DOI: 10.54254/2754-1169/93/20241068

The Impact of FDI Technology Spillovers on Local Firms' Innovation

-- Based on the Dualistic Perspective of Exploratory and Exploitative Innovation

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Abstract: Despite the fact that China has been facing huge technological spillovers from foreign direct investment (FDI), the situation of China's key core technologies being controlled by others and the risk of "being hit in the throat" still exists. Based on the unbalanced panel data of 2,239 non-foreign listed companies in the manufacturing sector in China from 2012 to 2022, this paper investigates the impact of FDI technology spillovers on the binary innovation of local firms in the host country by using a two-way fixed effects model. It is found that FDI technology spillovers promote the overall level of innovation and the level of utilized innovation of local firms in the Chinese manufacturing industry, but have a dampening effect on the level of exploratory innovation.

Keywords: FDI technology spillover, dual innovation, exploratory innovation, utilization innovation

1. Introduction

China has always had a strong attraction to foreign investment, with a steady growth in the quantity of foreign investment obtained and a continuous optimization of the quality of foreign investment. However, problems such as the existence of shortcomings in key core technologies are still the main constraints to China's realization of high-quality development, and it is still difficult to compete with developed countries in some core scientific and technological fields.

Both exploitative and exploratory innovations are essential for firms, whether it is to maintain an existing competitive advantage or to create a future core competitive advantage. Due to the limited innovation resources available to a firm, there is a tension in a firm's decision-making between the two types of innovation [1]. When faced with FDI technology spillovers, will local firms develop a binary innovation bias in order to absorb and utilize the technology spillovers? Will they prefer utilization innovation that optimizes and improves their existing products, or will they tend to engage in exploratory innovation in completely new areas? In order to answer this question, this paper conducts a study on Chinese manufacturing firms.

This paper identifies two gaps in existing research. First, although the research on the impact of FDI technology spillovers on innovation is relatively mature, scholars have not yet reached a unified view on the "impact of FDI technology spillovers on innovation of local enterprises", and seldom study the level of dual innovation. Secondly, the research on the relationship between FDI technology spillovers and dual innovation has not yet formed a clear analytical framework, and has not carried out an in-depth investigation of the specific channels of action. In terms of practical significance, this paper will help policymakers and local enterprises in the world's emerging economies to face the benefits and potential negative impacts of FDI technology spillovers more rationally. It will also provide some suggestions for policy makers.

2. Methodologies

2.1. Data source and processing

This paper selects listed companies that are classified as manufacturing companies according to the SEC 2012 industry classification as the research sample. The starting and ending time of the study is 2012-2022. In this paper, patent applications, citations, IPC patent classification numbers, inventor information, cited patents, and cited patents of listed companies in the manufacturing industry come from Pharmsnap database, and basic information, R&D data, financial data of listed companies come from WIND database, CSMAR database, RESSET database, and EPS data platform. In identifying the year corresponding to a patent, there is a lag of 2-3 years between the year of application and the year of grant [2]. Therefore, the year of application was chosen instead of the year of grant because the actual time of patent innovation is closer to the year of application [3].

The following processing steps were implemented for the initial data samples: (1) 1% and 99% shrinkage for continuous variables; (2) removal of samples with serious missing data; (3) removal of financial industry data; (4) removal of firms containing ST and *ST categories; and (5) removal of samples listed in the current year. The final unbalanced panel data obtained totaled 2,239 local enterprises and 13,187 observations. The empirical process uses excel, stata MP 17, and Jupyter Notebook software for variable construction, data matching, and model regression.

2.2. Regression Model

The model used in this paper is a panel regression model with a benchmark model for total innovation level:

$$ln\_patent\_count_{i,t+1}=\alpha_0+\alpha_1 ln\_spilltech_{i,t}+\alpha_2 ln\_spillsic_{i,t}+\alpha_3 Z_{i,t}+\sum year+\sum id+\varepsilon_{i,t} \tag{1}$$

The subscripts i and t denote listed firms and the corresponding time, respectively. z represents the control variables, and Year FE, firm FE denote year fixed effects as well as individual fixed effects, respectively. Note that in the main analysis, this paper focuses on firms' innovation strategies during the one-year period (i.e., time t+1). The paper uses a panel two-way fixed effects model in all of the following regression analyses and includes heteroskedastic standard errors to correct for possible heteroskedasticity in the model.

Numerous studies have demonstrated the validity of patents as a proxy for measuring innovation activity [4][5][6].

Overall patent application count (ln_patent_count): Defined as the total number of patents filed by the local company in year t and logarithmic.

Overall patent citations (ln_citation_count): Defined as the sum and logarithm of the number of citations for patents filed by the local company in year t within 3 years of filing.

Exploratory innovation level (unknown_area): Referring to existing studies [7], where the field to which a patent belongs can be differentiated by its IPC classification number, the number of patents filed by the company in previously unknown technology categories was calculated and scaled according to the total number of patents filed by the company per year. Unknown patent classes are those in which the company has not filed a patent application beforehand. More patents in unknown fields means exploring new areas.

Exploitative innovation level (know_area): The number of patents filed by the company in previously known technology classes, scaled by the total number of patents filed by the company each year. Known patent categories are those in which the company has filed patents. More patents in known fields imply innovation in the original technology field.

FDI technology spillover (spilltech): Referring to existing studies [7][8],The first four digits of the International Patent Classification (IPC) number are utilized to measure the technological fields covered by patents and the degree of technological similarity between these fields. Based on the categorization of the nature of equity in the Cathay Pacific database, foreign-funded and non-foreign-funded firms can be distinguished accordingly. For local firm i and foreign firm j, the technology similarity of the two firms is defined by the cosine value of their technology vectors in the technology space. The technological proximity between local firm i and foreign firm j in year t, is shown below:

$$tech_{ijt} = \frac{X_{it}X'_{jt}}{(X_{it}X'_{it})^{0.5}(X_{jt}X'_{jt})^{0.5}} \tag{2}$$

Specifically, assume that the first four digits of IPC classification numbers of all sample companies in the year have a total of T types, and each classification number represents an independent technology category, thus forming a T-dimensional technology space. $\mathbf{X_{it}} = (\mathbf{X_{i1t}}, \mathbf{X_{i2t}}, \cdots, \mathbf{X_{i\tau t}}, \cdots, \mathbf{X_{iTt}})$ is a vector representing the proportion of patents of each technology category held by local company i up to year t, where $\mathbf{X_{iTt}}$ is the share held by company i in class τ technology patents up to period t$(\boldsymbol{\tau} = \mathbf{1}, \mathbf{2}, \dots, \mathbf{T})$. The definition of $\mathbf{X_{j,t}}$ is similar. $\mathbf{tech_{i,j,t}}$ measures the correlation between the proportion of patents in each technology classification of a local company and a foreign company. The higher the correlation, the closer their technology areas are.

According to the technology proximity measure, the exposure of local firm i to FDI technology spillovers in year t is measured as follows:

$$spilltech_{it} = \sum_{j}^{J} tech_{ijt} * RD_{jt} \tag{3}$$

$\mathbf{RD_{j,t}}$ represents the R&D investment stock of foreign-funded company j in year t, represents the level of R&D investment of company j, and therefore also represents the intensity of technology diffusion between company i and company j. This intensity of technology diffusion, together with the closeness of the technological fields of the two firms ($\mathbf{tech_{i,j,t}}$), determines the level of knowledge transfer, and hence the level of technology spillovers between firms i and j. The total technology spillovers between local firms i and all other foreign firms at a given time reflect the total FDI technology spillovers faced by local firms i at a given time. The sum of technology spillovers between local firm i and all other foreign firms reflects the total FDI technology spillovers faced by local firm i at a given time. Therefore, the higher the value of $\mathbf{Spilltech_{it}}$, the larger the technology spillover effect of FDI to local firms.

FDI market competition effect ($\mathbf{spillsic_{it}}$): Similarly constructing variables to measure the effect of competition in the market.

$$spillsic_{it} = \sum_{j}^{J} sic_{ijt} * RD_{jt} \tag{4}$$

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Similarly, where $\mathbf{sic_{ijt}}$ denotes the correlation between the sales share of local firm i and foreign firm j in each industry in year t. The formula is as follows:

$$sic_{ijt} = \frac{S_{it}S'_{jt}}{(S_{it}S'_{it})^{0.5}(S_{jt}S'_{jt})^{0.5}} \tag{5}$$

$\mathbf{S_{it} = (S_{i1t}, S_{i2t}, \cdots, S_{ikt}, \cdots, X_{iKt})}$ is firm i's share of sales in each industry up to year t ($\mathbf{k = 1, 2, \ldots, K}$). The larger the value of **spillsic**, the higher the market competition effect between the two firms.

Human capital level(super_inventor): Referring to existing studies [7][9], super_inventor is defined as the number of super-inventors owned by a local firm. Superstar inventors are defined as inventors whose quality of patent generation observed in the sample exceeds that of their peers. The top 5% are considered superstar inventors by ranking the average number of citations to their patents over the same period for all inventors in year t+3. In a particular year, the percentage of patents having superstar inventors is used to determine a company's superstar percentage. The ratio of superstar inventors to the total number of inventors on a patent is used to determine the superstar inventor score for that patent if it has multiple inventors. A company has more highly competent human capital amassed if it has a larger number of star innovators.

Control variables: Referring to existing studies [7][10], R&D investment, firm size, cash-to-assets ratio, book-to-market ratio, financial leverage, return on assets, price-to-book ratio, Tobin's Q, and capital expenditure variables were used as control variables.

3. Results

3.1. Baseline regression analysis

The results of the impact of FDI technology spillovers on the overall innovation level of local firms in the manufacturing sector are displayed in Table 1, without distinguishing the type of innovation. Where equations (1) and (2) represent the baseline results of FDI technology spillover (ln_spilltech) on the number of patent applications (ln_patent_count) and the number of patent citations (ln_citation_count) of firms without control variables, respectively; and equations (3) and (4) subsequently add control variables.

The coefficients of ln_spilltech in equations (1) and (3) are all positive at the 1% significance level. The coefficients of ln_spilltech in equations (2) and (4) are positive at the 5% significance level, thus confirming that FDI technology spillovers have a significant positive impact on the overall innovation level of local firms in the host country.

Table 1: Impact of FDI technology spillovers on the overall level of innovation.

	(1) $\text{ln\_patent\_count}_{t+1}$	(2) $\text{ln\_citation\_count}_{t+1}$	(3) $\text{ln\_patent\_count}_{t+1}$	(4) $\text{ln\_citation\_count}_{t+1}$
ln_spilltech_t	0.038***	0.035**	0.035***	0.031**
	(2.88)	(2.26)	(2.66)	(2.03)
ln_spillsic_t	0.014***	0.017***	0.013***	0.015***
	(3.40)	(3.02)	(3.12)	(2.80)
control variables	No	No	Yes	Yes

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Table 1: (continued).

	(1) $ln\_patent\_count_{t+1}$	(2) $ln\_citation\_count_{t+1}$	(3) $ln\_patent\_count_{t+1}$	(4) $ln\_citation\_count_{t+1}$
$cons_t$	1.318***	1.044***	0.429	-0.942
	(4.92)	(3.32)	(0.52)	(-1.02)
N	13705	13705	13704	13704
Adjuster R^2	0.677	0.591	0.682	0.593
firm FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes

3.2. The Mechanism of FDI Technology Spillovers on Human Capital of Local Firms

The median FDI technology spillover was used to divide the sample into two groups for group regression. It is found that in the sample with larger technology spillover, FDI technology spillover (ln_spilltech) negatively affects the proportion of super inventors in local firms, a result that holds at the 5% significance level. On the contrary, no statistically significant impact is developed in the subgroups with smaller technology spillovers. The p-value of the difference in coefficients between the groups indicates a significant difference at the 10% level. This result suggests that local firms, when faced with relatively large FDI technology spillovers, reduce the firm's accumulation of star inventors.

Table 2: The Impact of FDI Technology Spillovers on Star Inventors.

	(1) super_inventor		(2) super_inventor
ln_spilltech	-0.001		-0.004**
	(-0.61)		(-2.17)
ln_spillsic	0.000		-0.000
	(0.97)		(-0.12)
control variables	Yes		Yes
cons	-0.001		-0.004**
	(-0.61)		(-2.17)
N	6538		6390
Adjuster R^2	0.179		0.241
Chow test p-value		0.073(*)	
firm FE	Yes		Yes
year FE	Yes		Yes

4. Conclusion

This paper analyzes the impact of FDI technology spillovers on the dichotomous innovation capacity of local manufacturing enterprises in the host country, and draws the following relevant conclusions: FDI technology spillovers have a certain impact on the innovation level of local enterprises in the host country. Specifically, FDI technology spillovers promote the overall innovation level and utilization innovation level of Chinese manufacturing local enterprises, but inhibit the level of exploratory innovation. FDI technology spillovers cause local enterprises to reduce their investment in high-skilled human capital, which may be one of the impact mechanisms by which FDI technology spillovers inhibit the exploratory innovation of enterprises.

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