Productivity Spillovers from Physical Proximity in the Manufacturing Industries of Taiwan, South Korea and Indonesia

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Abstract:

Theoretical models have long shown that spillovers from knowledge investments are of great economic importance to sustained economic growth and innovation and that these spillovers may be facilitated by physical and technological proximity. However, such localized spillovers have not been identified using data from developing countries. In this paper, we use a general measure of knowledge and a measure of geographical distance to examine the relationship between knowledge spillovers and both technological and geographical proximities using micro panel data from the Census of Manufactures in Taiwan (1986-1996), South Korea (1983-1988) and Indonesia (1990-1995).

Our results suggest that both physical and technological proximity are economically and statistically significant among manufacturing firms in all three countries. In particular, a firm's expected future TFP is positively and significantly affected by having more neighbors in the same location and industry: for any given location and industry, firms in the top half of the productivity distribution are significant sources of knowledge spillovers while firms in the bottom half are not. In addition, more productive firms are more likely to continue production while younger firms are more likely to exit.

1. Introduction

With the trend towards increasing globalization of production, knowledge spillovers have increasingly been recognized as an important source of innovation and economic growth in developing countries. The potential significance of these knowledge spillovers is apparent in the recent literature on the role of physical or spatial proximity as the mechanism of knowledge dispersion. The existence of such spatial externalities relies on direct physical observation and personal interaction whereby firms benefit not only from locating near sources of inputs and outputs, but also from the opportunity to observe and imitate one another from being located near each other.

While there is some empirical evidence to support the existence of spatial externalities in developed countries such as the U.S., the same is not true for research on this issue in developing countries.[1] This lack of evidence of local knowledge spillovers in developing countries may be related to the fact that existing studies have concentrated on specific sources of knowledge spillovers such as research and development (R&D) expenditures, FDI or more recently, export experience. For instance, studies which focus on knowledge spillovers coming from say, foreign producers might miss the possibility of spillovers generated by domestic producers. Finally, data-related problems including the paucity of firms formally involved in R&D or FDI, missing data, measurement error or the unreliability of the data are very likely contributors to this lack of spillover evidence in developing countries.

This paper builds on the basic framework developed by Winston (2002) in using a general measure of firm-level knowledge that takes the form of its total factor productivity

[1] Using R&D and patent citation in the U.S. as sources of knowledge, Adams and Jaffe (1996) and Jaffe, Trajtenberg and Henderson (1993) shows that geographical proximity facilitates the spread of knowledge. Aitken and Harrison (1999) and Clerides, Lach and Tybout (1998) do not find any role for locational spillovers from knowledge embodied in direct foreign investments (FDI) and export experience in developing countries.

(TFP). It is reasonable to assume that firms with large knowledge stocks are more likely to generate important productivity effects (that is, spillover benefits) for firms located in close proximity. Using firm-level data from the Taiwanese electronics industry, Winston finds that firms benefit from having more high-productivity neighbors in the same industry, a result that is consistent with the hypothesis that physical proximity facilitates the spread of knowledge among firms.

The empirical work in this paper is based on micro panel data from Census of Manufactures of three countries: Taiwan (1986-1996; 5-yearly data), South Korea (1991-1998; annual) and Indonesia (1990-1995; annual). Measures of knowledge stocks are constructed for each 2-digit industries in each county of the two countries. We control for endogenous firm exit and the productivity effects of location-specific characteristics. A firm's future TFP is estimated as a function of its local industry-specific knowledge. We analyze how the extent of knowledge spillover varies across different counties and different industries. Firms' ability to benefit from external knowledge depends on their absorptive capacity. This absorptive capacity is likely to be greater for firms within the same industry than across different industries.

When endogenous firm exit and the productivity effects of location-specific characteristics are controlled for, the results suggest that, in both Taiwan and South Korea, intra-industry local knowledge spillovers are both economically and statistically significant; specifically, a firm's expected future TFP is positively affected by having more neighbors in the same industry. The existence of intra-industry knowledge spillovers is further supported by evidence that, for a given location and industry, plants in the top half of the productivity distribution are significant sources of knowledge spillovers while plants in the bottom half are not.

The remainder of the paper is divided into five sections. In the next section, we summarize the theoretical and empirical frameworks. This is followed by a description of the data and the measurements of productivity and geographical distance and knowledge in section three. The fourth section details the empirical model specifications. In section five we discuss and interpret the estimation results. In the final section we summarize the major findings and conclusions.

2. Literature Review

Most spillover models in the empirical literature share a common structure in which each agent is assumed to have access to internal and external knowledge. Many studies of knowledge spillovers have used measures of technological proximity, but the literature on *local* knowledge spillovers is limited to those that incorporate geography as a measure of proximity. More recent work on the nature of spillover suggests that physical location plays a significant role in the spread of ideas. The degree to which firms are able to access each other's knowledge is facilitated by personal contacts and such contacts are enhanced by their geographical proximity to one another.

Early work on local knowledge spillovers consisted of case studies of the spread of specific new technologies. Griliches (1957) and Mansfield (1961) both showed that the spread of the use of hybrid seeds by American farmers was facilitated by a strong "demonstration effect" in which early adopters demonstrated the benefits of the hybrids to neighboring farmers. Other studies have sought to broaden the scope of the analysis of spillovers beyond a single technology viewing knowledge more generally as the product of activities such as research and development (R&D). Using a unique data set on patent registrations and citations to measure knowledge production and the technological proximity of firms, Jaffe (1986) estimated the spillover effects of firms' R&D expenditures on their technological neighbors' patent activity. Jaffe, Trajtenberg and Henderson (1993) combined Jaffe's patent data with location data to estimate the probability that two firms share the same location as a function of whether they have cited each other's patents. Their results suggest that location plays a significant role in the spread of ideas as measured by the patent data. This type of detailed data enables a rich characterization of the spillovers process; however, it is not available for most countries.

In the absence of such detailed data, the bulk of studies have estimated the effect of spillovers on a firm's productivity in production, testing the hypothesis that knowledge is discovered through R&D, imported through foreign direct investment (FDI), or learned through exporting experience. Each of these sources of knowledge is thought to potentially spillover from one firm to another. In the case of inter-firm spillovers, a firm's external knowledge is generally constructed as the sum of the knowledge of other firms weighted by the firm's proximity to one another.

Coe and Helpman (1995), Basant and Fikkert (1996), Adams and Jaffe (1996) and Bernstein and Yan (1997) use R&D expenditures as a measure of knowledge. Among these authors, only Adams and Jaffe addressed the issue of local knowledge spillovers by including location as a measure of proximity in their study of intra-firm spillovers. Using plant-level data, they found that the physical distance between a plant and its firm headquarters partially determines the extent to which the plant benefits from its firm's R&D.

Papers addressing the potential spillovers from FDI include Haddad and Harrison (1993), Blomstrom and Sjoholm (1998) and Aitken and Harrison (999). Of these studies only Aitken and Harrison included location as a test for local spillovers from FDI. Using plant level data from Venezuela, they constructed FDI knowledge stocks for both industries and locations and estimated the spillover effects from these stocks in a standard production function. Their results suggest that while FDI has positive spillovers among firms in the same 4-digit industry group, it actually has negative spillovers among firms in the same location.

Finally, case study evidence suggests that firms that export gain valuable product design information and processing technology from their foreign customers. Clerides, Lach and Tybout (1998) constructed a model that simultaneously estimates a firm's productivity and its decision to export. Using firm-level data from Colombia, Mexico and Morocco and the location information, they conclude that experienced exporters may demonstrate to their non-exporting neighbors *how* to export, but non-exporting firms do not benefit from the *knowledge* that their neighbors gain through exporting.

While much of the empirical literature uses firm-level data to assess the effects of local knowledge spillovers between firms, some papers use location data to assess the spread of knowledge within locations by including location characteristics such as the variety of industrial output and industrial concentration ratios have been used as proxies for local information dispersion. These proxies are used in Gleaser, Kallal, Scheinkman and Shleifer (1992) to predict employment growth in US cities and industries. The authors found evidence that local knowledge spillovers occur within industries but not between industries.[2] A common criticism of these models is that the use of location characteristics as proxies to measure information dispersion may be picking up the effects of something other than knowledge spillovers.

Overall, evidence of local knowledge spillovers has been found in the few studies that have used location data from developed countries such as the U.S. However, studies that have

[2] For other examples of location studies see Audretsch and Feldman (1996) and Ciccone and Hall (1996).

used data from developing countries have not found evidence of local knowledge spillovers from specific sources of knowledge such as FDI and exporting experience.

One reason may be that inter-firm linkages are weaker in these countries unlike countries such as Taiwan and South Korea where strong subcontracting relationships may be more important and where the potential for spillover benefits may be greater than those in other developing countries. Indeed, according to Hobday(1995) and Schive (1990), the contribution of exports and FDI to the East Asian economies goes beyond simple transfer of foreign technology from a foreign buyer or a parent firm to the local firm. By sharing technical knowledge with their suppliers in developing countries, foreign buyers stimulate learning among these suppliers. Other domestic firms, in turn, benefit from these knowledge transfers through effective interaction within the industry's tightly connected networks of shared production. FDI often served as demonstrators for local firms to imitate, and some trained local firms to supply goods under subcontracting relationships. If the knowledge transmission process takes time, then access to a large stock of proximate knowledge today is likely to affect future TFP or growth in productivity. The means by which knowledge is passed from the source to each firm may be something as simple as one firm observing the successful practices of another firm. Thus, knowledge transmission is facilitated between neighboring firms. The degree to which agents are able to access each other's knowledge is measured by their proximity to one another.

Another more likely explanation for the lack of evidence of local knowledge spillovers in developing countries is that studies such as Aitken and Harrison (1999) and Clerides, Lach and Tybout (1998) have focused on the productivity effects of *specific* sources of knowledge. Instead of focusing on specific sources of knowledge, this paper use TFP to measures a firm's knowledge (regardless of its source). Differences in TFP among firms may arise from differences in product design, processing technologies, organizational technologies, and/or managerial skill. Each of these differences can be interpreted as part of a firm's collective knowledge, and each is also a potential source of knowledge spillovers. If firms can observe other firms in the same location, they may improve their own TFP by adopting and improving upon the technologies of their neighbors.

While TFP does not measure a firm's knowledge directly, nor does it allow us to identify the source of the knowledge spillover, it is able to capture the extent of knowledge accumulated and potentially available for other firms to learn from or imitate. By using TFP as a more general measure of a firm's knowledge, the model can be estimated using a wide variety of micro-level data sets. The model has broader applicability because many data sets from developing countries contain limited data on R&D, DFI and export behavior, but sufficient data to calculate TFP.

3. The Theoretical and Empirical Framework

Our empirical framework is based on Hopenhayn's (1992) model of firm dynamics and Winston's (2001) extension to include knowledge spillovers from physical proximity. The model contains three basic elements. First, it specifies the knowledge creation process as one that generates internal and external knowledge. Second, it includes a measure of geographical proximity to capture how knowledge spills over. Third, the model accounts for firm exit since endogenous turnover determines which firms are observed in the data and thus play an important role in empirically estimating spillover effects.

Given that the knowledge accumulation process and the spillovers associated with it are subject to uncertainty, new ideas are modeled as a random draw. In every period t, a representative firm i utilizes its current period stocks of internal (θ_{it}) and external knowledge in physical location L (Θ_{it}^{L}) to produce new ideas, κ_{it}.[3, 4] The quantity or quality of the new ideas and exogenous firm characteristics (x_{it}), such as firm age and size, determine the family of knowledge distributions,

$$K\left(\theta_{it}, \Theta_{it}^{L}, x_{it}\right) \qquad (1)$$

from which the firm can randomly draw its new knowledge. However, since the transformation of new ideas into new knowledge takes time, κ_{it} can only be incorporated into the next period stock of knowledge. In addition, as technology advances and products and markets change, the knowledge required evolves. “Old” knowledge may be rendered obsolete and replaced with new knowledge. Thus, the evolution of knowledge stock over time is specified as:

$$\theta_{it+1} = (1-\delta)\theta_{it} + \kappa_{it} \qquad (2)$$

where δ denotes the proportion of the internal stock of knowledge destroyed in each period.

In every period t, given its own stock of production knowledge (θ_{it}), firm i produces total output (y_{it}) from labor input (w_{it}), capital input (k_{it}), and inputs of raw materials, fuel and electricity (m_{it}) according to a production technology represented by $Y_{it}\left(\theta_{it}, w_{it}, k_{it}, m_{it}\right)$. In addition, the plant forms a rational expectation of its future knowledge and, thus its future output, in order to decide whether or not to stay in the market. The exit-entry decision is based on an inter-temporal optimization of profits. In particular, in every period, firm i compares the sum of

[3] Note that the Census of Manufactures for Taiwan is at the firm level but those for South Korea and Indonesia ae at the plant level.

[4] The ‘new-ness’ of knowledge is with respect to plant i only. In other words, plant i’s new knowledge may be another plant’s old knowledge. Thus, there is no distinction between imitation or innovation in this framework.

all present discounted value future profits relative to its current scrap value. If the current scrap value exceeds the present discounted value of all future profits, then the firm will choose to exit. This implies a productivity threshold the plant uses to make exit decisions. This threshold level varies across firms and depends on a firm's individual characteristics and its knowledge evolution process. The firm's decision rule is then specified as:

$$F_{it} = \begin{cases} 1 \text{ if } \theta_{it} \geq \underline{\theta}_{it}\left(z_{it}, \Theta_{it}^{L}\right) \\ 0 \text{ otherwise} \end{cases} \quad (3)$$

where the productivity threshold, $\underline{\theta}_{it}$, is a latent variable which depends on z_{it}, a vector of exogenous characteristics which affect the exit decision, such as age and the value of physical assets as well as its external knowledge stock. The observed binary choice variable, F_{it}, takes on the value of 1 if the firm chooses to continue production and 0 otherwise.

The structure of the empirical model parallels that of the theoretical model, which specifies equation (2) that governs the evolution of a firm's knowledge over time and equation (3) that governs a firm's exit behavior. The empirical model of local knowledge spillovers specifies reduced forms of these two equations and estimates them jointly as a Heckman selection model. TFP is used as a measure of knowledge in both equations.

In the theoretical model, a firm draws its future knowledge from a distribution that depends on its current internal and external knowledge as well as other firm characteristics. The empirical model specifies the evolution of a firm's TFP from year t to year $t+1$ as a reduced form knowledge evolution equation:

$$\ln(\theta_{it+1}) = \alpha_0 + \alpha_1 entrantd_{it} + \alpha_2 \ln(age_{it}) + \alpha_3 \ln(\theta_{it}) + \alpha_4 extknow_{it} + \varepsilon_{it+1}.$$

The dummy variable, $entrantd_{it}$, equals 1 for firms that have entered between the last census year and the current census year and zero otherwise. It is included in the estimation because recent entrants have not yet been subject to productivity shocks, thus the evolution of entrants' TFPs may be somewhat different. The natural log of a firm's age is included to capture possible vintage capital effects that are not accounted for in the index measure of TFP. The variable $extknow_{it}$ characterizes the local external knowledge stock available to each firm; the productivity effects of this measure are the focus of the analysis of local knowledge spillovers. ε_{it+1} is a random error term with a standard normal distribution. Each estimated coefficient in the knowledge evolution equation can be interpreted as the effect of the associated independent variable on the mean of the distribution from which a firm's future knowledge is drawn.

The theoretical model also specifies an exit decision based on a firm's present discounted value of future profits (which depends on its future knowledge). This binary exit decision is empirically modeled as a reduced form selection equation,

$$\chi_{it} = \beta_0 + \beta_1 entrantd_{it} + \beta_2 \ln(age_{it}) + \beta_3 \ln(capital_{it}) + \beta_4 \left(\ln(capital_{it})\right)^2 +$$

$$\beta_5 \ln(\theta_{it}) + \beta_6 extknow_{it} + u_{it},$$

where $\chi_{it} = 1$ if the firm chooses to continue and $\chi_{it} = 0$ if the firm exits. The measures of capital stock, $\ln(capital_{it})$ and $\left(\ln(capital_{it})\right)^2$, are included in the selection equation to control for the effects of a firm's size on its exit decision, because theory suggests that larger firms would be more willing to cover the variable costs of operation and continue to produce even if they draw an unfavorable TFP. u_{it} is random error term with a standard normal distribution.

The endogenous optimal exit behavior specified in the theoretical model becomes an important aspect of the empirical model because turnover determines which firms are active and observable in each period. Correlation between the random unobserved shocks that affect a firm's future TFP and the random shocks that affect its exit decision would bias parameters of an independently estimated knowledge evolution equation. A standard Heckman selection model was employed to estimate the two equations simultaneously and thus eliminate the selection bias. By accounting for possible correlation between the random error terms ε_{it+1} and u_{it}, the parameters of the evolution equation were estimated conditional upon a firm's survival.

The knowledge production process specified in the theoretical model prescribes a specific role for knowledge spillovers in the knowledge evolution process, but it does not specify how a firm's external knowledge should be measured empirically. The ability to construct a measure of proximity between any given pair of firms is an important advantage of using detailed data such as the patent data used by Jaffe (1986) and Jaffe, Trajtenberg and Henderson (1993), because the links between pairs of firms make it possible to assess the spillovers that result from these pair-wise interactions. Without such detailed data, the pair-wise interactions must be proxied as interactions between each firm and the groups of firms to which it belongs. Thus, the distribution of knowledge within each group represents the external stock of knowledge available to the members of each group. The empirical model groups firms according to their locations; within each location firms are also grouped according to their 2-digit industry. Each firm's external knowledge is represented as the distribution of the knowledge of other firms in its location and the distribution of the knowledge of other firms in its location *and* its industry.

Since a firm's external knowledge depends on the number of interactions the firm has with other firms as well as the level of knowledge accessed in each interaction, it can be empirically proxied by two measures: the median TFP of a firm's location and the number of firms in that location. The first measure captures the notion that higher TFP firms provide better external knowledge from which their neighbors can produce new ideas. The second measure captures the notion that firms with more neighbors have either more opportunities to produce new ideas or a greater variety of external knowledge. To estimate the effects of intra-industry local knowledge spillovers, these measures are constructed for each location and for each 2-digit industry within each location.

The empirical model is specified as the reduced form of equations (2) and (3) such that

$$\begin{aligned} \theta_{it+1} &= \alpha_0 + \alpha_1\theta_{it} + \Theta_{it}^{I,L}\beta + x_{it}\gamma + \varepsilon_{it+1} \\ F_{it}^{*} &= \lambda_0 + \lambda_1\theta_{it} + \Theta_{it}^{I,L}\varphi + z_{it}\psi + \mu_t \\ F_{it} &= \begin{cases} 1 \text{ if } F_{it}^{*} > 0 \\ 0 \text{ otherwise} \end{cases} \end{aligned} \tag{4}$$

where $\Theta_{it}^{I,L}$ is a vector of measures of external knowledge available for plant i in period t, x_{it} and z_{it} are vectors of plant characteristics. Furthermore, the set $\{\alpha_0, \alpha_1, \beta, \gamma, \lambda, \lambda_1, \varphi, \psi, \rho, \sigma\}$ contains the parameters to be estimated using Heckman's sample selection maximum likelihood estimation method.

An important observation from the derivation of equations (2) and (3) is that in every period t, the turnover of plants determines the stock of external knowledge available to plant i. As a result, it is possible for the unobservable terms, ε_{it+1} and μ_{it}, in equation (4) to be correlated with each other. In the empirical estimation, we assume ($\varepsilon_{it+1}, \mu_{it}$) ~ bivariate normal$[0, 0, 1, \sigma, \rho]$.

To estimate the system of equations in (4), we need to construct the measures of external knowledge (Θ_{it}^{L}) with three properties. First, for any firm i, Θ_{it}^{L} must reflect the distribution of internal knowledge of all other plants located in each region. Second, the measures must capture within-sector spillover. Finally, the measures must reflect the level of possible human interactions between firm i and its neighbors in each location.

To fulfill the first property, we construct Θ_{it}^{L} for firm i as the median of the internal knowledge (θ_{jt}) of all j firms, $j \neq i$, producing in each location L. Θ_{it}^{L} is constructed across all industrial sectors. In line with the second property, we construct $\Theta_{it}^{I,L}$ for each firm i as the median TFP of all j plants, $j \neq i$, in industry I and location L. Consistent with the final property, we construct $\#\, firms_{it}^{I,L}$ which represents the total number of firms in each location L and industry I, excluding firm i from each measure. In the measures described above, the superscripts attached to the spillover measures, I and L, capture the degree of technological and geographical proximity, respectively.

We estimate four basic model specifications. Each specification uses different variations of the measure of external knowledge. Productivity spillovers exist in the model if the coefficients on Θ_{it}^{L}, $\Theta_{it}^{I,L}$, $\#\, firms_{it}^{L}$ and $\#\, firms_{it}^{I,L}$ are positive. Other things equal, a higher $\Theta_{it}^{S,L}$ implies a higher quantity or better quality of external knowledge from which new ideas can be drawn and converted into new knowledge, which translates into improved future internal knowledge and productivity. Similarly, a higher $\#\, firms_{it}^{I,L}$ implies greater opportunities of interacting with and learning from neighboring firms and, therefore, impacting on the quality of the firm's future stock of new ideas and thus, productivity.

4. Empirical Results

Four specifications of the model are estimated to assess the empirical importance of intra-industry local knowledge spillovers within 2-digit industrial breakdown for each country. The first specification does not include measures of external knowledge but establishes a baseline for the remaining specifications. The second specification includes measures of each location's TFP distribution. The third specification tests for intra-industry local knowledge spillovers by adding measures of external knowledge in each 2-digit industry within each location. The fourth specification uses a different characterization of the 2-digit industry-specific local knowledge stocks to support the findings of the third specification. The data are pooled across the two years for which both future and current TFP measures are available for Taiwan (1986 and 1991) and across all seven years for Korea (1991-1997) and six years for Indonesia (1990-1995). Tables 1 through 6 report the results of the knowledge evolution and selection equations for the three countries.

Taiwan

Column 1 of Table 1 reports the estimated parameters of the baseline TFP evolution equation. The independent variables in the regression includes year dummies, an entrant dummy, *Entrant*, the natural log of firms' age in years, $\ln(age_{it})$, and the natural log of firms' TFP, $\ln(\theta_{jt})$. Column 1 of Table 2 reports the estimated parameters of the selection equation. In addition to the parameters of the evolution equation, the selection equation includes the natural log of capital, $\ln(capital_{it})$,and its square, $\ln(capital_{it})^2$.

The predictions of the theoretical model are confirmed by the estimated parameters of the empirical knowledge evolution equation reported in Column 1 of Table 1. The coefficient on $\ln(\theta_{jt})$ suggests that, on average, firms with higher current TFP will draw higher future TFP and thus a firm's knowledge does not depreciate completely during the five-year intervals between census years. The more rapid general productivity growth that occurred between the 1991 and 1996 census years is reflected in the negative coefficient on the 1986 year dummy, and the negative coefficient on $\ln(age_{it})$ indicates that there may be vintage capital effects which may lead to measurement errors in the calculation of TFP. The coefficient on the new entrant dummy is not statistically significant.

The theoretical model makes several predictions regarding firms' endogenous exit decisions. Consistent with these predictions, the results in Column 1 of Table 2 suggest that larger and more productive firms are more likely to continue production while recent entrants are more likely to exit. The negative coefficient on the square of the capital stock indicates that the effect of size tends to diminish. The estimated correlation between ε_{it+1} and u_{it} is not statistically significant.

The second specification of the model introduces measures of the TFP distribution of each location: $med\,\Theta_{it}^{L}$ measures the natural log of the median TFP of the location and $\#\,frms_{it}^{L}$ measures the natural log of the number of firms in the location. The results of the joint estimation of the knowledge evolution equation and the selection equation are reported in the second column of Table 1 and the second column of Table 2 respectively. The positive and significant coefficient on $med\,\Theta_{it}^{L}$ in the evolution equation seems to suggest that a high median local TFP offers a firm the opportunity to access superior external knowledge and to produce more (or more fruitful) new ideas.

The results of the estimation suggest that a 10% difference in a firm's own TFP would have a 1.95% effect on its future TFP, whereas a 10% difference in the median TFP of its location would have an even larger (2.25%) effect on its future TFP. The magnitude of the estimated coefficient on $med\,\Theta_{it}^{L}$ may be influenced by the omission of important location characteristics from the model. Variables such as port facilities or cheap labor, which are available to all firms in a given location but missing from the model, may function as local public goods and thus affect the general level of TFP in each location. Therefore, the coefficient on $med\,\Theta_{it}^{L}$ may be picking up the effects of these missing variables and should not be interpreted as knowledge spillovers. If $med\,\Theta_{it}^{L}$ captures the effects of local public goods available to all firms within a location, then this measure can be used to control for these missing location characteristics when estimating the degree of local knowledge spillovers between firms in the same 2-digit industry and location (as done in the next specification).

The estimated coefficient on $\#\,frms_{it}^{L}$, which represents the number or variety of opportunities a firm has to combine knowledge and produce new ideas, is positive and statistically significant, suggesting that firms with more neighbors have either more opportunities to produce new ideas or a greater variety of external knowledge.

The inclusion of $med\,\Theta_{it}^{L}$ and $\#\,frms_{it}^{L}$ has little effects on the remaining parameters of the model. The small reduction in the coefficient on $\ln(\theta_{jt})$ may be attributed to the positive correlation between current TFP and the measures of knowledge stocks.

The second specification demonstrates that location is an important element of the evolution of a firm's TFP, but it is unable to distinguish the effects of local knowledge spillovers from the effects of location specific characteristics. The third specification incorporates information about each firm's 2-digit industry classification to assess whether the location effects are stronger when firms share the same industry. Studies such as Aitken and Harrison (1999) and Gleaser et al. (1992) have provided empirical evidence to support the intuitive hypothesis that industry is an important element of technological proximity. In the context of the current model, this hypothesis suggests that firms generate more ideas by combining their knowledge with firms in the same 2-digit industry than by combining knowledge with firms in other 2-digit industries.

To test the hypothesis that local knowledge spillovers are stronger among firms that share the same industry, for each location/industry combination industry-specific local measures of the natural log of median TFP, $med\Theta_{it}^{I,L}$ and the natural log of the number of firms, $\#\,frms_{it}^{I,L}$, are constructed and then added to the previous specification. The general location measures used in the second estimation play an important role in this specification by controlling for the productivity effects of local public goods used by firms in all industries. As long as the local public goods are not specific to each 2-digit industry, correlation between firms' TFP and $med\Theta_{it}^{I,L}$ or between firms' TFP and $\#\,frms_{it}^{I,L}$ will not bias the results. Consequently, the parameters on $med\Theta_{it}^{I,L}$ or $\#\,frms_{it}^{I,L}$ will identify intra-industry local knowledge spillovers while controlling for general location differences.

The results of the third specification (reported in the third column of Table 1 and the third column of Table 2) indicate that $med\Theta_{it}^{I,L}$, the measure of median industry TFP within each location, has no significant effect on the evolution of a firm's TFP. Thus, the productivity enhancing local characteristics captured by of $med\Theta_{it}^{L}$ do not seem to be industry specific. The coefficient on the number of firms in each industry within each location, $\#\,frms_{it}^{I,L}$, indicates that having more opportunities to combine knowledge with neighbors in the same industry has a small, positive and statistically significant effect on future TFP. There is good reason to believe that this evidence of local scale economies at the industry level captures local knowledge spillovers rather than the effect of industry-specific local public goods because, without the promise of higher TFP, there is no compelling reason for firms in a particular industry to favor a particular location. Thus, $\#\,frms_{it}^{I,L}$ would not necessarily be correlated with location characteristics that are not captured by the general location measures.

The magnitude of the local knowledge spillovers also makes economic sense. Compared to the average firm, a firm that has twice as many neighbors from the same industry will draw its future TFP from a distribution with a median that is 1% higher than the average firm's.[5] A 1% return on the number of location/industry neighbors is economically significant because there are many cases where one location/industry has several times the population of another location/industry.

The fourth and final specification of the model lends support to the claim that $\# frms_{it}^{I,L}$ captures the effects of local knowledge spillovers. If high productivity neighbors are better sources of knowledge than low productivity neighbors, then the spillovers associated with the number of high productivity neighbors should be greater than the spillovers associated with the number of low productivity neighbors. To test this hypothesis, we replace $\# frms_{it}^{I,L}$ with $High\# frms_{it}^{I,L}$ and $Low\# frms_{it}^{I,L}$ representing the number of firms for each location/industry with above median TFP and below median TFP levels, respectively. The median TFP of the location, $med\Theta_{it}^{L}$ is retained in the final specification to account for the effects of local public goods.[6]

As reported in Column 4 of Table 3, the coefficient on the number of neighbors from the top half of the TFP distribution $High\# frms_{it}^{I,L}$ is positive and significant while the coefficient on the number of firms from the bottom half of the TFP distribution, $Low\# frms_{it}^{I,L}$ is negative and

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[5] The coefficient on $\# frms_{it}^{L}$ becomes negative and significant in the third specification, which suggests that the significance of the coefficient on $\# frms_{it}^{I,L}$ may be due to correlation between $\# frms_{it}^{L}$ and $\# frms_{it}^{I,L}$. Dropping $\# frms_{it}^{L}$ from the third specification reduces the coefficient on $\# frms_{it}^{I,L}$ from .02 to .01, but the coefficient remains statistically and economically significant.

[6] $\# frms_{it}^{I,L}$ is not included in the fourth specification because it would be nearly perfectly colinear with the quartile counts.

statistically significant. These results indicate that only high productivity firms are important sources of knowledge spillovers, which suggests that firms benefit most from combining their internal knowledge with the external knowledge of those neighbors that have high TFP. Compared to the average firm, a firm with twice as many high productivity neighbors from the same industry can expect to have a future TFP that is between 2%-4% higher than the average firm's.

Finally, we take a closer look at how the group of high productivity firms differ from their counterparts in the lower half of the TFP distribution in each location-industry category. More specifically, we calculated the share of firms with foreign ownership in the variables $High\#\,frms_{it}^{I,L}$ and $Low\#\,frms_{it}^{I,L}$ in 1986 and 1996, the only two census years for which there is information of foreign ownership in firms. Our results indicate that firms with below median TFP actually have a higher share of FDI than those in the top half of the TFP distribution. In 1986, the FDI share in $High\#\,frms_{it}^{I,L}$ is 23 percent increasing to 27 percent in 1996, while the corresponding figures for $Low\#\,frms_{it}^{I,L}$ is 29 percent in 1986 and 48 percent ten years later. These results suggest that foreign-owned firms in Taiwan are not systematically associated with higher productivity compared to domestically owned firms, a pattern consistent with the findings in Aw (2003).[7]

[7] Aw (2003) examines the cross-sectional differences in average productivity of firms that have some foreign capital and those that are domestic-owned in Taiwan in 1986-1996. Except for the textile industry in 1996, the coefficients of the FDI variable in the regression are all positive implying that foreign firms are more productive than non-foreign firms. However, only half of the coefficients in 1986 and one-third in 1996 are significantly different than zero. These coefficients range from 6.3 (electric/electronics industry in 1996) to 18.4 percent (chemicals in 1986). The author speculates that one possible reason for the weak correlation between foreign-ownership and productivity, particularly in 1996, is that starting in 1991, the sample of domestic-owned firms includes Taiwanese MNCs with relatively high productivity.

Korea

There are several important differences in the results for Korea compared to Taiwan. In the baseline regression reported in column 1 of Table 3, the coefficient estimate of current level of TFP is also statistically significant but the magnitude is considerably larger at .677 in Korea compared to .195 in Taiwan. The main reason for this difference is that the Korean results are based on annual data unlike the 5-yearly census data for Taiwan. It is reasonable that the effect of last year's productivity on a firm's current productivity is larger than the firm's productivity five years ago. The positive and significant coefficients on the new entrant and age variables suggest that, unlike Taiwan, new entrants as well as older firms have higher productivity.

Table 4 reports the estimated parameters of the selection equation. In addition to the parameters of the evolution equation, the selection equation includes the natural log of capital and its square. Like Taiwan, larger firms are more likely to survive. However, unlike Taiwan, new entrants, younger and less productive firms are more likely to survive. These latter results are generally inconsistent with the predictions of the theoretical model regarding plants' endogenous exit decisions where older and more productive plants are more likely to survive while recent entrants are more likely to exit. These patterns may be related, in part, to the greater role for government intervention in Korea than in Taiwan. Several researchers including Pack and Westphal (1986), Levy (1991) and Rodrik (1995) have documented the importance of government investment subsidies in Korea. These policies have resulted in the channeling of credit at negative interest rates to Korea's conglomerates and provided them with insurance against failure. In this context, whether or not a firm survives to the next period will reflect whether they have access to the necessary finance, contacts and insurance provided by the government, and less related to the past productivity.

Column 2 of Table 3 reports the coefficient estimates of the external knowledge variables in the knowledge-evolution equation: $med\,\Theta_{it}^{L}$ and $\#\,frms_{it}^{L}$, with the former measuring the median TFP of the neighboring plants and the latter capturing the number of neighbors in a given location. The coefficient estimates for $med\,\Theta_{it}^{L}$ is positive and statistically significant. A 10% higher median TFP of the closest neighbors is associated with a 4% higher future TFP. This variable could also be capturing the productivity enhancing effects of location in an area with favorable characteristics that having nothing to do with spillovers. To the extent that these location characteristics affect plant productivity, $med\,\Theta_{it}^{L}$ can be used as a control variable in subsequent modifications of the model.

The estimated coefficient on $\#\,frms_{it}^{L}$ is negative and statistically significant at .022, suggesting that the larger number of firms in all industries located within a given county has a negative impact on a given firm's productivity. This is not so surprising given that the measure includes firms from very different industries that may be competing with each other for the same set of resources, particularly if they are located in the same area. The magnitude of this effect appears to be extremely small compared to the effect from the external knowledge spillover generated by high productivity neighbors.

Are local knowledge spillovers stronger among plants that share the same 2-digit industry? The results bear similarities with Taiwan and are displayed in the column 3 of Table 3. The measure of median industry TFP within each county, $med\,\Theta_{it}^{I,L}$, has no significant effect on the evolution of a firm's TFP, suggesting that the productivity enhancing local characteristics captured by $med\,\Theta_{it}^{L}$ are not industry specific. However, having more opportunities to combine knowledge with neighbors within the same industry ($\# \, frms_{it}^{I,L}$) has a positive and significant, although small, effect on future TFP.

Finally, we replace $\# \, frms_{it}^{I,L}$ by productivity level, with $High \# \, frms_{it}^{I,L}$ and $Low \# \, frms_{it}^{I,L}$ representing the number of firms for each location/industry with above median TFP and below median TFP levels, respectively. The results are reported in column 4 of Table 3. It is interesting to note that this particular modification of the model changes the magnitude and significance of the coefficient on $med\,\Theta_{it}^{L}$ suggesting that once we include the number of neighbors in a specific location/industry and their position in the productivity distribution, any productivity enhancing local characteristics captured by $med\,\Theta_{it}^{L}$ disappears.

The estimated coefficient of the number of plants in the top half of the TFP distribution is positive and significant while the coefficient of the number of plants in the bottom half of the TFP distribution is negative and statistically significant. This implies that plants benefit more from combining their internal knowledge with the external knowledge of high productivity neighbors than low productivity neighbors in a given location and industry. Compared to the average plant, a plant with twice as many high productivity neighbors from the same location and industry can expect to have a future TFP that is about 3.5% higher than the average plant's. The corresponding figure for Taiwan is 6.1%. Conversely, being located in the same location and industry with low productivity neighbors has a negative effect on plant productivity: -3.0% for Korea and –5.8% in Taiwan.

Using TFP as a measure of knowledge, the empirical model produces statistically significant estimates of the positive effects of intra-industry local knowledge spillovers while controlling for the effects of local public goods and endogenous firm exit. The results suggest that spillovers arise from the number of opportunities a firm has to interact with other firms in the same industry and that interactions with high productivity neighbors are most productive.[8]

Indonesia

Table 5 reports the estimation results of the baseline model and two specifications that take geographical and technological spillovers into account in the case of Indonesia. All the regressions in the table are based on data pooled over all industrial sectors for the time period from 1990 to 1995. We do not report the results of the coefficients on the sector and year dummies.

Column 2 of Table 5 reports the estimated coefficients of the baseline model. Clearly, current level of TFP is a strong and statistically significant determinant of future TFP. A 10% increase in current period TFP increases future TFP by 6.54%. The negative signs of the estimated coefficient of the entrant and age indicate that entering and young firms have a negative correlation with a firm's future TFP. However, the magnitude of the effect is small. These results are consistent with the observation that, in contrast to incumbent plants, recent entrants and young firms are low productivity firms. The estimated parameters of the selection equation in Table 6 indicate that young firms are less likely to survive, while entering firms as well as small size firms are more likely to survive

Column 3 of Table 5 reports the coefficient estimates of the external knowledge variables in the knowledge-evolution equation: $med\,\Theta_{it}^{L}$ and $\#\,frms_{it}^{L}$. There is evidence of localized knowledge spillovers when we consider median TFP of neighboring firms as a measure of external knowledge. The coefficient estimates for median TFP of the immediate neighbors in the same location ($med\,\Theta_{it}^{L}$) is positive and statistically significant. A 10% higher median TFP of

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[8] A test for serial correlation finds that one cannot reject the null hypothesis of no serial correlation in ε_{it+1}.

firms in the same location is associated with 0.7% higher future TFP. The relatively small values of $med\,\Theta_{it}^{L}$ compared to the coefficient of the internal knowledge ($\widehat{\theta}_{it}$) indicate that the latter is a much more important factor in the process of knowledge-evolution.[9] The coefficient on the number of firms in the same location, $\#\,frms_{it}^{L}$, is negative but not statistically significant. The inclusion of $med\,\Theta_{it}^{L}$ and $\#\,frms_{it}^{L}$ has negligible effects on the remaining parameters of the model. In particular, the coefficient on the firm's own productivity on its future productivity, $\widehat{\theta}_{it}$, falls from .654 to .648 suggesting little correlation between current TFP and measures of external knowledge stocks and therefore alleviating the concern that $med\,\widehat{\Theta}_{it}^{L}$ may be picking up the effects of local public goods available to all firms in a given location.

As in the previous two countries, Column 4 incorporates a test for technological proximity. $med\,\Theta_{it}^{I,L}$ is the natural log of median TFP of all firms in industry I and location L. It is interesting to note that this coefficient is statistically significant at .068, the same magnitude as the coefficient on $med\,\Theta_{it}^{L}$ (column 3), which becomes statistically insignificant. This implies that the relationship between our location spillover term and the firm's future productivity is limited to within the same industry. Finally, $\#\,frms_{it}^{L}$, is positive and $\#\,frms_{it}^{I,L}$ is negative and both coefficients are very small but statistically significant. These results imply that firms with more neighbors have either more opportunities to produce new ideas or a greater variety of external knowledge and thus positively affect their future productivity. However, having more

[9] This finding is in contrast to that of Winston (2001) who found the effect of external knowledge in the Taiwanese electronics industry was almost three times as large as the internal knowledge effect. He attributed his finding to the possibility of omitting the effects of local public goods available to all firms in a given location. Also, instead of annual date, his data is based on census collected every 5 years.

opportunities to combine knowledge with neighbors within the same industry appears to have a competitive effect, reducing a firm's future productivity by a very small magnitude.

Finally, the last column of Table 5 reports the results when $\#\,frms_{it}^{I,L}$ is substituted with $High\#\,frms_{it}^{I,L}$ and $Low\#\,frms_{it}^{I,L}$, representing the number of firms for each location/industry with above median TFP and below median TFP levels, respectively. The results follow the same pattern as those obtained for Taiwan and South Korea: the coefficient of the number of firms in the top half of the TFP distribution is positive and significant while the coefficient of the number of firms in the bottom half of the TFP distribution is negative and statistically significant. As in Taiwan and Korea, firms benefit more from combining their internal knowledge with the external knowledge of high productivity neighbors than low productivity neighbors in a given location and industry. Compared to the average firm, a firm with twice as many high productivity neighbors from the same location and industry can expect to have a future TFP that is about 3.5% higher.

It is interesting to note that the final modification of the model, the coefficient on $med\,\Theta_{it}^{L}$ is negative and statistically significant suggesting that once we include the number of neighbors in a specific location/industry and their position in the productivity distribution, any productivity enhancing local characteristics captured by $med\,\Theta_{it}^{L}$ disappears.

5. Summary and Conclusions

Theoretical models have suggested both that knowledge spillovers are potentially of great economic importance and that such spillovers may be facilitated by physical proximity. Using data on R&D and patent citations, some studies have found empirical evidence that physical proximity plays an important role in the spread of knowledge in developed countries. Although there are reasons to expect physical proximity to facilitate the spread of knowledge in developing countries as well, local knowledge spillovers have not been identified using data from the developing world. The lack of evidence of local knowledge spillovers in developing countries may be due to the fact that the existing literature has focused on the spillovers associated with specific knowledge sources such as DFI and export participation. This paper takes a broader view of the sources of spillovers by characterizing a firm's knowledge as anything that increases its TFP.

The theoretical model described in this paper draws on Hopenhayn's (1992) model of industry evolution to describe the evolution of firms' productivities and endogenous exit decisions. In Hopenhayn's model, a firm's productivity in each period is a random draw from a family of distributions determined by the firm's previous productivity; this paper suggests that the randomness assumed in Hopenhayn's model may be the result of the uncertainty of the knowledge production process.

In this paper, we develop empirical measures of knowledge spillovers that are broader then existing measures in order to test the dynamic productivity effects of knowledge stocks based on physical and technological proximity. Like Winston (2001), instead of focusing on specific sources of knowledge, we use TFP as a measure of a firm's knowledge. The data we use come from the manufacturing census of the three countries: Taiwan, South Korea and Indonesia. In our model, productivity spillover is determined by the level of knowledge accessed as well as the extent of interactions the firm has with other firms in each location and/or industrial sector. The evolution of a firm's knowledge is specified as a reduced form equation that estimates a plant's future TFP as a function of its current TFP, location-specific knowledge stocks and other plant characteristics. The estimation accounts for endogenous plant exit by employing the Heckman selection model.

The most robust result across all three countries is that a firm's expected future TFP is positively affected by having more high productivity neighbors in the same industry. Neighboring firms with lower than median TFP in a given location and industry have a significant and negative effect of future productivity. In South Korea and Indonesia, a firm with twice as many high (low) productivity neighbors from the same location and industry can expect to have a future TFP that is about 3.5% higher (3-4% lower). In the case of Taiwan, the corresponding figures are 6.1% and –5.8%. The other common result across all three countries is that current productivity has a positive and significant effect on future productivity. The magnitude of this effect is several times larger than the spillover effect. A 10% increase in current productivity increases future productivity by 1.8% in Taiwan, 6.2% in Korea and 6.4% in Indonesia.

The principal difference in the results across the three countries is related to the importance of the pure location spillover variable after accounting for the effect of distribution of productivity of firms located in the same county and industry on future productivity. In the case of Taiwan, neither the average productivity nor the number of firms in a given location matters in determining future firm productivity. In the case of South Korea, the median productivity of firms in a given location is still very important, while the coefficient on the number of neighbors in a location is negative and statistically significant. For Indonesia, on inclusion of the productivity levels of firms in a given county and industry, the number of neighbors in a given location is positively correlated with future TFP but the median TFP of all firms in the location is negative and statistically significant.

Given the non-rival and partial-excludability of investments in knowledge and ideas, firms are likely to under-invest in these activities. The findings of this paper regarding the significance of locational spillovers from high productivity firms support general policy measures that provide firms with incentives to invest in new knowledge or ideas that potentially can generate spillovers to neighboring firms in the industry. In particular, firms in the higher end of the productivity distribution in a given location and industry are more likely sources of spillovers, implying that fiscal incentives concerning, for example, R&D expenditures could be tied to productivity performance at the firm level.

Our findings draw attention to the economic significance of agglomeration. Firms do benefit from being in the same physical location and industry with other firms that have above average productivity of the region and industry. Development of high quality public infrastructure that effectively draws firms to locate within close proximity of each other is consistent with measures that increase the potential for reaping agglomeration benefits.

Any information on the characteristics of firms that generate spillovers and those that are major recipients will be helpful in identifying policies that maximizes the gains from locational spillovers. While our paper identifies high productivity firms to be the primary sources of local knowledge spillovers, we have not specifically identified who are the primary beneficiaries of the spillovers, except that they are firms located in the same county and in the same industry. If the primary beneficiaries are low productivity firms, then encouraging the development of geographically dispersed population of high productivity firms could take maximum advantage of the externalities. However, if high productivity firms are the principal beneficiaries, then government policy should aim to encourage concentrated pockets of high productivity firms.

Nevertheless, at the minimum, the empirical evidence in this paper support incentives to boost firm-level productivity via encouraging firm investments in spillover-generating activities.

The method of analyzing local knowledge spillovers developed in this paper can be extended in many interesting directions. While this paper assumes that all firms in a location access the same external knowledge stock, it is possible that the physical distance *between* firms *within* each location also determines the extent of knowledge spillovers. Approximate measurements of the physical distance between any two firms could be made using the more detailed location information included in the Taiwanese data, and the approximate distance between two firms could then be used to weight each firm's knowledge contribution to the other. Thus, the effect of local knowledge spillovers could be estimated using firm-specific, weighted average external knowledge stocks.

Another useful direction would be to run separate regressions for the different industries. Comparisons across industries could be used to address the theoretical prediction that local knowledge spillovers are more important in industries with rapidly changing technologies such as electronics and less important in traditional industries such as textiles.

Because knowledge is measured as a TFP index, the methodology developed here does not require data on R&D expenditures or other specific measures of knowledge. As a result, the model can be applied to a wide range of firm-level data sets from countries where the spread of knowledge may have important economic effects, even though few firms make formal investments in R&D. Studies that examine spillovers in different countries could compare the importance of local knowledge spillovers in vertically integrated sectors, such as South Korean manufacturing, relative to the importance of spillovers in highly decentralized sectors, such as Taiwanese manufacturing.

Appendix: Construction of Plant-Level Output, Inputs, and Productivity

To construct the index of total factor productivity $\ln TFP_t^i$ defined in the text we need to construct output, input, and cost-share variables for each plant-year observation. The value of plant output is measured as the sum of total revenues from sales, repairing and fixing services, the revenue from performing subcontracted work, and the change in inventory of final goods between the beginning and end of the year. The value of output is deflated by a producer price index defined at the 2-digit industry level.

In our analysis, each producer uses four inputs in production: labor, capital, intermediate materials, and subcontracting services. The labor input is measured as the number of production and non-production workers. Total payments to labor are measured as total salaries to both groups (unfortunately, these do not include fringe benefits and pensions). The cost share of labor is the ratio of total payments to labor to the value of plant output.

The capital input is estimated as the book values of tangible assets, including building, machinery, tools, and transport equipment at the beginning of the year. To control for price level changes in new capital goods, using the 1988 book values (1986 in Taiwan) as the basis, we deflate the changes in each plant's book values between the censuses by the producer price indices for capital goods. By adjusting these deflated changes to the 1988 book values, we scale the 1983 and 1993 (1981 and 1991 in Taiwan) book values of capital goods to the 1988 basis. The cost share of capital is measured as the residual after subtracting the shares of labor, material, and subcontracting services.

The material input includes raw materials, fuel, and electricity used by the plant. Expenditures on raw materials are deflated by the producer price index for manufacturing raw materials. Fuel expenditures are deflated by an energy producer price index, and electricity expenditures are deflated by an electricity producer price index. The cost share of materials is the ratio of total expenditures on intermediate materials to the value of plant output. The cost incurred for the work that is subcontracted out to other plants is included as an input expenditure since it comprises the principle's payments to subcontractors for the labor, capital services, and expenditures on fuel and electricity by the latter. These costs are deflated by the producer price index of the industry to construct a subcontracting input. The cost share of subcontracting services is the ratio of the principle's payments to the plant's output value.

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Table 1. Productivity Evolution Estimates (Taiwan)
Maximum Likelihood Estimation of Selection Model – Dependent Variable : θ_{it+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry with High/Low Porductivity
constant	0.204* (0.014)	0.156* (0.022)	0.182* (0.024)	0.159* (0.026)
$year86d_{it}$	-0.074* (0.006)	-0.080* (0.006)	-0.081* (0.006	-0.068 * (0.007)
$I(entrantd_{it})$	-0.001 (0.007)	-0.006 (0.007)	-0.006 (0.007)	0.004 (0.007)
$ln(age_{it})$	-0.024* (0.003)	-0.023* (0.003)	-0.023* (0.003)	-0.021* (0.003)
$ln\theta_{it}$	0.195* (0.006)	0.189* (0.007)	0.186* (0.007)	0.182* (0.007)
$med\Theta_{it}^{L}$		0.225* (0.044)	0.188* (0.052)	-0.022 (0.054)
$\# firms_{it}^{L}$		0.008* (0.002)	-0.002 (0.005)	0.003 (0.005)
$med\Theta_{it}^{I,L}$			0.045 (0.035)	
$\# firms_{it}^{I,L}$			0.010* (0.005)	
$High\# firms_{it}^{I,L}$				0.061* (0.007)
$Low\# firms_{it}^{I,L}$				-0.058* (0.008)
$Cov(\varepsilon_{it+1}, u_{it+1})$	-0.426 0.024)	-0.435 (0.024)	-0.436 (0.024)	-0.435 (0.024)
Log likelihood	-35332.43	-35261.14	-35254.82	-35116.90
Sample size	48,232	48,232	48,232	48,191

*, ** indicates statistical significance at the 0.05, 0.1 level

Table 2 : Survival Equation Estimates (Taiwan)

Maximum Likelihood Estimation of Sample Selection Model – Dependent Variable : S_{t+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry Measure with High/Low Productivity
constant	-5.581* (0.188)	-5.844* (0.192)	-5.822* (0.194)	-5.911* (0.197)
$year86d_{it}$	-0.347* (0.015)	-0.300* (0.017)	-0.296* (0.017)	-0.249* (0.017)
$I(entrantd_{it})$	-0.512* (0.018)	-0.489* (0.018)	-0.488* (0.018)	-0.453* (0.019)
$ln(age_{it})$	-0.013 (0.009)	-0.014 (0.009)	-0.015** (0.009)	-0.009 (0.009)
$\ln(k_{it})$	1.034* (0.037)	1.004* (0.037)	1.002* (0.037)	0.996* (0.037)
$(\ln(k_{it}))^2$	-0.040* (0.002)	-0.039* (0.002)	-0.039* (0.002)	-0.038* (0.002)
$\ln\theta_{it}$	0.393* (0.021)	0.398* (0.022)	0.407* (0.022)	0.379* (0.022)
$med\Theta_{it}^{L}$		-0.642* (0.143)	-0.433* (0.169)	-1.664* (0.177)
$\#\ firms_{it}^{L}$		0.049* (0.006)	0.039* (0.015)	0.066* (0.015)
$med\Theta_{it}^{I,L}$			-0.264* (0.112)	
$\#\ firms_{it}^{I,L}$			0.010 (0.015)	
$High\#\ firms_{it}^{I,L}$				0.211* (0.023)
$Low\#\ firms_{it}^{I,L}$				-0.233* (0.026)

*, ** indicates statistical significance at the 0.05, 0.1 level

Table 3. Productivity Evolution Estimates (Korea)
Maximum Likelihood Estimation of Selection Model – Dependent Variable : ω_{it+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry Measures with High/Low Productivity
constant	0.069* (0.017)	0.103* (0.022)	0.115* (0.023)	0.178* (0.024)
$I(entrantd_{it})$	0.106* (0.010)	0.106* (0.010)	0.106* (0.010)	0.107* (0.010)
$ln(age_{it})$	0.037* (0.003)	0.013* (0.003)	0.013* (0.003)	0.016* (0.003)
$\ln\theta_{it}$	0.677* (0.005)	0.618* (0.005)	0.617* (0.005)	0.624* (0.005)
$med\Theta_{it}^{L}$		0.407* (0.015)	0.382* (0.031)	0.387* (0.015)
$\#\ firms_{it}^{L}$		-0.022* (0.002)	-0.030* (0.004)	-0.031* (0.004)
$med\Theta_{it}^{I,L}$			0.026 (0.028)	
$\#\ firms_{it}^{I,L}$			0.008* (0.004)	
$High\#\ firms_{it}^{I,L}$				0.035* (0.006)
$Low\#\ firms_{it}^{I,L}$				-0.030* (0.006)
$Cov(\varepsilon_{it+1}, u_{it+1})$	-0.264 (0.019)	-0.151 (0.021)	-0.148 (0.021)	
Log likelihood	-48474.71	-44494.56	-44489.15	
Sample size	63,909	63,909	63,909	

*, ** indicates statistical significance at the 0.05, 0.1 level

Table 4 : Survival Equation Estimates (Korea)
Maximum Likelihood Estimation of Sample Selection Model – Dependent Variable : S_{t+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry Measures with High/Low Productivity
constant	-0.636* (0.086)	-2.283* (0.113)	-2.293* (0.115)	-2.092* (0.117)
$I(entrantd_{it})$	0.521* (0.021)	0.894* (0.023)	0.896* (0.023)	0.899* (0.024)
$ln(age_{it})$	-0.287* (0.010)	-0.205* (0.011)	-0.205* (0.011)	-0.212* (0.011)
$\ln(k_{it})$	0.047** (0.026)	-0.171* (0.029)	-0.172* (0.029)	-0.152* (0.029)
$(\ln(k_{it}))^2$	0.0004 (0.002)	0.014* (0.002)	0.014* (0.002)	0.013* (0.002)
$\ln\theta_{it}$	-0.122* (0.017)	0.173* (0.019)	0.180* (0.019)	0.159* (0.019)
$med\Theta_{it}^{L}$		-5.313* (0.071)	-5.082* (0.122)	-5.449* (0.072)
$\#\,firms_{it}^{L}$		0.252* (0.009)	0.250* (0.016)	0.232* (0.015)
$med\Theta_{it}^{I,L}$			-0.240* (0.105)	
$\#\,firms_{it}^{I,L}$			0.005 (0.014)	
$High\#\,firms_{it}^{I,L}$				0.257* (0.023)
$Low\#\,firms_{it}^{I,L}$				-0.287* (0.026)

*, ** indicates statistical significance at the 0.05, 0.1 level

Table 5. Productivity Evolution Estimates (Indonesia)
Maximum Likelihood Estimation of Selection Model – Dependent Variable : θ_{it+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry Measures with High/Low Productivity
constant	0.012 (0.011)	-0.022** (0.013)	0.017 (0.013)	-0.003 (0.014)
$I(entrantd_{it})$	-0.017* (0.006)	-0.017* (0.006)	-0.017* (0.006)	-0.016* (0.006)
$ln(age_{it})$	-0.014* (0.002)	-0.013* (0.002)	-0.012* (0.002)	-0.012* (0.002)
$ln\theta_{it}$	0.654* (0.004)	0.648* (0.004)	0.640* (0.004)	0.639* (0.004)
$med\,\Theta_{it}^{L}$		0.068* (0.014)	0.007 (0.017)	-0.082* (0.020)
$\#\ firms_{it}^{L}$		-0.001 (0.002)	0.004** (0.004)	0.005** (0.003)
$med\,\Theta_{it}^{I,L}$			0.068* (0.018)	
$\#\ firms_{it}^{I,L}$			-0.006* (0.003)	
$High\#\ firms_{it}^{I,L}$				0.035* (0.003)
$Low\#\ firms_{it}^{I,L}$				-0.040* (0.003)
$Cov(\varepsilon_{it+1}, u_{it+1})$	-0.005 (0.023)	-0.007 (0.023)	-0.007 (0.023)	-0.014 (0.023)
Log likelihood	-20944.17	-20891.95	-20868.96	-18830.08
Sample size	43,674	43,674	43,674	40,517

*, ** indicates statistical significance at the 0.05, 0.1 level

Table 6 : Survival Equation Estimates (Indonesia)
Maximum Likelihood Estimation of Sample Selection Model – Dependent Variable : S_{t+1}

	Baseline	Location Measures	Location/Industry Measures	Location/Industry Measures with High/Low Productivity
constant	-0.677* (0.223)	-0.687* (0.225)	-0.693* (0.225)	-0.442* (0.241)
$I(entrantd_{it})$	0.159* (0.031)	0.153* (0.032)	0.152* (0.031)	0.139* (0.032)
$ln(age_{it})$	-0.145* (0.012)	-0.154* (0.012)	-0.154* (0.012)	-0.148* (0.012)
$\ln(k_{it})$	-0.070* (0.035)	-0.039 (0.036)	0.038 (0.036)	0.026 (0.036)
$(\ln(k_{it}))^2$	0.002 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
$ln\theta_{it}$	-0.007 (0.023)	0.049* (0.024)	0.024 (0.024)	0.011 (0.024)
$med\,\Theta_{it}^{L}$		-0.455* (0.074)	-0.622* (0.095)	-2.408* (0.149)
$\#\,firms_{it}^{L}$		-0.064* (0.009)	-0.068 (0.014)	-0.217* (0.024)
$med\,\Theta_{it}^{I,L}$			0.191* (0.068)	
$\#\,firms_{it}^{I,L}$			0.005 (0.013)	
$High\#\,firms_{it}^{I,L}$				0.257* (0.021)
$Low\#\,firms_{it}^{I,L}$				-0.269* (0.021)

*, ** indicates statistical significance at the 0.05, 0.1 level