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Abstract

This paper empirically examines the effects of knowledge capital on offshore outsourcing choices based on original survey data of Japanese firms. The results of a multinomial logit model demonstrate that firms' offshoring is positively correlated with knowledge capital measured by their R&D activities or patenting, even after controlling for other firm characteristics including productivity, capital intensity, firm age, and export status. Further, knowledge-intensive firms are more inclined to choose foreign insourcing rather than outsourcing, suggesting that firms tend to internalize their technological knowledge in offshore sourcing.

Keywords: offshoring, outsourcing, productivity, R&D, and patent.
JEL classification: D24; F14; L14

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1. Introduction

In recent decades, a successful global sourcing strategy has been central in achieving a competitive advantage for firms. Sourcing strategies involve decision making on the part of firms on whether to choose foreign insourcing (FI) through vertical integration or foreign outsourcing (FO) to an unrelated firm, which include decisions with respect to their organizational form in the global context. To address this issue, theoretical studies have formalized concepts based on property rights theories that explain “make-or-buy” decisions. On the other hand, empirical evidence on the determinants of sourcing choices is scarce because of limitations of sourcing data. This paper aims to demonstrate empirical evidence by using firm-level data that not only identify the type of sourcing, i.e., whether domestic or foreign, but also disclose whether a firm is sourcing to an unrelated firm or to its own subsidiary.

Previous studies in international economics that have explored the determinants of offshore sourcing activities have suggested that firm productivity plays a vital role in a firm’s choice of sourcing mode. Antràs and Helpman (2004) combined firm heterogeneity (Antràs, 2003; Melitz, 2003) and property rights theory (Grossman and Hart, 1986) for simultaneously explaining the dimensions of sourcing location and firm boundaries. Based on assumptions of incomplete contractibility and relationship-specific investment, their model considers two types of transactions: vertical integration and outsourcing where the outside option is different. If a firm chooses vertical integration, its outside options increase by obtaining the residual rights of control and foregoing the supplier’s incentive to invest in the relationship. Antràs and Helpman also assume the hierarchical order of fixed costs associated with sourcing activities because the costs are higher for insourcing than for outsourcing and are higher in the case of foreign sourcing than in domestic sourcing. As a result, the model proposed by Antràs–Helpman predicts the different sourcing choices according to firm productivity. More specifically, firms that realize higher productivity engage in FO to an unrelated supplier, while firms with lower productivity level choose domestic insourcing from a vertically integrated supplier. Further, the most productive firms pursue FI through vertical integration of a foreign supplier, whereas the least productive firms choose domestic outsourcing. Empirical analyses also support the theoretical prediction on sourcing modes by productivity. Tomiura (2007) found evidence that firms engaged in FDI realize a higher productivity level than firms engaged in FO using Japanese firm-level data. Kohler and Smolka (2009) reported that the productivity of firms engaged in insourcing through vertical integration tends to be higher than that of firms choosing to outsource through an arm’s length transaction using Spanish firm-level data.

On the other hand, traditional discussions on the motivation of horizontal FDI have emphasized the internalization of technological knowledge as discussed in Markusen (1995). Firms facing substantial transaction costs of preventing the leakage of technological knowledge may choose vertical integration. It is therefore expected that greater accumulation of technological knowledge will give firms greater incentive to engage in FDI, which in turn will lead to FI. Although many studies have reported that R&D intensity is positively related to intra-firm trade (e.g., Antràs, 2003; Yeaple, 2006), the issue of which factors have the greatest impact on firms’ offshoring choices has received little attention in empirical literature. Further, the literature on management provides a contradictory view. In recent decades, various factors such as the development of information technology, increased pressure of global competition, and technology complexity have forced firms to shift from in-house innovation to open innovation (Christensen et al., 2005). Hence, knowledge-intensive firms may succeed in innovations using outside resources through buyer–supplier network, strategic alliance, or research collaboration with an unrelated firm. To investigate the two contradictions, Mol (2005) examined the relationship between the R&D intensity and outsourcing using industry-level data on 52 Dutch manufacturing industries. The paper demonstrated that while R&D intensity is positively correlated with outsourcing during the 1990s, a negative correlation is found in the early 1990s, after which period R&D-intensive sectors started to rely on open innovation. Although the paper presented interesting evidence showing how “make-or-buy” decisions are made, the data on outsourcing is not distinguished from those on foreign sourcing, and characteristics at the firm level are not controlled in the presence of industry-level data.[1]

This paper empirically examines the determinants of sourcing choices distinguished in terms of sourcing location and firm boundaries. With respect to data on sourcing, we conduct a questionnaire survey on the sourcing behavior of Japanese firms by the collaboration of the Research Institute of Economy, Trade and Industry (RIETI). This survey covers not only the sourcing of production activities, but also the sourcing of services such as R&D. Further, the survey successfully identifies the sourcing mode each firm selects. This data helps us estimate each firm’s choice model in terms of make-or-buy decision and sourcing location.[2] We use a multinomial logit model on a large sample of Japanese manufacturing firms from 2000 to 2005. In this paper, we specifically focus on the influence of knowledge capital on sourcing behavior, a topic that has not been examined adequately using firm-level data. As a proxy for knowledge capital and in addition to the R&D intensity in line with previous studies, we also introduce a patenting firm dummy into the model. The results indicate that firms’ offshoring is strongly correlated with knowledge capital measured by their R&D activities and patenting even after controlling other firm characteristics such as productivity, capital intensity, firm age, and export status. As for firm boundaries in offshoring, R&D-intensive or patenting firms are

[1] Ito and Wakasugi (2007) examined the determinants of overseas R&D undertaken by multinational enterprises, using affiliate firm level data, and reported that knowledge intensive parent firms expand their overseas R&D activities.
[2] Ito et al. (2007) provided a comprehensive description of this survey.

more inclined to choose FI than outsourcing. These results suggest that knowledge-intensive firms internalize their technological knowledge while actively exploiting foreign resources.

The rest of the paper is organized as follows. In the next section, we present our data and empirical strategy for examining the relation between offshoring choices and firm characteristics. Section 3 presents descriptive statistics and estimation results of our multinomial logit model. Section 4 concludes with a summary.

2. Sourcing modes and Firm Characteristics

2.1 Data

We obtain basic information on firm characteristics and performances from the *Basic Survey of Japanese Business Structure and Activities* (Kigyo Katsudo Kihon Chosa, in Japanese) for the period 1997–2005, conducted by the Japan Ministry of Economy, Trade and Industry (henceforth METI survey). This annual national survey is mandatory for all firms with 50 or more employees and paid-up capital or investment fund exceeding 30 million yen in the mining, manufacturing, wholesale, retail, and food and beverage industries.

The data on offshore sourcing activities were collected from the *Survey of Corporate Offshore Activities* (Kigyo Kaigai Katsudo Chosa, in Japanese), an academic survey conducted by RIETI (henceforth RIETI survey) on 14,062 manufacturing firms listed in the METI survey. The RIETI survey succeeded in collecting responses from 5,528 firms. Given that other previously available firm-level data on offshoring had been unable to cover the entire manufacturing industry and included only a limited number of firms, this survey is clearly advantageous in terms of its coverage. This survey also provides direct information on the binary choice of domestic sourcing and foreign sourcing, both of which are explicitly distinguished from arm's-length purchases in marketplace.[3] The data on the status of offshore sourcing five years ago is also made available as a retrospective question, while the present survey itself is a one-shot survey. Hence, we match the METI data with the RIETI data in 2000 and 2005. As a result, we draw from 8,615 observations on 4,799 firms with accurate information on the variables of interest.

With respect to data on sourcing modes, foreign sourcing modes are further differentiated into FI, defined as contracting out to a firm's own foreign affiliates while holding majority ownership and FO, which is contracting out to unrelated firms; in contrast, domestic sourcing modes are not differentiated in terms of firm boundaries. Therefore, we can identify the three types of sourcing modes for each firm: FI, FO, and domestic both insourcing and outsourcing (DOM), and no sourcing with subcontracting out (NO). As the RIETI survey allows the respondent firms two or more answers, crossing over three modes may be included in the data. Cases where two modes or more are engaged at the same time account for 27 percent of the total sourcing firms. We find that firms engaging in foreign sourcing are also engaged in domestic sourcing, while only 1.8 percent of sourcing firms exclusively conduct FI or FO other than domestic sourcing. These facts support the order of fixed costs for each sourcing mode. As in Antràs and Helpman (2004), we assume that the order of fixed costs f can be shown as follows: $f_I^F > f_O^F > f_I^D > f_O^D$, where each superscript denotes foreign or domestic, and each subscript denotes insourcing or outsourcing. To construct a categorical variable that exclusively indicates a sourcing mode, we assign each firm to a unique category corresponding to the highest fixed cost. For example, if a firm simultaneously engages in FI, FO, and DOM, we assign it to the FI mode. Table 1 shows the distribution of firms with respect to the sourcing modes for the two periods. In the sample, approximately two-thirds of

[3] In this survey, "sourcing" is defined as contracting out to other independent legal entities based on explicit contracts detailing specifications or other dimensions of the outsourced tasks. See Ito et al. (2007) for detailed information of the RIETI survey.

the firms engage in sourcing activities involving contracting out. The share of foreign sourcing firms (FI and FO) increases from 16 percent to 21 percent for five years (2000–2005), while that of domestic sourcing firms decreases by 4 percentage point.

(Table 1)

2.2 Empirical Strategy and Specification

On the basis of Japanese firm-level data that identifies sourcing modes, we assume that firms have four choices: (1) FI: offshore sourcing from related suppliers, (2) FO: offshore sourcing from unrelated foreign suppliers, (3) DOM: sourcing from domestic suppliers, and (4) NO: non-sourcing. In order to empirically test the relation between knowledge capital and specific choices of sourcing modes, we employ a multinomial logit model using the firms' chosen sourcing modes as a qualitative variable. The multinomial logit model, which provides probabilities for a choice *m* taken by firm *i*, is expressed as follows:

$$P_i\left(Y_i = m \middle| \mathbf{X_i}\right) = \frac{\exp\left[\boldsymbol{\beta}'_\mathbf{m}\mathbf{X_i}\right]}{\sum_{m=1}^{4}\exp\left[\boldsymbol{\beta}'_\mathbf{m}\mathbf{X_i}\right]} \qquad \text{for } m = 1, 2, 3, \text{ and } 4, \tag{1}$$

where Y_i denotes the profit obtained from different choices; $\mathbf{X_i}$ denotes the vector of explanatory variables comprising firm characteristics that affect profit; $\boldsymbol{\beta}'_\mathbf{m}$ is the vector of parameters on choice *m*. Taking the coefficients of choice 3 (DOM) as the base category, namely $\boldsymbol{\beta}'_3 = 0$, the log-odds ratios of choosing *m* over the base choice can be formulated as follows:

$$\ln \frac{P_i\left(Y_i = m \middle| \mathbf{X_i}\right)}{P_i\left(Y_i = 3 \middle| \mathbf{X_i}\right)} = \boldsymbol{\beta}'_{\mathbf{m}}\mathbf{X}, \qquad \text{for } m = 1, 2, \text{and } 4. \tag{2}$$

The estimated coefficients are obtained by applying the maximum likelihood method under the assumption of the independence of irrelevant alternatives (IIA). For firm characteristics, we introduce the following variables as independent variables. The key explanatory variable in this study is the proxy variable for a firm's knowledge capital. We employed two observable variables as proxies. One is the R&D intensity measured as the R&D investment over value added (I / Y), and the other is patenting firm dummy (P), which takes the value one if the firm has a patent and zero if otherwise.[4] As shown by Tomiura (2007) and Kohler and Smolka (2009), firm productivity would affect the choices of the sourcing modes if the amount of fixed costs varies across sourcing activities, as Antràs and Helpman (2004) have suggested in their theoretical analysis. As a productivity measure at the firm level, we use estimated TFP for each firm for the period 1997–2005. To avoid the endogeneity problem of input, the production function is estimated by the procedure put forth by Levinsohn and Petrin (2003).[5] We retrieve data on real value-added,[6] labor input measured on the basis of the number of employees and real capital stock[7] from the METI survey. Assuming that investment cost sharing in physical capital is easier than cost sharing in

[4] Regarding patent data, the sampled firms report zero accounts for two-thirds of the observations. We therefore focus on the discrete change in probability when a firm turns out to be patenting firm, although data on the number of patents are available.

[5] Purchase of input is used as a proxy variable of productivity shock. Labor share and capital share are set at 0.76 and 0.23, respectively. We have also used investment as an alternative proxy, as proposed by Olley and Pakes (1996); however, the results were almost the same. To cover firms with zero investment, we choose the estimator from the Levinsohn–Petrin procedure.

[6] Value added is defined as the total sales minus the total cost of the goods sold and general and administrative costs plus wage payments, rental, depreciation, and tax costs. The data on value is deflated by the input and output deflator at the three-digit industry level provided by the Japan Industry Productivity (JIP) Database 2008 published from RIETI.

[7] While firms report the book value of fixed tangible assets, this is transformed into real values using the ratio of the real value of fixed tangible assets to their book value at the 3-digit industry level provided by Tokui et al. (2007). The investment goods deflator used for deflating the value of investment flows and the depreciation rate have been taken from the JIP Database 2008. The real capital stock is calculated by the perpetual inventory method.

labor input, Antràs (2003) showed that firms engaged in FO are more labor intensive than firms engaged in FI. To incorporate this intuition, the capital-labor ratio (*K/L*) calculated as real capital stock over the number of employees is also included in the model. The accumulated experience of firms might be a factor in increasing the probability of decisions regarding further sourcing. Therefore, for the estimation, we include the firm age (*AGE*), which is defined as the number of years since the firm was established in the equation. The degree of a firm's internationalization may also influence the probability of decisions on the sourcing modes. Exporting firms may obtain more information on overseas markets and suppliers through dealings with foreign countries and may engage more easily in FO. To control for this factor, we introduce exporter dummy (*EX*) in the model. The base estimation equation is rewritten as follows.

$$\ln\frac{P_i\left(Y_i = m \middle| \mathbf{X_i}\right)}{P_i\left(Y_i = 3 \middle| \mathbf{X_i}\right)} = \beta_{m,0} + \beta_{m,1}\ln TFP_{it} + \beta_{m,2}\ln\left(\frac{K}{L}\right)_{it} + \beta_{m,3}AGE_{it} + \beta_{m,4}\left(\frac{I}{Y}\right)_{it} + \beta_{m,5}P_{it} + \beta_{m,6}EX_{it} + \varepsilon_{it} \quad \text{for } m = 1, 2, \text{and } 4, \qquad (3)$$

where t denotes the two years, 2000 and 2005, for which data on the sourcing modes are available. In this specification, we first focus on the coefficient of the R&D intensity, $\beta_{m,4}$. There is, however, a possibility that passing through TFP exists under the influence of the R&D intensity on the probability of decisions on the sourcing modes, because TFP can be explained by R&D input, given that TFP is a residual of the production function. In other words, TFP is considered an endogenous variable, and the correlation with the unobserved factor is in question. On the other hand, the standard instrumental variable (IV) regression technique cannot be applied to a discrete choice model. To control for the contribution of R&D through TFP and a possible endogeneity of TFP, we employ the control function (CF) approach to the limited dependent variable model proposed by Blundell and Smith (1989). One key feature of the CF approach is that the unobserved factor is treated as an omitted variable. The procedure is summarized as follows. In the first stage, we gain OLS residuals from the regression of the endogenous variable on IV and covariates of the second stage equation. In the second stage, we estimate the choice model including the OLS residuals as explanatory variables. For the error structure of TFP expressed in the first stage equation, we derive the model of TFP growth explained by the R&D intensity based on the production function framework. A firm's TFP growth is explained by technical change attributed to the growth of knowledge stock Δr_{it}. Because it is difficult to directly observe the growth of the knowledge stock, we express it in an alternative manner as follows:[8]

$$\gamma \Delta r_{it} = \gamma \ln\left(1 + \frac{\Delta R_{it}}{R_{it}}\right) \approx \gamma \frac{\Delta R_{it}}{R_{it}} = \frac{\partial Y_{it}}{\partial R_{it}} \frac{R_{it}}{Y_{it}} \frac{\Delta R_{it}}{R_{it}} = \rho \frac{\Delta R_{it}}{Y_{it}}, \tag{4}$$

where γ is the knowledge-stock elasticity of value added, $\rho = \partial Y / \partial R$, and ΔR_{it} is the R&D investment expressed in flow (I_{it}). We take a one-period lag for the R&D intensity as is customary in studies on productivity and R&D. The structure of the current TFP level is therefore presented as the following equation, wherein we bring the lagged TFP term to the right-hand side.

$$\ln TFP_{it} = \theta \ln TFP_{it-1} + \phi z_{it} + \rho\left(I_{it-1}/Y_{it-1}\right) + e_{it} \quad , \tag{5}$$

[8] For the derivation of knowledge capital flow, we drew on Griffith et al. (2003), Jones (2002), and Fors (1996).

where e_{it} is the error term. Hence, lagged TFP level and R&D intensity can be used as IV in the first stage. For an estimation of equation (5), we also add covariates used in the second stage, 2-digit industry dummy variables for industry-specific factors and a year dummy for a macroeconomic shock as explanatory variables. Table 2 describes the summary statistics for the main variables of interest according to sourcing mode. The first column shows that firms engaged in FI through vertical integration are the most productive and followed, in a descending order of productivity level, by FO firms, DOM, and NO. This order is consistent with the theoretical prediction by the Antràs–Helpman model. A similar ordering is found in the firm age, R&D intensity, patent holder, and exporter dummy. As for the logarithm capital-labor ratio, FI firms are also the most capital intensive, whereas the sorting among other sourcing modes is unclear. In other words, firms engaged in FI are likely to be the most productive, capital-intensive, knowledge-intensive, exporting and the most experienced. Although this descriptive information provides a basis for our analysis, we need to investigate further to determine which factors have a dominant effect on the firms' choices of the sourcing mode. In the next section, we present the estimation results for the choice model of the sourcing mode and demonstrate the contribution of each variable.

(Table 2)

3. Empirical Results

The multinomial logit model is estimated for the pooling data of 2000 and 2005. The estimation results are shown in Table 3. All models include industry dummies and a year dummy. The choice of domestic sourcing (DOM) is set as the base choice, and the estimated coefficients therefore indicate the difference with the coefficient of the DOM mode. To interpret the results, the relative risk ratio (RRR), which is the exponential of the estimated coefficient, is useful. RRR can be interpreted as a change in the odds ratio of choosing *m* relative to DOM by a unit change in the explanatory variable.

Column [1] presents the estimates from a specification without the R&D intensity, patent dummy, and exporter dummy. For all models considered here, a possible endogeneity of TFP is controlled for by adding OLS residuals in the first stage regression. First, the estimated results show that the order of firm productivity is consistent with that of fixed costs as we assumed. It is found that the coefficients of TFP are significant and positive for FI and FO, while the negative coefficient is exposed in the choice of NO. Further, the Wald test result for examining the difference in the coefficient positively shows that TFP of firms choosing FI is higher than that of firms choosing FO. In other words, these results demonstrate that the order of the sourcing mode is sorted by productivity (i.e., FI > FO > DOM > NO), which is in line with the theoretical conjecture by Antràs and Helpman (2004) and other previously presented evidence (e.g., Tomiura, 2007; Kohler and Smolka, 2009). The same order of TFP is also found in the results of capital intensity and firm age. However, the significance of these basic firm characteristics decreases by adding R&D, patent, and export status.

Column [2] presents the results with the R&D intensity and show that the difference in the R&D intensity with respect to the base choice is significant for all modes. The largest coefficient and the second largest coefficient are found for FI and FO, respectively, while the coefficient with respect to NO has a negative sign. Further, the Wald test statistics for the equality of coefficients on the R&D intensity between FO and FI is 14.98 with a p-value of 0.0001, reinforcing that the difference between the two coefficients is significant. This result indicates that firms tend to start sourcing activity and engage in FO and FI when their R&D intensity rises, with all other factors held constant. In column [3], we introduce the patent holder dummy into the model instead of the R&D intensity. Switching to the patent holder has a significant and sizable contribution to choosing foreign sourcing. For FI and FO, the Wald test result also rejects the equality of coefficients on the patent holder dummy. Column [4] shows the results of the model including those for both R&D intensity and patent dummy. R&D intensity is still statistically significant at a 1 percent level, and its order of the sourcing mode is not changed with the added patent dummy and *vice versa*. Again, the Wald test result rejects the equality of the coefficient on the R&D intensity between FI and FO (chi-square is 7.06 with a p-value of 0.008). The Wald test for the equality of the coefficient on the patent holder dummy also positively shows that the difference is significant (chi-square is 35.33 with a p-value of 0.000). For the FI mode, RRR is exp (0.0343) or 1.035 with respect to the coefficient of the R&D intensity, which means an increase in the probability relative to DOM by 3.5% when a firm increases the R&D intensity by 1 percentage point. Similarly, RRR is 1.0188 for FO, which is interpreted as an increase in the relative probability by 1.9% for a unit change in R&D intensity, while for NO, RRR is 0.97, which indicates a decrease in the odds ratio by 3 percent. The results of RRR with respect to the patent dummy are interpreted by understanding how the probability of choosing the sourcing mode *m* relative to DOM changes if the firm is a patent holder, keeping the other variables constant. Moreover, for FI, RRR is 2.46, which indicates an increase in the odds ratio of choosing FI relative to DOM by 146 percent for a sourcing firm that turned patent holder. For the FO mode, the difference in the patent holder status is also significant and sizable, with an increase in the odds ratio by 35 percent. In contrast, for NO firms, the result shows a decrease in the odds ratio by 31 percent for a firm that turned patent holder.

Column [5] shows the results of the estimated model including exporter dummy. The coefficients of the exporter dummy are all significant at a 1 percent level, and the results indicate that, as expected, an exporting firm is more inclined to choose FO than domestic sourcing. It is remarkable that the odds ratio of FI relative to DOM is still influenced by both R&D intensity and patent holder dummy, while the difference in the odds ratio of FO over

DOM diminishes after the export status is added. As for the R&D intensity, an increase is observed in the odds ratio when choosing FI relative to DOM by 2.1 percent, if the sourcing firm increases the R&D intensity by 1 percentage point. The coefficient of patent holder is also significant and sizable with respect to FI, with an increase in the odds ratio by 73 percent. The results suggest that firms' sourcing behavior in terms of "make-or-buy" decision is sensitive to their knowledge asset.[9] For other variables, the log of capital intensity and firm age also show a positive and significant sign with respect to FI, but the magnitude is quite marginal. For instance, RRR is indicates that a 1 percent increase in capital intensity raises the odds ratio of choosing FI relative to DOM by 0.18 percent.[10] RRR with respect to the firm age for FI shows that an additional year of experience is associated with an increase in the odds ratio by 0.9%.

(Table 3)

Regarding the validity of the IIA assumption, we check Hausman's specification test that examines whether the difference in coefficients in a full model is significant when the model is estimated excluding one choice. We examine the test by omitting a sourcing mode one by one. Most results support the null hypothesis, i.e., the IIA assumption, while showing rejection or negative chi-square statistics in some cases.[11] Table 4 displays the estimation results of the model excluding NO. The main results are not changed significantly, while the estimation here is carried on by setting FO as the base choice for the purpose of comparison. For the odds ratio of FI over FO, the coefficient of R&D intensity is positive and significant,

[9] One would expect that patenting would reflect firm size effects. We also estimate the model introducing firm size proxied by total sales or total employees instead of TFP; however, the results were found to be almost the same.

[10] For logarithm variables, RRR is calculated as an exponetial of the estimated coefficient multiplied by 0.01, so as to obtain the change in the odds ratio of choosing FI relative to DOM with an increase in the logarithm variable by 1 percent, i.e. $\ln(X_{it} \times 1.01) \approx \ln(X_{it}) + 0.01$.

[11] Hausman and McFadden (1984) note that negative test statistics is evidence that the IIA assumption holds.

whereas the odds ratio for DOM over FO is consistently negative and significant. The coefficients of patenting firm dummy also show the same sign as R&D intensity. The coefficients of both R&D intensity and patenting firm dummy with respect to the odds ratio of FI over FO are still significant even after the exporter dummy is added into the model. The positive and significant coefficients of both variables indicate that an R&D-intensive or a patenting firm is more inclined to choose FI than FO. Overall, the results from the choice model indicate that firms' R&D and patenting activities contribute to offshore sourcing, and they have a large impact on the probability of choosing insourcing through vertical integration rather than outsourcing.

(Table 4)

4. Concluding Remarks

The relation between R&D and firms' sourcing behavior has received little attention in the empirical literature. Furthermore, the issue of which factors have the greatest impact on firms'offshoring choices has not been addressed. To shed light on these points, this paper examines the relation between sourcing choices and various firm characteristics using Japanese firm-level data in manufacturing industries for the years 2000 and 2005. The empirical results of the multinomial logit model indicate that firms' technological knowledge asset is highly associated with offshore sourcing. These results suggest that global sourcing activities have been expanded by R&D-intensive firms. Moreover, they are likely to choose FI through vertical integration as expected by the theoretical view of internalization. Although one might expect that patent holders would not hesitate to subcontract to an unrelated foreign supplier if their technological knowledge is protected by patent rights, the estimation results contradict this view. Our results may imply that knowledge-intensive firms are likely to engage in offshore insourcing to avoid technology leakage and litigation risk, even if their technological knowledge can be protected by intellectual property rights. This intuition is also reasonable, when we consider that expanding global sourcing is often accompanied by technology transfer to foreign suppliers. While the phenomenon designated as “open innovation” is observed in the utilization of foreign resources by knowledge-intensive firms, it has not progressed much in terms of redefining firm boundaries for Japanese firms.

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Table 1. Firm Distribution by Sourcing Modes

	FI[a]	FO[b]	DOM[c]	NO[d]	*Total*
2000	323	325	1,955	1,544	*4,147*
	7.8%	7.8%	47.1%	37.2%	*100%*
2005	472	463	1,957	1,576	*4,468*
	10.6%	10.4%	43.8%	35.3%	*100%*
Total	*795*	*788*	*3,912*	*3,120*	*8,615*

[a]foreign insourcing; [b]foreign outsourcing; [c]domestic sourcing; [d]non-sourcing.

Table 2. Summary Statistics

Sourcing modes		ln(TFP)	ln(K/L)	Age (year)	R&D/Y (%)	Patent holder dummy	Exporter dummy
FI: Foreign insourcing	Mean	1.699	2.148	47.728	7.875	0.682	0.766
	S.D	0.455	0.783	17.830	10.761	0.466	0.424
	Min	0.193	-2.251	0	0	0	0
	Max	3.872	5.174	109	83.056	1	1
FO: Foreign outsourcing	Mean	1.632	1.875	42.280	4.766	0.471	0.497
	S.D	0.501	0.908	16.572	8.234	0.499	0.500
	Min	-0.805	-2.079	0	0	0	0
	Max	3.436	4.745	94	78.186	1	1
DOM: Domestic sourcing	Mean	1.578	1.917	41.145	3.224	0.364	0.271
	S.D	0.438	1.088	16.533	6.842	0.481	0.445
	Min	-0.104	-6.781	0	0	0	0
	Max	4.032	5.541	132	63.326	1	1
NO: Non-sourcing	Mean	1.468	1.889	40.157	1.836	0.240	0.157
	S.D	0.440	1.088	16.005	4.570	0.427	0.364
	Min	-0.763	-4.454	0	0	0	0
	Max	4.053	5.569	107	52.541	1	1
Total	*Mean*	*1.554*	*1.924*	*41.498*	*3.291*	*0.358*	*0.296*
	S.D	*0.453*	*1.050*	*16.601*	*6.971*	*0.480*	*0.457*
	Min	*-0.805*	*-6.781*	*0*	*0*	*0*	*0*
	Max	*4.053*	*5.569*	*132*	*83.056*	*1*	*1*

Table 3. Estimation Results of the Multinomial Logit Model

		[1]			[2]			[3]			[4]			[5]	
	FI	FO	NO	FI	FO	NO	FI	FO	NO	FI	FO	NO	FI	FO	NO
ln(TFP)	0.724***	0.318***	−0.554***	0.398***	0.217*	−0.456***	0.499***	0.235**	−0.470***	0.289**	0.180	−0.418***	−0.0109	0.0403	−0.385***
	(0.122)	(0.117)	(0.0739)	(0.122)	(0.117)	(0.0743)	(0.125)	(0.118)	(0.0748)	(0.124)	(0.118)	(0.0748)	(0.130)	(0.121)	(0.0756)
ln(K/L)	0.293***	0.0779*	−0.0823***	0.241***	0.0545	−0.0592**	0.237***	0.0549	−0.0576**	0.204***	0.0409	−0.0458*	0.174***	0.0228	−0.0436*
	(0.0450)	(0.0404)	(0.0252)	(0.0463)	(0.0409)	(0.0253)	(0.0470)	(0.0409)	(0.0254)	(0.0478)	(0.0412)	(0.0254)	(0.0506)	(0.0421)	(0.0253)
Age	0.0234***	0.00619**	−0.00367**	0.0204***	0.00513**	−0.00238	0.0169***	0.00383	−0.00128	0.0156***	0.00348	−0.00085	0.00951***	0.000427	0.000014
	(0.00247)	(0.00249)	(0.00158)	(0.00251)	(0.00250)	(0.00160)	(0.00256)	(0.00254)	(0.00162)	(0.00257)	(0.00254)	(0.00162)	(0.00267)	(0.00258)	(0.00164)
R&D/Y (%)				0.0461***	0.0241***	−0.0427***				0.0343***	0.0186***	−0.0308***	0.0207***	0.00934*	−0.0249***
				(0.00469)	(0.00537)	(0.00560)				(0.00483)	(0.00554)	(0.00560)	(0.00502)	(0.00567)	(0.00552)
Patent holder							1.039***	0.368***	−0.466***	0.900***	0.294***	−0.372***	0.548***	0.124	−0.335***
dummy							(0.0904)	(0.0861)	(0.0579)	(0.0934)	(0.0893)	(0.0602)	(0.0975)	(0.0919)	(0.0610)
Exporter													1.823***	0.900***	−0.311***
dummy													(0.104)	(0.0929)	(0.0683)
Residuals of 1st	−0.592***	−0.225	0.303**	−0.00323	−0.108	0.197	−0.362*	−0.147	0.245**	0.0313	−0.0934	0.188	0.112	−0.0516	0.176
stage	(0.219)	(0.206)	(0.119)	(0.213)	(0.206)	(0.120)	(0.219)	(0.205)	(0.120)	(0.214)	(0.207)	(0.121)	(0.220)	(0.208)	(0.122)
Year dummy	0.269***	0.323***	0.0303	0.285***	0.327***	0.0305	0.319***	0.339***	0.0208	0.325***	0.339***	0.0238	0.339***	0.340***	0.0270
	(0.0818)	(0.0807)	(0.0493)	(0.0827)	(0.0807)	(0.0495)	(0.0828)	(0.0808)	(0.0496)	(0.0833)	(0.0809)	(0.0496)	(0.0859)	(0.0815)	(0.0497)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−4.135***	−2.341***	0.652***	−3.641***	−2.202***	0.519***	−3.910***	−2.219***	0.518***	−3.581***	−2.146***	0.452***	−3.522***	−2.026***	0.410***
	(0.264)	(0.254)	(0.157)	(0.262)	(0.253)	(0.157)	(0.267)	(0.254)	(0.158)	(0.265)	(0.254)	(0.158)	(0.274)	(0.256)	(0.159)
Observations		8615			8615			8615			8615			8615	
Log likelihood		−9471			−9359			−9323			−9266			−9011	
df		72			75			75			78			81	
LR test chi2		1132			1356			1428			1544			2053	

Notes: Domestic sourcing (DOM) is set as the base. Standard errors in parenthesis; *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 4. Estimation Results of the Multinomial Logit Model (Non-sourcing Omitted)

	[1]		[2]		[3]		[4]		[5]	
	FI	DOM	FI	DOM	FI	DOM	FI	DOM	FI	DOM
ln(TFP)	0.396***	−0.307***	0.179	−0.215*	0.251	−0.221*	0.102	−0.174	−0.0393	−0.0364
	(0.151)	(0.117)	(0.152)	(0.118)	(0.154)	(0.118)	(0.154)	(0.119)	(0.158)	(0.122)
ln(K/L)	0.234***	−0.0789*	0.199***	−0.0543	0.194***	−0.0529	0.172***	−0.0388	0.160***	−0.0195
	(0.0571)	(0.0417)	(0.0581)	(0.0421)	(0.0587)	(0.0422)	(0.0592)	(0.0424)	(0.0612)	(0.0433)
Age	0.0171***	−0.00577**	0.0154***	−0.00473*	0.0131***	−0.00338	0.0123***	−0.00305	0.00913***	0.000265
	(0.00316)	(0.00250)	(0.00317)	(0.00252)	(0.00325)	(0.00256)	(0.00325)	(0.00257)	(0.0033)	(0.00261)
R&D/Y (%)			0.0222***	−0.0251***			0.0159***	−0.0190***	0.0115*	−0.00970*
			(0.00577)	(0.00547)			(0.00597)	(0.00559)	(0.00614)	(0.0057)
Patent holder dummy					0.663***	−0.382***	0.599***	−0.309***	0.424***	−0.148
					(0.114)	(0.0867)	(0.117)	(0.0896)	(0.119)	(0.0923)
Exporter dummy									0.912***	−0.906***
									(0.126)	(0.0931)
Residuals of 1st stage	−0.343	0.202	0.105	0.0973	−0.202	0.132	0.121	0.0864	0.125	0.0554
	(0.269)	(0.204)	(0.268)	(0.207)	(0.268)	(0.204)	(0.269)	(0.208)	(0.269)	(0.209)
Year dummy	−0.0574	−0.335***	−0.0484	−0.335***	−0.027	−0.348***	−0.0229	−0.345***	−0.0142	−0.344***
	(0.105)	(0.0811)	(0.105)	(0.0812)	(0.105)	(0.0813)	(0.105)	(0.0814)	(0.106)	(0.0822)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.811***	2.319***	−1.475***	2.198***	−1.689***	2.187***	−1.449***	2.131***	−1.529***	1.998***
	(0.330)	(0.255)	(0.329)	(0.256)	(0.332)	(0.256)	(0.331)	(0.257)	(0.335)	(0.26)
Observations	5495		5495		5495		5495		5495	
Log likelihood	−4128		−4080		−4056		−4031		−3840	
df	48		50		50		52		54	
LR test chi2	537		633		681		732		1114	

Notes: Foreign outsourcing (FO) is set as the base. Standard errors in parenthesis; *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.