and/or computer aided engineering (CAE) | 27.1 | 1.3 |
| CAD output used to control manufacturing machines (CAD/CAM) | 12.9 | 0.6 |
| Digital representation of CAD output used in procurement activities | 6.0 | 0.2 |
| ***Fabrication and Assembly*** | | |
| Flexible manufacturing cell (FMC) or systems (FMS) | 6.8 | 0.2 |
| Numerically controlled and computer numerically controlled (NC/CNC) machines | 15.0 | 2.8 |
| Materials working laser | 2.4 | 0.0 |
| Pick and place robots | 3.5 | 0.3 |
| Other robots | 3.0 | 0.0 |
| ***Automated Material Handling*** | | |
| Automated storage and retrieval Systems (AS/RS) | 3.0 | 0.2 |
| Automated guided vehicle systems (AGVS) | 1.1 | 0.0 |
| ***Inspection and Communications*** | | |
| Automated sensor-based equipment used for inspection/testing of incoming or in-process materials | 6.1 | 1.0 |
| Automated sensor-based equipment used for inspection/testing of final products | 6.8 | 1.4 |
| Local area network for technical data | 10.5 | 0.4 |
| Local area network for factory use | 8.1 | 1.0 |
| Inter-company computer network linking plant to subcontractors, suppliers, and/or customers | 7.5 | 0.1 |
| Programmable controller | 17.1 | 1.9 |
| Computer used for control on the factory floor | 15.6 | 1.5 |
| ***Manufacturing Information Systems*** | | |
| Materials requirement planning (MRP) | 15.7 | 1.3 |
| Manufacturing resource planning (MRP II) | 8.5 | 0.2 |
| ***Integration and Control*** | | |
| Computer integrated manufacturing (CIM) | 6.1 | 0.5 |
| Supervisory control and data acquisition (SCADA) | 7.5 | 1.0 |
| Artificial intelligence and/or expert systems | 1.5 | 0.0 |

This dataset is the same dataset used in No (2005). The advantage of using this dataset lies in the rich set of information it contains regarding technology adopters. With the information on the time of adoption for 22 advanced manufacturing technologies for the entire manufacturing sector across Canada at the plant level, this dataset allows the separate identification of knowledge spillovers from prior adopters to potential adopters. Using this dataset to examine the effects of organizational capabilities on knowledge spillovers is imperative, given the exceedingly rare occurrence of datasets that enable such distinct identification of knowledge spillovers. Furthermore, using the same dataset is vital for conducting a comparable analysis to the previous findings on the impact of knowledge spillovers on technology adoption. This ensures that the results obtained in this study are not driven by factors such as differences in technology, country, time, and industries; rather, they reflect how the effects of knowledge spillovers are conditional on the organizational capabilities of potential adopters.

Additional information on plant characteristics, such as geographical location, employment, output, country of ownership, plant age, and multi-plant status, are obtained from the *Annual Survey of Manufactures* (ASM), a longitudinal database of Canadian manufacturing plants, including almost all of 35,000 to 40,000 manufacturing plants, for each year.[3] A total of 1,902 plants out of the 2,500 plants surveyed in the SIAT are also surveyed in the ASM.

The characteristics of regional economies, such as local manufacturing activities, regional demography, and regional forward and backward linkages, are measured utilizing information obtained from the ASM, the Census of Population as well as the National Input-Output Tables. The National Input-Output Tables are used at the most detailed level available, *w*, which consists of 145 3- and 4-digit manufacturing SIC codes for the period 1983–1992. These tables record the values of the intermediate inputs and outputs that each industry buys and sells, respectively, to other industries. The calculation of forward and backward linkages is performed using this data.

This study employs "economic regions" and "census divisions" as geographic units. An economic region is a statistically categorized region, which comprises one or more census divisions but is confined within a province or a territory.[4]

**Table 2.** Variable Names and Definitions

| ***Variable Name*** | ***Definition*** |
|---|---|
| ***Potential Channels of Agglomeration Externalities*** | |
| *A. Technology Spillovers* | |
| Prior adopters in similar industries | No. of plants in similar industries in region $r$ that use tech $\tau$ |
| Prior adopters in moderately similar industries | No. of plants in moderately similar industries in region $r$ that use tech $\tau$ |
| Prior adopters in different industries | No. of plants in different industries in region $r$ that use tech $\tau$ |
| *B. Employment Effects* | |
| Regional employment | No. of employees in region $r$ |
| Emp in similar industries | No. of employees in similar industries in region $r$ |
| Emp in moderately similar industries | No. of employees in moderately similar industries in region $r$ |
| Emp in different industries | No. of employees in different industries in region $r$ |
| *C. Other Agglomeration Effects* | |
| INPUT | Output of upstream suppliers in industry $i$ in region $r$ |
| OUTPUT | Output of downstream consumers in industry $i$ in region $r$ |

[3] Plant information in ASM includes geographical location, employment, output, country of ownership, plant age and multi-plant status.

[4] There are ten provinces and two territories in Canada, with each province and territory divided into several economic regions. There are a total of 68 economic regions, and each economic region is divided into one or more census divisions. There were 290 census divisions across provinces and territories in 1991.

| *Variable Name* | *Definition* |
|---|---|
| ENGINEER | Share of scientists and engineers among the population in region $r$ |
| LOCALIZATION INDEX | Share of industry $i$'s employment over national employment |
| DIVERSIFICATION INDEX | Weighted share of 4-digit SIC industries in region $r$ |
| *D. Other Controls* | |
| AVG_IND_REGION | Mean adoption rate of overall technologies by industry $i$ in region $r$ |
| AVG_IND_TECH | Mean adoption rate of technology $\tau$ in industry $i$ across regions |
| ***Organizational Characteristics*** | |
| SIZE | Total no. of employees of plant |
| COMMODITY | No. of different commodities produced by a plant |
| DIVERSITY | No. of 4-digit SIC industries in which a plant operates |
| SMALL | Dummy variable for small plants (emp<20) |
| FOREIGN | Dummy variable for foreign-owned plants |
| SINGLE | Dummy variable for single-plant firms |

## 3.2. Estimation Method

In identifying the effects of knowledge spillovers from prior adopters to potential adopters, this study employs the identification method developed by No (2005) which estimates the impact of the local presence of technology adopters on other plants' probability of technology adoption. Moreover, to measure the extent of the knowledge spillovers from prior adopters to potential adopters based on the "relatedness" between their respective industries, this study also utilizes the method used in No (2005), where the similarities in input purchases measure the "relatedness" across industries. Based on information on the patterns of input purchases obtained from the National Input-Output Tables for 145 3- and 4-digit SIC industries, each industry pair, $i$ and $j$, is categorized into one of three groups: Similar industries, Moderately similar industries, and Different industries.

For each technology $\tau$, $T_{\tau iRt}$ represents the number of plants in industry $i$ within region $R$ that have adopted technology $\tau$ as of period $t$.

$$T_{\tau iRt} = \sum_{p \in i,R} (w_p * I^{\tau}_{p\tau iRt})$$

where

$$I^{\tau}_{p\tau iRt} = \begin{Bmatrix} 1 \text{ if plant } p \text{ in industry } i \text{ in region } R \text{ already adopted technology } \tau \text{ prior to time } t \\ 0 \text{ otherwise} \end{Bmatrix}$$

$w$ is the plant weight that is provided in the survey to ensure the sample is representative of the population. The number of technology adopters is calculated at the level of the economic region, denoted as $R$, to have enough observations in each cell to ensure they are representative of the population.

The number of plants in similar industries within the same economic region that have adopted technology $\tau$ as of time t is calculated as,

$$PriorAdopter\_Similar_{\tau iRt} = \ln \sum_{j \in F} T_{\tau jRt}$$

where $i$ and $j$ indexes industry, and $S$ represents a group of industries that are categorized as similar industries for each industry $i$. The number of plants in the *moderately similar* and *different* industries that have adopted technology $\tau$ by time $t$, $PriorAdopter\_Mod.Similar_{\tau irt}$ and $PriorAdopter\_Different_{\tau irt}$ are calculated likewise, respectively.

To estimate the impact of the local presence of prior adopters, the probability of a plant's technology adoption decision is given as follows:

$$\Pr(Adoption_{p\tau irt}) = f(KnoweldgeSpillover_{\tau irt}, plant\ characteristics_p, controls)$$

*where* $p$ indexes plant, $i$ indexes industry, $r$ indexes region, $\tau$ indexes technology, and $t$ indexes time. $Adoption_{p\tau irt}$ is a binary variable indicating whether plant $p$ in the industry $i$ in region $r$ adopts technology $\tau$ at time $t$.

The dependent variable is given as follows:

$$ADOPTION_{p\tau irt} = \begin{Bmatrix} 1 \text{ if plant } p \text{ in industry } i \text{ in region } r \text{ adopts technology } \tau \text{ at time } t \\ 0 \text{ otherwise} \end{Bmatrix}$$

This analysis considers three time periods: 1985–1987, 1988–1990, and 1990–1992. In each period, a plant decides whether or not to adopt technology $\tau$. For each plant-technology pair, if plant $p$ adopts technology $\tau$ in Period 1, then the adoption decision of technology $\tau$ is no longer applicable for plant $p$ for the two subsequent periods.

To examine whether small plants receive greater marginal effects from knowledge spillovers from prior adopters, *PlantSize* is interacted with knowledge spillovers from prior technology adopters in related industries. The coefficient of the interaction term captures how plant size marginally affects the probability of a plant's technology adoption after separately controlling for the effects of knowledge spillovers from prior adopters and the effects of plant size.

$$\begin{aligned}\Pr(ADOPTION_{p\tau irt}) = F(&\alpha_0 + \beta_1 PlantSize_{pir,t-1} + \beta_2 OtherPlantCharacteristics_{pir,t-1} \\ &+ \beta_3 TechAdopters_{\tau ir,t-1} + \beta_4 PlantSize_{pir,t-1} * TechAdopters_{\tau ir,t-1} \\ &+ \beta_5 RegionalEmployment_{r,t-1} + \beta_6 PlantSize_{pir,t-1} * RegionalEmployment_{r,t-1} \\ &+ \beta_7 ENGINEER_{r,t-1} + \beta_8 INPUT_{ir,t-1} + \beta_9 OUTPUT_{ir,t-1} \\ &+ \beta_{10} AVG\_IND\_REGION_{ir} + \beta_{11} AVG\_IND\_TECH_{i\tau} \\ &+ \delta_r + \gamma_i + \varphi_\tau + \lambda_t + \varepsilon_{p\tau irt})\end{aligned}$$

Similarly, to determine whether single-plant firms with limited access to information networks derive greater marginal benefits from knowledge spillovers from prior technology adopters, *Single*, a dummy variable for single-plant firms, is interacted with knowledge spillovers from prior technology adopters in related industries. The coefficient of the interaction term captures the extent to which single plants benefit more from the spillover effects of prior adopters compared with plants belonging to multi-plant firms after separately controlling for the effects of plant status and knowledge spillovers.

$$
\begin{aligned}
\Pr(ADOPTION_{p\tau irt}) = F(\alpha_0 &+ \beta_1 Single_{pir,t-1} + \beta_2 OtherPlantCharacteristics_{pir,t-1} \\
&+ \beta_3 TechAdopters_{\tau ir,t-1} + \beta_4 Single_{pir,t-1} * TechAdopters_{\tau ir,t-1} \\
&+ \beta_5 RegionalEmployment_{r,t-1} + \beta_6 Single_{pir,t-1} * RegionalEmployment_{r,t-1} \\
&+ \beta_7 ENGINEER_{r,t-1} + \beta_8 INPUT_{ir,t-1} + \beta_9 OUTPUT_{ir,t-1} \\
&+ \beta_{10} AVG\_IND\_REGION_{ir} + \beta_{11} AVG\_IND\_TECH_{i\tau} \\
&+ \delta_r + \gamma_i + \varphi_\tau + \lambda_t + \varepsilon_{p\tau irt})
\end{aligned}
$$

Furthermore, to investigate Hypothesis 2 (i.e., whether plants with a greater absorptive capacity benefit from knowledge spillovers that originate from a wider range of prior adopters, including those that are *"not-so-similar,"* whereas plants with less absorptive capacity benefit from knowledge spillovers originating from a narrower set of prior adopters that are similar to them), the full sample is divided into two groups. First, the sample is divided based on employment size, small plants with less than 100 employees as opposed to large plants with more than 100 employees. For each group, the effects of knowledge spillovers from prior adopters with varying degrees of similarities are estimated separately. Second, the sample is divided based on plant status, single-plant firms versus multi-plant firms, and the effects of knowledge spillovers from prior adopters with varying degrees of similarities are estimated separately.

Finally, to investigate whether the geographical scope of knowledge spillovers from prior adopters is dependent on organizational capabilities, prior adopters in related industries are categorized into three geographical proximities: located within 300 km, between 300 km to 1000 km, and beyond 1000 km. The effects of the knowledge spillovers from prior adopters in different geographical proximities are estimated separately for the two groups based on plant size: small plants with less than 100 employees and large plants with more than 100 employees.

$$
\begin{aligned}
\Pr(ADOPTION^{Small}_{p\tau irt}) = F(\alpha_0 &+ \beta_1 Tech\_S\_300km_{\tau ir,t-1} + \beta_2 Tech\_S\_1000km_{\tau ir,t-1} \\
&+ \beta_3 Tech\_S\_over1000km_{\tau ir,t-1} + \beta_5 RegionalEmployment_{r,t-1} \\
&+ \beta_7 ENGINEER_{r,t-1} + \beta_8 INPUT_{ir,t-1} + \beta_9 OUTPUT_{ir,t-1} \\
&+ \beta_{10} AVG\_IND\_REGION_{ir} + \beta_{11} AVG\_IND\_TECH_{i\tau} \\
&+ \delta_r + \gamma_i + \varphi_\tau + \lambda_t + \varepsilon_{p\tau irt})
\end{aligned}
$$

The above equation is estimated separately for larger plants. Similar analyses are conducted separately for plants belonging to single-plant firms and those belonging to multi-plant firms.

# 4. Results and Policy Implications

## 4.1. Effects of Knowledge Spillovers Conditional on Organizational Capabilities

This section presents the results on how the effects of knowledge spillovers from prior adopters differ for plants with different organizational capabilities. Table 3 presents the influence of various plant characteristics on the probability of technology adoption. The results reveal that the coefficient on *SIZE* (a plant's total employment) is 0.056, which is positive and statistically significant, whereas the coefficient on *SMALL* (the dummy variable for plants with less than 100 employees) is -0.04, which is negative and statistically significant. This implies that the likelihood of a plant to adopt technologies increases with its size. Also, even after controlling for employment size, the probability of technology adoption is lower for small plants with less than 100 employees, as indicated by the negative coefficient on the dummy variable. Furthermore, the coefficient on *SINGLE* (the dummy variable for single-plant firms) is -0.18, negative and significant. This indicates that plants belonging to single-plant firms are less likely to adopt technologies than plants belonging to multi-plant firms. This negative effect for plants belonging to single-plant firms cannot be attributed to their small size because the effect of size is controlled in the equation. This indicates that, aside from the size effect, single plants lack something regarding technology adoption (or multi-plant firms have some features, other than plant size, that make them more likely to adopt technology). According to the results concerning plant size and plant status, plants with greater organizational capabilities along either dimension (i.e., plant size or status) are more likely to adopt technologies.

**Table 3.** Plant Characteristics

Dependent Variable: $ADOPTION_{p\tau irt}$

| Variable Name | Coefficient |
|---|---|
| SIZE | .557* |
| (total employment) | (.0076) |
| AGE | -.0752* |
| | (.009) |
| SEGMENT | .100* |
| (# of the SIC-4 industry in which a plant operates) | (.0085) |
| COMMODITY | -.115* |
| (# of commodity a plant produces) | (.0091) |
| SMALL (=1) | -.0407* |
| | (.020) |
| FOREIGN (=1) | .0860* |
| | (.015) |
| SINGLE (=1) | -.182* |
| | (.016) |
| Observations | 106,188 |
| Log Likelihood | 67,936 |

**Notes:**

1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Also included are plant characteristics, other agglomeration effects, control variables, and fixed effects.

Column (1) in Table 4 presents the benchmark results for the spillover effects from local prior adopters in various groups when groups are categorized based on the similarities in input usage as estimated in No (2005). The coefficients of the prior adopters in *Similar* and *Moderately similar* industries are positive and statistically significant, indicating that there exist positive spillover effects from prior adopters. Recognizing that plants with greater organizational capabilities are more likely to adopt technologies and that the effects of the spillovers from local prior adopters are positive, as shown in Table 3 and Column (1) in Table 4, the key question this study aims to answer whether these effects of knowledge spillovers from prior adopters are contingent on the organizational capabilities of potential adopters. In particular, do small plants benefit more from knowledge spillovers than large plants do? If this is the case, then it is more critical for small plants to be in regions that facilitate inter-plant learning. To answer this question, the variable of interest is the interaction term between plant size and prior adopters.

**Table 4.** Effects of Knowledge Spillovers conditional on Plant Size

Dependent Variable: $ADOPTION_{p\tau irt}$

| **Variable Name** | **(1)** Coeff. | **(2)** Coeff. | **(3)** Coeff. | **(4)** Coeff. | **(5)** Coeff. |
|---|---|---|---|---|---|
| **<u>Interaction Terms</u>** | | | | | |
| Small* Prior Adopters in related ind | | .0177* | | | .012* |
| | | (.0036) | | | (.0038) |
| Size*Prior Adopters in related ind | | | -.0051* | | |
| | | | (.0013) | | |
| Size*Any Prior Adopters in the region | | | | -.0152* | |
| | | | | (.0015) | |
| Small*Regional Emp | | | | | .010* |
| | | | | | (.0020) |
| ***<u>Tech Spillovers</u>*** | | | | | |
| (Prior Adopters in Similar ind)$_{\tau iR,t-1}$ | .0355* | .0280* | | . | .0297* |
| | (.0030) | (.0032) | | | (.0032) |
| (Prior Adopters in Moderately similar ind)$_{\tau iR,t-1}$ | .0249* | .0194* | | . | .0211* |
| | (.0030) | (.0031) | | | (.0032) |
| (Prior Adopters in Different ind)$_{\tau iR,t-1}$ | -.0182* | -.0169* | | | -.0171* |
| | (.0042) | (.0043) | | | (.0043) |
| Technology users in region | | | | .0072* | |
| | | | | (.0083) | |
| Technology users in related industries | | | .0749* | | |
| | | | (.0065) | | |
| Observations | 105,902 | 105,902 | 105,902 | 105,902 | 105,902 |
| Log Likelihood | 67,937 | 67,962 | 68,025 | 67,816 | 67,988 |

**Notes:**
1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects, control variables, and fixed effects.

Columns (2)–(6) in Table 4 present the results on the interaction terms between plant size and technology spillovers. *SIZE*, a plant's total number of employees, and *SMALL*, a dummy variable for small plants with less than 100 employees, are used to measure the size effects. *SIZE* and *SMALL* are interacted with prior adopters in related industries in the region. The coefficient of the interaction term between *SMALL* and prior adopters, as shown in Column (2) of Table 4, is 0.018, which is positive and statistically significant. This indicates that small plants with less than 100 employees receive greater benefits from prior adopters in the region. The coefficient of the interaction term of *SIZE* × *Prior Adopters*, as shown in Column (3) of Table 4, is -0.005. This negative and significant result implies that the greater the size of a plant, the smaller the spillover effects from an increase in the number of prior adopters in related industries. Columns (4) and (5) display comparable results even after altering the specification to include prior adopters in the region regardless of their industries or regional employment. These results support the hypothesis that small plants receive greater benefits from the presence of local prior adopters of technology than do larger plants. With respect to knowledge spillovers, this study identifies size-related differences that the benefit of knowledge spillovers from prior adopters is conditional on the plant size of potential adopters.

**Table 5.** Marginal Effects of Knowledge Spillovers conditional on Plant Status

Dependent Variable: $ADOPTION_{p\tau irt}$

| Variable Name | (1) Coeff. | (2) Coeff. | (3) Coeff. | (4) Coeff. | (5) Coeff. |
|---|---|---|---|---|---|
| ***Interaction Terms*** | | | | | |
| Single* Prior Adopters in related ind | | .0214* (.0038) | | | .0161* (.0040) |
| Single* Prior Adopters in region | | | .0090* (.0044) | | |
| Single*Regional Emp | | | | .0500* (.0081) | .0405* (.0084) |
| ***Technology Spillovers*** | | | | | |
| (Prior Adopters in Similar ind)$_{\tau iR,t-1}$ | .0355* (.0030) | .0254* (.0033) | .0329* (.0030) | .0332* (.0030) | .0270* (.0033) |
| (Prior Adopters in Moderately similar ind)$_{\tau iR,t-1}$ | .0249* (.0030) | .0167* (.0033) | .0241* (.0030) | .0245* (.0030) | .0185* (.0033) |
| (Prior Adopters in Different ind)$_{\tau iR,t-1}$ | -.0182* (.0042) | -.0173* (.0043) | -.0215* (.0048) | -.0172* (.0043) | -.0173* (.0043) |
| Observations | 105,902 | 105,902 | 105,902 | 105,902 | 105,902 |
| Log Likelihood | 67,937 | 67,970 | 67,942 | 67,976 | 67,993 |

**Notes:**

1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects, control variables, and fixed effects.

Similarly, this study further investigates whether there are plant-status-related differences with respect to knowledge spillovers. To examine whether single-plant firms benefit more from the experience of prior adopters in the region, the dummy variable for single-plant firms, *SINGLE*, is interacted with prior technology adopters. The results are presented in Table 5. The coefficient of the interaction term between *SINGLE* and *Prior Adopters*, as shown in Column (2), is 0.021, which is positive and significant. This result supports Hypothesis 2b, which states that plants belonging to single-plant firms benefit more than those belonging to multi-plant firms from knowledge spillovers from local prior adopters. This finding is consistent with the claim that because multi-plant firms have greater information networks through their internal firm resources and can extract information that is not necessarily local, the marginal benefit of a local knowledge source is greater for single plants that lack such organizational capabilities. A similar result was obtained in Columns (3)– (5) when the specification was altered in various ways, such as local prior adopters of any industries or local employment. The results presented in Tables 4 and 5 suggest that plants with limited resources and information networks, as proxied by plant size and plant status, benefit more from the localized knowledge spillovers of prior adopters than plants with greater resources and information networks. Therefore, the spillover effects from prior adopters to potential adopters identified in the previous work are now found to be conditional on the organizational capabilities of potential adopters. Small plants and single plants have been observed to benefit more from spillovers from local prior adopters of technologies.

### 4.2. Functional Scope of Knowledge Spillovers Conditional on Organizational Capabilities

The previous section shows that plants with limited internal resources or information networks benefit more from knowledge spillovers from local prior adopters. Now that we understand that plants benefit differently from knowledge spillovers, do plants differ in their ability to benefit from different sources of knowledge spillovers? If plants differ in their ability to receive knowledge from different sources, plants with greater absorptive capacity can benefit from knowledge that originates from adopters that are *more different* from them, which requires a higher level of adaptability. To examine how plants with different organizational capabilities benefit differently from different knowledge sources, the full sample of plants is divided into two sub-samples based on plant size, and the effects of spillovers from different types of prior adopters are estimated separately.

Table 6 presents the effects of spillovers from prior adopters with different degrees of similarities for small- and large- plants separately. Knowledge that originates from prior adopters with a high degree of similarities in input usage can be easily used without much modification and would not require high absorptive capacity on the side of potential adopters. However, knowledge that originates from prior adopters with a low degree of similarities in input usage would require a higher absorptive capacity to be modified and used by potential adopters. Column (1) in Table 6 presents a benchmark result of how plants in the full sample benefit from prior adopters with different degrees of similarities[5]. As identified in the No's (2005) research, plants benefit from prior adopters that are *Similar* and *Moderately Similar*. Columns (2) and (3) estimate the same effect for small- and large- plants separately. Column (2) shows that small plants receive spillover benefits only from similar prior adopters but not

[5] This result is estimated in No (2005).

from moderately similar prior adopters. Unlike the full sample, the spillover effects from prior adopters in moderately similar industries are not present for small plants. This suggests that small plants do not benefit from knowledge originating from prior adopters that are not remarkably similar to them. This is because they tend to lack the capacity to adapt knowledge to their specific needs. They only benefit from knowledge that is ready to pick up and use. In contrast, the results in Column (3) show that large plants receive positive spillovers from both prior adopters that are similar and moderately similar to them. Because large plants tend to have greater absorptive capacity, they can leap benefits from knowledge originating from not-very-similar adopters by applying or modifying knowledge to their specific needs. The results in Table 6 indicate that the functional scope of knowledge spillovers from prior adopters is greater for large plants than for small plants.

**Table 6.** Functional Scope of Knowledge Spillovers: Small vs. Large Plants

Dependent Variable: $ADOPTION_{p\tau irt}$

| Variable Name | Full sample | Small Plants Only | Large Plants Only |
|---|---|---|---|
| | **Coeff.** | **Coeff.** | **Coeff.** |
| ***Tech Spillovers*** | | | |
| (Prior Adopters in Similar ind)$_{\tau iR,t-1}$ | .0388* | .0301* | .0425* |
| | (.0030) | (.0039) | (.0049) |
| (Prior Adopters in Moderately similar ind)$_{\tau iR,t-1}$ | .0214* | .0048 | .0516* |
| | (.0030) | (.0039) | (.0048) |
| (Prior Adopters in Different ind)$_{\tau iR,t-1}$ | -.0187* | -.0371* | -.0022 |
| | (.0043) | (.0059) | (.0067) |
| Observations | 105,902 | 77,153 | 28,749 |
| Log Likelihood | 68,172 | 40,523 | 21,569 |

**Notes:**
1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects, control variables, and fixed effects.

Table 7 presents results on the functional scope of knowledge spillovers based on plant status. Column (2) in Table 7 shows that single-plant firms benefit from prior adopters that are similar and moderately similar. However, the effects of spillovers from similar adopters are approximately twice as large as those from moderately similar adopters. This indicates that, even though spillover effects from prior adopters come from both similar and moderately similar adopters, single plants benefit more from the knowledge that originates from similar adopters. In contrast, Column (3) in Table 7 shows that not only do multi-plant firms benefit from both similar and moderately similar prior adopters, but also the spillover effects from those two types of adopters are identical in magnitude. This implies that multi-plant firms have greater capability to use knowledge that may require higher absorptive capacity. The results in Table 7 are indicative of a greater functional scope of knowledge spillovers from prior adopters for multi-plant firms than for single plants.

Regardless of whether organizational capabilities are measured based on plant size or plant status, the results shown in Tables 6 and 7 indicate that the functional scope of knowledge spillovers is greater for plants with greater organizational capabilities. This can be interpreted that plants with less organizational capabilities interact more with similar plants; hence, their learning is greater from similar plants than from moderately similar plants. An alternative interpretation is that plants with less organizational capabilities lack adaptability in terms of learning. Knowledge from other plants is likely to contain some plant-specific know-how and must be adapted to each plant's context. Intuitively, knowledge from similar plants is more likely to be similar and adaptable without much modification. Thus, plants with less organizational capabilities that lack their adaptation capabilities would benefit more from users in similar industries than users in moderately similar industries. In contrast, large plants or plants belonging to multi-plant firms with greater internal resources and inside knowledge are more likely to benefit from knowledge spillovers from not-very-similar users.

**Table 7.** Functional Scope of Knowledge Spillovers: Single vs. Multi-plants

Dependent Variable: $ADOPTION_{p\tau irt}$

| **Variable Name** | **Full sample** | **Single-plants Only** | **Multi-plants Only** |
|---|---|---|---|
| | **Coeff.** | **Coeff.** | **Coeff.** |
| ***Tech Spillovers*** | | | |
| (Prior Adopters in Similar ind)$_{\tau iR,t-1}$ | .0388* | .0370* | .0257* |
| | (.0030) | (.0037) | (.0054) |
| (Prior Adopters in Moderately similar ind)$_{\tau iR,t-1}$ | .0214* | .0163* | .0289* |
| | (.0030) | (.0036) | (.0054) |
| (Prior Adopters in Different ind)$_{\tau iR,t-1}$ | -.0187* | -.0257* | -.0071 |
| | (.0043) | (.0056) | (.0070) |
| Observations | 105,902 | 71,527 | 34,375 |
| Log Likelihood | 68,172 | 48,217 | 20,953 |

**Notes:**

1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects, control variables, and fixed effects.

## 4.3. Geographical Scope of Knowledge Spillovers Conditional on Organizational Capabilities

The preceding section shows how differences in plants' absorptive capacities can lead to different functional scopes of the knowledge spillovers from prior adopters. Similarly, differences in plants' internal resources and information networks can cause differences in plants' ability to receive information from distant sources. Hence, this can result in different geographical scopes of knowledge spillovers based on organizational capabilities. This section presents the results on how the geographic extent of knowledge spillovers from prior adopters are conditional on potential adopters' organizational capabilities. If a plant with greater resources and extensive networks can obtain knowledge from geographically distant sources, then geographical proximity to the knowledge sources would not matter much. Conversely, if a plant with limited resources is bound to obtain knowledge locally, then the geographic proximity from the knowledge source is a critical factor for the effects of knowledge spillovers. The result of this hypothesis is presented in Table 8.

Table 8 presents the estimated effects of knowledge spillovers from prior adopters at different geographical proximities for small and large plants. Column (1) in Table 8 presents the benchmark results from No's (2005) study. This shows that spillovers from prior adopters are greatest in case of prior adopters' geographical proximity, and the effects decrease as the distance increases between prior adopters and potential adopters. The effects of knowledge spillovers from prior adopters exhibit a clear decaying pattern in geographical distance. Column 2 in Table 8 presents results for small plants. It shows that small plants receive positive and significant knowledge spillovers from prior adopters that are within a 1000 km radius. However, as shown in Column (3) in Table 8, for large plants, there is no evidence of geographical decay in the effects of knowledge spillovers from prior adopters. Large plants benefit from the spillovers from technology adopters located at a proximity of less than 300 km and more than 1000 km. Although the effects of geographically distant technology adopters are not monotonic for large plants, it indicates that large plants benefit from prior adopters that are geographically further away, and hence, their geographical scope is larger.

**Table 8.** Geographical Scope of Knowledge Spillovers: Small vs. Large Plants

Dependent Variable: $ADOPTION_{p\tau irt}$

| **Variable Name** | **Full sample** | **Small Plants Only** | **Large Plants Only** |
|---|---|---|---|
| | **Coeff.** | **Coeff.** | **Coeff.** |
| ***Tech Spillovers*** | | | |
| Similar tech user < 300 km | .0478*<br>(.0165) | .0515*<br>(.0236) | .0498*<br>(.0241) |
| Similar tech user 300<x< 1000 km | .0369*<br>(.0055) | .0590*<br>(.0070) | -.0295*<br>(.0099) |
| Similar tech user > 1000 km | .0132*<br>(.0032) | -.0186*<br>(.0043) | .0449*<br>(.0050) |
| Observations | 105,902 | 77,197 | 28,749 |
| Log Likelihood | 68,123 | 40,363 | 21,591 |

**Notes:**

1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects, control variables, and fixed effects.

Table 9 presents a similar analysis wherein the geographical scope of knowledge spillovers is compared between plants belonging to single-plant firms and those that belong to multi-plant firms. Column (2) in Table 9 shows that the effects of the spillovers of prior adopters located less than 300 km away is 0.12, whereas those of prior adopters located less than 1000 km away is 0.045, which is almost a third of the former value. Moreover, the effects of the spillovers of prior adopters situated more than 1000 km away is 0.018, which is only a tenth of the value for the less than 300km group. These results demonstrate an even more apparent geographic decaying pattern for single-plant firms. However, as evidenced by Column 3 in Table 9, the results for multi-plant firms are different. Plants belonging to multi-plant firms benefit from prior adopters located at any geographical distance. The effects of spillovers from prior adopters at different geographical proximities are all positive and statistically significant, with the effects from prior adopters at more than 1000 km being the largest. For plants belonging to multi-plant firms, there are no monotonically decreasing effects of spillovers from prior adopters based on geographical distance, as shown in the case of plants belonging to single-plant firms. The results in Table 9 suggest that geographical proximity to knowledge sources is essential for plants belonging to single-plant firms. However, it is not critical for plants belonging to multi-plant firms because they can benefit from knowledge spillovers that are not necessarily local. The results in Tables 8 and 9 imply that plants with low organizational capabilities tend to benefit from knowledge spillovers with a narrower geographic scope while plants with more organizational capabilities tend to benefit from knowledge spillovers less bounded by geographic proximity.

**Table 9.** Geographical Scope of Knowledge Spillovers: Single vs. Multi-plants

Dependent Variable: $ADOPTION_{p\tau irt}$

| **Variable Name** | **Full sample** | **Single Plants Only** | **Multi-plants Only** |
|---|---|---|---|
| | **Coeff.** | **Coeff.** | **Coeff.** |
| ***Tech Spillovers*** | | | |
| Similar tech user < 300 km | .0478*<br>(.0165) | .1189*<br>(.0177) | .0546*<br>(.0175) |
| Similar tech user 300<x< 1000 km | .0369*<br>(.0055) | .0456*<br>(.0046) | .0664*<br>(.0066) |
| Similar tech user > 1000 km | .0132*<br>(.0032) | .0181*<br>(.0073) | .1226*<br>(.00112) |
| Observations | 105,902 | 71,571 | 34,375 |
| Log Likelihood | 68,123 | 48,023 | 21,366 |

**Notes:**
1) Standard errors are in parentheses.
2) * $\chi^2$ statistically significant at $p < 0.05$
3) Related industries include both "similar" and "moderately similar" industries.
4) Also included are plant characteristics, prior adopters, other agglomeration effects,
5) control variables, and fixed effects.

### 4.4. Policy Implications

The results found in this study reveal that the effects of localized knowledge spillovers from prior adopters of technologies are dependent on the size and the status of the potential adopters. Plants that are small or belong to single-plant firms receive greater benefits from local prior adopters than do large or multi-plant firms. Furthermore, for small and single-plant firms, the effects of knowledge spillovers from prior adopters are more likely to be bounded functionally and geographically. The results indicate that localized knowledge spillovers, and hence the regional environment, are more significant for small or single-plant firms.

The actual experiences support these empirical results found here. One of the most well-known experiences that fits these empirical results is in Silicon Valley and Boston's Route 128 areas. Both regions started to boom in the 1960s and 1970s with the discovery of the integrated chip and the expansion of computer-related industries. However, by the late 1980s, it was clear that Silicon Valley continued to soar whereas Route 128 declined. According to Saxenian (1994, 1996), the different paths of the two regions are due to the regional differences. On the one hand, firms in the Silicon Valley area were small and entrepreneurial, and most firms were single-pioneering companies. There was active communication and networks among workers and firms. On the other hand, in the Route 128 area, there were few dominant companies with hierarchical industry structures. Communication or networking among firms was sporadic and limited. Saxenian claims these differences in the two regions resulted in the different paths of the two.

This study's findings are not just quantitative results from data but are firmly supported by actual experiences of the two regions, as claimed by Saxenian's theory (1994, 1996). As small or single-plant firms are more conducive to knowledge spillovers through their reliance on their neighboring firms, Silicon Valley succeeded as a cluster of high-tech industries. Route 128 area, with few large dominant companies that have a relatively closed and restrictive relationship with its related suppliers, provided a rather hindering environment for information sharing and knowledge spillovers.

Policymakers often attempt to develop industrial clusters to facilitate industrial growth and competitiveness through knowledge spillovers. The results of this paper suggest that not every type of firm equally benefits from industrial clusters, but certain types of plants are more likely to benefit from such clusters. Therefore, more careful consideration must be made in designing or promoting industrial clusters rather than merely focusing on the size of clusters.

## 5. Conclusion

This study analyzes how plants' technology adoption is facilitated differently by knowledge spillovers from prior technology adopters depending on the potential adopters' organizational capabilities. By identifying the knowledge spillover effects along the interaction of *technology* × *industry* × *region* × *time*, this study extends the previous literature in the following domains: (1) examining how the estimated effects of knowledge spillovers from prior adopters are conditional on the organizational capabilities, measured by plant size and plant status, of potential adopters, (2) how plants with different organizational capabilities benefit differently from knowledge spillovers that originate from prior adopters with varying degrees of similarities in product processes (i.e., input usage), and (3) how plants with different organizational capabilities benefit from knowledge spillovers from prior adopters with different geographical proximities. The estimations are analyzed after controlling for the effects of other various agglomeration externalities, exogenous effects, local amenities, and plant heterogeneity with extensive sets of fixed effects at region, industry, time, and technology as well as the *industry* × *region* and *industry* × *technology* levels. Hence, the possibility that the results obtained in this study are driven by spurious correlations that operate at any level is carefully eliminated.

This study finds that there are size- and status-related differences with respect to localized knowledge spillovers from prior adopters. The learning advantages obtained from the experiences of local prior adopters are greater for plants that are small or belong to single-plant firms than for plants that are large or belong to multi-plant firms. Furthermore, this study discovers that plants with lower organizational capabilities tend to benefit from prior adopters that are like them. In comparison, plants with greater organizational capabilities benefit from a wider range of prior adopters that are less similar. Similar results are found in terms of the geographical scope of knowledge spillovers. While the effect of spillovers by prior adopters is geographically bounded at specific levels for small plants or those belonging to single-plant firms, the effects of the spillovers from prior adopters are less bounded by geographical proximity for large plants or those belonging to multi-plant firms. In particular, the geographical decay of knowledge spillovers from prior adopters is prominent for single-plant firms. At the same time, there is no sign of geographical decay of knowledge spillovers from the prior adopters in the case of multi-plant firms.

The findings of this study suggest that localized knowledge spillovers are significant for plants with lesser organizational capabilities because they have limited internal resources and rely heavily on the local milieu. In contrast, because plants with greater organizational capabilities can obtain information that is not local, the local environment is less crucial for such plants. The often-claimed localization of knowledge spillovers is not independent of the internal resources of a plant, but plants' internal resources and information networks substitute some of the advantages of being in a geographical cluster. This study demonstrates that plants with less organizational capabilities are more susceptible to regional agglomeration and the economic environment where they reside, which has significant policy implications.

This is the first study to establish that there are size- and status-related differences with respect to localized knowledge spillovers from prior adopters to potential adopters on technology adoption. Consequently, further research is needed in this area. Due to the rarity of data that allows empirical examination of this topic, this paper employs data that are not the most recent. To reflect the current improvement in IT technology and the changing behavior of firm interactions and information sharing, future research that employs more recent data would be valuable.

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