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Technology Spillovers of FDI and Their Determinants: Evidence from China

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[ABSTRACT]
This paper aims at estimating the technological impact of FDI in China with an eight-year balanced industry level panel data set. Compared with previous studies, this paper allows for the impact of FDI to vary across time and industries, and in addition this paper also examines how the three factors, namely the technology gap, relative factor intensity, and relative labor supply, affect the technological impact of FDI. It is found that on average the FDI exerts a negative impact on domestic industries' productivity and for a 1% increase in the technology transfer by FDI, domestic industries' productivity will decrease by 0.1114%. However, through learning, domestic industries are handling the FDI's challenge better and better as time goes by. The technology gap is found to play a negative role in the happening of technology spillovers, and the relative factor intensity and relative labor supply play a positive role.

[KEY WORDS] Technology Spillovers, FDI, China

JEL Classification: F2, O1, O3

1. Introduction

In addition to serving as a part of physical capital accumulation, one major contribution of the foreign direct investment (hereafter FDI) is the potential technology spillovers to domestic firms, which is an important area in the studies of FDI. The aim of this paper is to test the technology spillover effect of FDI inflow in China and its determinants, using an industry level data. Our study is different from previous research in that we allow for the impact of FDI to vary across time and industries, and use a proxy for technology transfer of FDI, which, different from the commonly used proxy for FDI, allows us to alleviate the problem of round-tripping FDI in China.

The empirical testing of spillover effect of FDI has much mixed results in the sense that some find positive spillovers, while others find negative spillovers or nonexistence of spillovers. For example, Caves (1974), Chuang & Lin (1999), Sinani & Meyer (2004), Branstetter (2006), and Kohpaiboon (2005) find positive spillovers of FDI in Australia, Taiwan, Estonia, the United States, and Thailand respectively, while Aitken & Harrison (1999) and Sadik & Bolbol (2001) find negative evidence in Venezuela and five Arab countries respectively[①]. However, in regard to mainland China, most of studies find positive technology spillover effect by FDI, for example Li et. al. (2001), Liu (2002), Buckley, Clegg, & Wang (2002), Cheung & Lin (2004), and Chuang & Hsu (2004). Liu (2008) finds that an increase in FDI lowers domestic firms' short-term productivity level, but raises their long-term rate of productivity growth.

This paper is organized as follows. Section 2 discusses the estimation approach and data sets that are commonly used in previous studies. Section 3 gives an overview on the FDI inflow in China. Section 4 proposes the analytical framework used in this study; Section 5 deploys the econometrical specification and hypothesis testing of the analytical framework. Section 6 presents the data set and constructs variables used in the estimation. Section 7 is the estimation results and relevant discussions. Section 8 concludes.

2. Estimation Approach and Data Sets

The previous empirical studies can be summarized from three aspects: the methodology, the data set, and some issues that shall be paid attention to in testing the spillover effect.

First, at the aspect of methodology, the commonly used method is to regress the proxy of technology, the labor productivity or the total factor productivity, against the proxy for FDI, usually called foreign presence, by controlling for the relevant factors that have a direct effect on the proxy of technology, such as the capital intensity and human capital etc. By doing so, it is implicitly assumed that there exists

[①] A more complete survey of empirical studies on technology spillovers of FDI can be found in Gorg & Greenaway (2004).

a production function for the firm/industry and its technology is a function of relevant factors, such as the FDI, the market concentration, the technology gap, and human resources etc, in which the FDI is the variable of interest. The significance and magnitude of the coefficient of FDI is the focus of the study. Thus it is important to choose an appropriate proxy for the FDI.

Conventionally, there are three kinds of proxies for FDI, which are also called foreign presence, i.e. the share of foreign owned firms' equity in the whole industry, the share of foreign owned firms' employment in the whole industry, and the share of foreign owned firms' production in the whole industry. For these three proxies, there are different deficiencies in them. For the share of foreign owned firms' equity in the whole industry, it is argued that FDI tends to flow into the capital intensive industry, particularly in the developing countries. Hence, this measurement of FDI will usually over-estimate the presence of FDI. Besides, the capital share is also easily distorted by the host country's ownership restriction (Kohpaiboon 2005). For the share of foreign owned firms' employment in the whole industry, the similar argument applies, i.e. the FDI tends to invest in more capital-intensive industry and compared with their counterparts they are usually less labor intensive, and thus it will underestimate the presence of FDI (Kohpaiboon 2005). For the share of output of foreign owned firms in the whole industry, it is argued that since the dependent variable is the productivity, which usually is calculated from the output, it is thus more appropriate to measure the foreign presence by inputs (Caves 1974). In one word, these three proxies always distort the true measurement of foreign presence, and unless the distortion is uncorrelated with the explanatory variables, the estimation will always be biased and inconsistent. The kind of distortions may also contribute to the mixed empirical results, and to some extent make the estimation results sensitive to the choice of FDI proxy (Gorg & Strobl 2001).

For the productivity, the proxy of technology, it is also argued that the conventional measure reflects not only the technical efficiency, but also the market power (Branstetter 2006). In the process of empirical estimation, it shall also be noted that the gross output data is preferable to the value-added data since the value-added is calculated by assuming a competitive market and constant return to scale and thus tends to make a spurious relation between productivity and spillover (Basu & Fernald 1995).

In addition to the widely used approach, other approaches include, for example Branstetter (2006) and Sadik & Bolbol (2001). The approach of Branstetter (2006) differs with the traditional approach in that different proxies for the technology of FDI are used. In Branstetter's analysis, the patent citation is used as a proxy for the technology. This excludes other technology such as secret technical know-how. Besides the definition of technology spillovers is also too narrow in the sense that only the spillovers that lead to innovations are treated as spillovers. Thus, Branstetter's approach underestimates the true technology spillovers from FDI in the host country. Sadik & Bolbol (2001) adopted a growth accounting framework to study the technology spillovers from incoming FDI. In their approach, FDI is treated as part of the domestic capital stock, and at the same time it also has an effect on the technology of the production function. The potential problem comes from the poor fit of the growth accounting method for the reality, as is seen that the R square of Sadik & Bolbol's study is very low, which indicates that some important factors are left out.

Second, at the aspect of data set, either the cross-sectional or panel data sets are used in these studies, and these data sets are either on a firm level or on an industry level. So this is a two dimension issue. For the cross-sectional data set, the major problem is that it tends to overestimate the magnitude of technology spillovers. As found in Gorg & Stroble's (2001) studies, using cross-sectional data set finds systematically more technology spillovers from FDI than those studies using panel data set. One reason is that there is usually reverse causality from productivity to FDI, i.e. not only the presence of FDI may increase the productivity of domestic firms, but also FDI often tends to flow into the industry with higher productivity. The solution to this reverse causality problem is either to find a instrumental variable, which seems rather difficult in reality in that the variables that are correlated with FDI usually are also correlated with the productivity, or to use simultaneous equation system, which is not used by all previous studies that employ a cross-sectional data set. In contrast, in addition to the usual advantages, such as it can increase the degree of freedom and reduce the multi-collinearity problem (Hsiao 2003), the panel data set can also accommodate the reverse causality problem easily, for example by using the lagged FDI as the instrument. Besides, the technology spillover itself has a dynamic nature, i.e. the technology spillovers usually happen through time. This means the cross-sectional data set may not be able to capture all relevant aspects of technology spillovers. In this sense, the panel data set is preferable to the cross-sectional data set.

The other dimension concerning the data set is the aggregating level. As argued by Caballero & Lyons (1989), the spillover at a lower aggregating level may be internalized at a higher aggregating level, which means if the lower aggregating level gives a correct estimation of magnitude of technology spillovers then the higher aggregating level will probably underestimate the magnitude, and vice versa. Thus, the estimation by using firm-level (disaggregating) data set and industry-level (aggregating) data set will tend to present contrasting results. Compared with the firm-level data, the industry-level data is unable to control for differences in productivity across sectors which might be correlated with, but not caused by, foreign presence (Aitken & Harrison 1999). However, from the researchers' point of view, industry level data are often much easier to obtain than firm level data, because industry level data usually are published officially while firm level data are often census data.

Third, there are other issues that are worthy of attention in the estimation. As argued by Gorg and Strobl (2001), a proper definition of foreign presence, proxy for FDI, is important to capture the technology spillover effects. The conventional measurements all have some deficiencies. Thus while using these proxies, the specific situation from which the data come should be examined carefully. For example in the country where the ownership is restricted, the capital share should not be used. One alternative is to use the number of affiliates of MNCs which is weighted by measures of the size of the affiliates, as Branstetter (2006) used. Another alternative is to construct the proxy for technology transfer of FDI, as is done in this study. Moreover the appropriate control variables should be selected carefully. The technology is transferred across country boundaries via several channels, which are the international trade, particularly trade of capital goods, the technology licensing, and FDI (Pack & Saggi 1997). Technology spillovers may take place in all three channels. Thus it is better to control for the other two channels while studying the third channel[②]. In the meantime factors that directly contribute to the development of technology, such as the capital intensity, will also be controlled.

3. Overview of FDI in China

3.1 Growth trends

Since the opening and reform in 1979, China has become a major recipient of FDI inflow. From 1985 to 2004, the average annual FDI inflow growth rate is as high as 15.2 per cent. In 2004, the inflow of FDI reached 60.6 billion US $. Figure 1 presents a picture of China's economic growth and FDI inflow since 1985. The bars in the figure represent the annual growth rate of GDP and FDI inflow. We can see that they have a similar trending pattern. The correlation between the annual growth rate of GDP and FDI inflow is as high as 0.7. This demonstrates that FDI inflow in China contributes to its economic development[③]. The curve in the figure shows the trending of FDI inflow, which indicates that except in 1998-99 FDI inflow in China has always kept a growing trend while the decline of FDI inflow in 1998-99 happened only because of a political event that undermined foreign investors' confidence in the government's policy.

<insert Figure 1 here>

FDI is also an important part in the formation of fixed capital asset. Figure 2 shows the contribution of foreign capital. Since 1981, the foreign capital on average takes account of 6.3 per cent of the total fixed capital asset formation annually. Except from 1994 to 1999, the contribution of foreign capital appears to fluctuate around 5 per cent. Given the large scale of physical capital accumulation in China, 5 per cent is not a negligible number.

<insert Figure 2 here>

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② However due to the data constraint, we are not able to do so in this paper.

③ Meanwhile it is also possible that that higher economic growth rate and bigger economy will attract more FDI inflow. Hence this tells nothing about the direction of causality.

3.2 Industry distribution

The major characteristic of FDI's industry distribution in China is its focus on the manufacturing sector. The manufacturing sector has always taken the first position in taking the FDI inflow. From the stock perspective, the manufacturing sector is the biggest recipient of FDI inflow in China, which roughly takes account of 2/3 of China's total FDI stock. The real estate industry accounts for about 21 per cent of total FDI stock, and other industries account for about 8 per cent of total FDI stock (MOFCOM 2005). In contrast, the FDI inflow in the service trade industries takes a much slower progress. For example, FDI inflow in all sectors in 2004, except in the service trade industries, grew positively, while FDI inflow in the service trade industries suffered a negative growth. Figure 3 presents an industry distribution of FDI in China in 2004. The manufacturing sector along accounted for 71 per cent of actually utilized FDI in the year.

<insert Figure 3 here>

One reason for the focus on the manufacturing sector of FDI inflow in China may be attributed to the government's policy emphasis. In order to optimize its industry structure, China's central government has launched the Guidance Category for Foreign Investment in China since 1995, which classified all industries into four categories: the encouraged, allowed, restricted, and prohibited. Many sub-industries of the manufacturing sector fall into the encouraged category.

This kind of classification also brings the potential problem for empirical FDI studies in China, the endogeneity problem. If the standard of the classification is set according to the growth prospects of industries, for example high growth industries are classified as being encouraged, then FDI inflow will self-select into the high growing industries. It is also possible that the standard happens to be correlated with the growth prospect of industries. For example the high-tech industries are usually encouraged, but high-tech industries also usually grow more quickly than other industries. However, as will be discussed in Section 7, the endogeneity test by using instrument variables finds no evidence of the endogeneity problem.

3.3 Problem of fake FDI

Another issue in the empirical studies on FDI in China is the round-tripping FDI problem, which is also called fake FDI. China offers many policy privileges to FDI invested firms, including low tax rates, favorable land use rights, convenient administrative support, and favorable financial services from domestic and foreign financial institutions (Xiao 2004). This gives domestic capital a large incentive to first flow out and then return, pretending to be FDI, in order to make use of various privileges offered by both central and local governments. According to a World Bank's estimation (2002, cited in Xiao 2004), the round-tripping FDI inflow could be as high as one quarter of total FDI inflow. The estimate of Xiao (2004) is even higher, 40 per cent of total FDI inflow.

Compared with true FDI inflow, the round-tripping (fake) FDI inflow also serves as a kind of capital accumulation. Nevertheless, it is doubtful that it will have the same technology effect as the true FDI inflow. Hence, in measuring the technology effect it is better to distinguish the fake FDI. However, due to lack of information and data, it is difficult to completely distinguish them. One simple approach is to look at the source country of FDI inflow since the domestic capital usually flows out to countries and regions that have less control on capital movement. If the FDI inflow comes from developed countries, it is more likely that it is true FDI. If the FDI inflow comes from offshore financial centers or countries and regions that enjoy a reputation of less capital movement control, then it is more likely that it is fake FDI. Table 1 shows the top 10 source countries and regions in 2001, 2002, and 2003. We can see that the FDI inflow from the Virgin Islands ranked top 2 consecutively in 2001, 2002 and 2003; FDI from Cayman Islands ranked top 9 in 2001 and top 8 in 2002 and 2003; and FDI from Samoa which is not reported in the table ranked top 11 in 2002 and top 10 in 2002 and 2003. Altogether, FDI from these three regions accounted for 14.2 per cent, 15.5 per cent, and 15.3 per cent in 2001, 2002 and 2003 respectively. Considering that these regions have less control over capital movement, it is reasonable to suspect FDI from these regions is more likely to be round-tripping.
<insert Table 1 here>

4. Analytical Framework

In an industry composed of domestic firms and multinational companies' affiliates, the output of the industry is described by an aggregate Cobb-Douglas production function, as:

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

where Y is the output; K is the stock of domestic physical capital and FDI; A is the technology; and L is the labor supply. In addition to the direct contribution of FDI as a part of the capital stock, it also exerts indirect impact on the output through the technology A, namely the potential technology spillovers. Hence the technology A in the industry depends on the technology brought by FDI, and is assumed as:

$$A = \left(A_f\right)^B \tag{2}$$

where A_f denotes the technology brought by FDI, namely the technology transfer from FDI. A_f is subject to an efficiency parameter B, which can be used to measure the existence of spillovers.

The technology spillovers exit if the technology transfer of FDI triggers a positive domestic technology accumulation. Hence the technology spillovers can be measured by the elasticity of domestic technology with respect to the technology brought by FDI ($\dfrac{\dot{A}/A}{\dot{A}_f/A_f}$, where A denotes technology stock and the subscript f denotes the technology brought by FDI). If the elasticity is positive, then the technology transfer of FDI generates positive domestic technology accumulation, and thus there exists technology spillovers from FDI. From equation (2), $\dfrac{\dot{A}/A}{\dot{A}_f/A_f} = B$. Therefore, the spillovers exist if and only if $B > 0$.

Since the parameter B denotes how efficient the domestic industry can utilize the technology brought by FDI, and can measure the existence of technology spillovers, B will be endogenously determined. Thus it is assumed to be determined by the interaction between representative domestic firms and FDI invested firms, as:

$$B = f(x_1, x) = \log\left(x/x_1 \right)$$

s.t

$$\frac{\partial f}{\partial x_1} < 0 \quad \frac{\partial^2 f}{\partial x_1^2} \geq 0 \qquad \text{(a1)}$$

$$\frac{\partial f}{\partial x} > 0 \quad \frac{\partial^2 f}{\partial x^2} \leq 0 \qquad \text{(a2)}$$

$$\frac{\partial^2 f}{\partial x_1 \partial x} \leq 0 \qquad \text{(a3)}$$

where x_1 is the research effort (expenditure on the research and development) of FDI invested firm (carried out in its parent firm and thus exogenous), and x is the research effort of domestic firm. The assumption (a1) says that the coefficient B will decrease with the increase of FDI invested firm's research effort, and the speed of decreasing will accelerate as the increase of x_1. The higher the FDI-invested firm's research effort, superior its technology level is, and the larger the technology gap will be[4]. Thus it is then more difficult for the domestic firm to learn from a FDI-invested firm and in turn the less the spillover effect will be. Furthermore, as x_1

[4] In regard to the role of technology gap in the spillovers, there is one thought that the bigger the technology gap, the quicker the catchup, i.e. a sort of convergence, for example Findlay (1978). However, there are some empirical studies supporting the thought that smaller technology gap makes larger technology spillovers, for example Chuang & Hsu (2004) and Li et.al. (2001).

increases, the marginal increase of degree of difficulty will become larger. Assumption (a2) says domestic firm's research effort is positively related to the spillover effect, but this positive relation is subject to decreasing speed. Assumption (a3) says that there is a substitution effect between the domestic research effort and FDI invested firm's research effort. By firms' profit maximization, we can derive the optimal behavior of domestic firm's research efforts.

To do so, suppose firms are endowed with fixed resources, capital K and labor L, for simplicity⑤. The firm's problem is to decide the allocation of the endowment between the research and development (R&D) and production, in order to maximize its profit. The role of R&D is to increase the productivity in the production process. The firm is faced with a linear market demand, $p = a - bQ$, and exogenous factor price, w (labor wage) and r (real interest rate). The firm's production function is $Q = Q(k_1, l_1, X)$; the R&D function is $x = x(k_2, l_2)$; the firm's total cost (opportunity cost) is $TC = Kr + Lw$, which is fixed; the resource constraints are: $k_1 + k_2 = K$ and $l_1 + l_2 = L$, where the subscript 1 denotes resources (capital and labor) used in production, and 2 denotes resources used in R&D.

Then the firm's problem is to:

$$\max_{\{k_1, l_1, k_2, l_2\}} \pi = [a - bQ(k_1, l_1, x(k_2, l_2))]Q(k_1, l_1, x(k_2, l_2)) - TC$$

s.t. $k_1 + k_2 = K$, and $l_1 + l_2 = L$.

Solving the problem, we can obtain:

$$Q_{k_1}^{'} = Q_x^{'} X_{k_2}^{'}$$

$$Q_{l_1}^{'} = Q_x^{'} X_{l_2}^{'}$$

which says the marginal product of capital/labor used in production should be equal to the marginal product of capital/labor used in R&D.

Then in order to solve for k_2 and l_2 explicitly, functional forms of production and R&D are specified. Following the convention, the Cobb-Douglas functional form is assumed, as follows:

⑤ To maximize the profit, the firm is faced with a two-stage problem. At stage 1, it decides how many resources (capital and labor) to buy in the factor market. Then at stage 2 it decides the allocation of resources between R&D and production. However, here the stage 1 problem is abstracted away.

$$Q = k_1^{\alpha} l_1^{\beta} x$$

$$x = A^{\lambda} k_2^{\gamma} l_2^{\eta}$$

Hence, we can solve for k_2 and l_2 as:

$$k_2 = \frac{\gamma}{\alpha+\gamma} K, \quad l_2 = \frac{\eta}{\beta+\eta} L$$

Then the optimal research effort of domestic firms is:

$$x = CA^{\lambda} K^{\gamma} L^{\eta}$$

where $C \equiv \left(\frac{\gamma}{\alpha+\gamma}\right)^{\gamma} \left(\frac{\eta}{\beta+\eta}\right)^{\eta}$.

The similar reasoning can be applied to determine the optimal level of the research effort of FDI-invested firms. We can find $x_w = CA_w^{\lambda} K_w^{\gamma} L_w^{\eta}$, where the subscript *w* denotes the world. Thus:

$$B = -\lambda \log\left(\frac{A_w}{A}\right) + \gamma \log\left(\frac{K/L}{K_w/L_w}\right) + (\eta - \gamma)\log\left(\frac{L}{L_w}\right) \quad (3)$$

where the subscript *w* denotes the world.

Equation (3) is says the efficiency parameter B is determined by three components: the technology gap, the relative capital-labor ratio (relative factor intensity), and relative labor supply[⑥]. The technology gap A_w/A has a negative impact on B. The larger the technology gap, the less capability the domestic industry has to absorb technology transferred. From Equation (3), $\frac{\partial B}{\partial \log(A)} = \lambda > 0$, which says that if a country has larger technology stock, it will be easier to use the foreign technology. This is consistent with the effect of the learning curve. The relative capital-labor ratio, $\frac{K/L}{K_w/L_w}$, characterizes the comparison of characteristics between the foreign

⑥ It should be noted that equation (3) implicitly assumes the domestic and foreign R&D functions have same parameters.

country and host industry[7]. If the spillover effect is driven by economic fundamentals, the capital-labor ratio is able to capture these economic fundamentals. Capital and labor here proxy the economic environment in the industry. Equation (3) says that if the capital-labor ratio at home is higher than that in the world, then domestic firms will be more capable of using technology introduced through FDI because the economic environment at home is better than the rest of the world. If this ratio is less than 1, it means domestic industry is not able to make full use of the technology brought in through FDI. The relative labor supply, L/L_w, may have a positive/negative/insignificant impact on B, which depends on the parameters of R&D function.

5. Econometric Specification and Hypothesis Testing

Plug equation (2) and (3) into equation (1), and take log at both sides, we can get:

$$\log Y = -\lambda \log \frac{A_w}{A} \log A_f + \gamma \log \frac{K/L}{K_w/L_w} \log A_f + (\eta - \gamma) \log \frac{L}{L_w} \log A_f + \alpha \log K + \beta \log L$$

Hence, the econometric specification can be written as:

$$\begin{aligned} \log(Y_{it}) &= \beta_0 + \delta_1 \log A_{f,it} \times \log rA_{it} + \delta_2 \log A_{f,it} \times \log rK_{it} \\ &+ \delta_3 \log A_{f,it} \times \log rL_{it} + \beta_1 \log K_{it} + \beta_2 \log L_{it} + v_{it} \qquad (4) \\ v_{it} &= \alpha_i + \lambda t + \gamma t^2 + u_{it} \end{aligned}$$

where the subscript i denotes the industry, the subscript t denotes time, rA denotes the technology gap, $rA = \frac{A_w}{A}$, rK denotes the relative factor intensity, $rK = \frac{K/L}{K_w/L_w}$, and rL denotes the relative labor supply, $rL = \frac{L}{L_w}$, and in the composite error term v_{it} we allow for the industry fixed effect (α_i), which controls for the industry heterogeneity in production and technology accumulation, and potential time constant omitted variables, a nonlinear time trend ($\lambda t + \gamma t^2$) which can control for other potential time varied omitted variables and is also adopted by Chow and Lin (2002), and an i.i.d. normal idiosyncratic errors (u_{it}).

In Equation (4), testing the existence of technology spillovers from FDI follows two

[7] For the determinants of technology spillover of FDI, Blomstrom & Kokko (1998) had a discussion on this.

steps: first test the joint significance of δ_1, δ_2, and δ_3. If there are jointly insignificant, then the technology spillovers do not exit. Secondly, differentiate Equation (4) with respect to $\log A_{f,it}$, we obtain the technology transfer elasticity:

$$\varepsilon = \delta_1 \log rA_{it} + \delta_2 \log rK_{it} + \delta_3 \log rL_{it} \tag{5}$$

where ε denotes the technology transfer elasticity. Plug the estimated δ_1, δ_2, and δ_3 in to Equation (5), and evaluate it at the industry's technology gap (in log form), relative factor intensity (in log form), and relative labor supply (in log form). If the evaluated elasticity is positive, then we conclude there exist technology spillovers from FDI as the technology transfer of FDI generates positive impact on domestic productivity. Equation (5) shows the elasticity depends on three factors: the technology gap, relative factor intensity, and relative labor supply, which can be different across industries. Hence the specification in Equation (4) allows for the possibility that FDI may have different impact in different industries and different time periods. This possibility is not accommodated for by most of previous studies.

In Equation (4), we can also examine the role of the technology gap, relative factor intensity, and relative labor supply in the industry's utilization efficiency of the technology transfer by FDI[⑧]. Differentiate Equation (5) with respect to $\log rA_{it}$, $\log rK_{it}$, and $\log rL_{it}$ respectively, we obtain $\frac{\partial \varepsilon}{\partial \log rA_{it}} = \delta_1$, $\frac{\partial \varepsilon}{\partial \log rK_{it}} = \delta_2$, and $\frac{\partial \varepsilon}{\partial \log rL_{it}} = \delta_3$. Hence the sign and significance of estimated δ_1, δ_2, and δ_3 will show the impact of the technology gap, relative factor intensity, and relative labor supply. As shown in the above, we expect the technology gap to play a negative role, i.e. δ_1 is negative, and the relative factor intensity to play a positive role, i.e. δ_2 is positive. No prior expectation can be made in regard to the role of the relative labor supply.

6. The Data

6.1 Summary of the original data set

The data set is an eight-year panel from 1995 to 2003, which comes from *China Statistical Yearbook* 1996-2004, and UNIDO INTSTAT3 database, 2004. It covers 23 industries in the manufacturing sector. However the 1998 data is not included due to

[⑧] In the case where the technology spillovers do happen (i.e. $\varepsilon > 0$), then we are actually examining the determinants of technology spillovers.

lack of FDI data.

The data that comes from *China Statistical Yearbook* contains the gross value of output in current price, value added in current price, number of employees, original value of fixed assets, annual balance of net value of fixed assets, and working capital. The data that comes from UNIDO INTSTAT3 database, 2004, contains the output value and value added in nominal US dollar, number of employees, and gross fixed capital formation in nominal US dollar. These four variables are used to construct the proxy for technology transfer by FDI, technology gap, relative factor intensity, and relative labor supply.

6.2 Construction of variables

There are nine variables included in the econometric analysis, namely the real value added, real capital stock, number of employees, proxy for technology transfer, technology gap, relative factor intensity, relative labor supply, time which is equal to the year, and time square.

The dependent variable used in the econometric analysis is the real value added, obtained by deflating the value added in current price using implicit deflators, which are the ratios of the gross output in current prices and in constant 1990 prices that are obtained from *China Statistical Yearbook of Industrial Economy* various issues. The number of employees is used to proxy for the labor supply, which even though is not the best measurement is the only available information.

The real capital stock is constructed closely following Liu (2002), in which Chow's method (1993) is employed to construct the real fixed capital stock that is then added to the real working capital to form the real capital stock. In constructing the real fixed capital stock, the nominal newly added fixed assets in each year is calculated[9], which is then deflated by the price index of investment in fixed assets obtained from *China Statistical Yearbook* to 1991 price. Then the initial real capital stock is assumed to be the deflated annual balance of net value of fixed assets in 1995. The annual real fixed capital stock is the sum of previous year's fixed capital stock and the annual increment. As argued by Liu (2002), it is not reasonable to exclude the working capital from the real capital stock as the size of working capital is substantial relative to that of fixed capital. Hence, the nominal working capital is then deflated to 1991 price using the ex-factory price index of industrial products obtained from *China Statistical Yearbook*. The deflated working capital is then added to the fixed capital stock to form the real capital stock.

In constructing the proxy for technology transfer by FDI, technology gap, relative factor intensity, and relative labor supply, the data from the UNIDO INTSTAT3

[9] Even though the 1998 FDI series is not available, other series such as the original value of fixed assets and working capital in 1998 are still available. Hence the construction of real capital stock is not affected by the unavailability of 1998 FDI serires.

database, 2004, is needed. However, due to the different industry classification methods[10], we must first reconcile these two industry classification methods. Table 2 presents the match between China's industry classification and the ISIC 3 digit. Moreover, all data that come from the UNIDO INTSTAT3 database, such as the output value, value added, and gross fixed capital formation, are deflated to the 1995 price before using them to construct the above four variables, by using the producer price index obtained from the International Financial Statistics, 2004. The data from the UNIDO INSTAT3 database are two-year lagged, reflecting the possibility that technology brought by FDI is lagged, and are summation over 13 countries and regions, namely Hong Kong, the United States, Japan, South Korea, Singapore, Germany, the United Kingdom, Canada, France, Australia, Malaysia, Italy, and Indonesia. This should be able to represent the FDI inflow in China as the inflow from these 13 countries and regions accounts for over 70 per cent since 1995. Furthermore this will also help us alleviate the impact of fake FDI, as discussed in Section 2.

For the proxy for technology transfer by FDI, it is computed according the formula $A_f = \frac{D}{K^w} A^w$, where A_f denotes technology transfer by FDI, D denotes the total assets of FDI invested enterprises, K^w denotes the world gross fixed capital formation, and A^w is the world labor productivity. Assuming the technology is embodied in the capital evenly, this formula says that if the world capital is \$10, of which \$1 flows into China, then 10% of the world technology is transferred into China, as long as the machines of the \$1 are not inferior/superior to the machines of the rest \$9, i.e. the technology is evenly embodied in the capital. This proxy is robust to the incentive of FDI inflow, i.e. no matter whether the FDI inflow in China is due to China's comparative advantages or China's big domestic market, the technology transfer will be proportional to the world technology, if the FDI is of the same quality as the world capital, which is reasonable to assume.

The technology gap is the ratio of the world labor productivity over the labor productivity in China. The relative factor intensity is the ratio of the fixed capital stock per worker in China over the world fixed capital stock per worker. The UNIDO INTSTAT3 database provides the data of gross fixed capital formation, which is deflated and summed to compute the fixed capital stock, assuming the deflated value of gross fixed capital formation in the initial period to be the fixed capital stock in that period. The relative labor supply is the ratio of the number of employees in China over that of the world.
<insert Table 2 here>

6.3 Descriptive statistics
Table 3 presents the descriptive statistics for variables used in the regression analysis. We can see that the sample mean for the log value of technology gap, relative factor

[10] China uses its own national economy industry classification method, and UNIDO uses ISIC.

intensity, and relative labor supply are all positive, indicating that the world has a higher technology level, proxied by the labor productivity, and a higher capital labor ratio and labor supply, which is reasonable.
<insert Table 3 here>

7. Empirical Results and Discussions

7.1 Estimation Strategy

To estimate Equation (4), we first assume the FDI inflow in China is exogenous, and then the fixed effect and random effect estimators are applied. However, it is likely that the idiosyncratic error terms in Equation (4) are serially correlated. To check this, the Wooldridge (2002) test for AR(1) autocorrelation is adopted. The Wooldridge test regresses the residuals, obtained from the regression of the first-differenced variables, against their one-period lag, and under the null of no serial correlation in the idiosyncratic error terms the coefficient estimated is -0.5. The test statistic is the usual *t* statistic on the estimated coefficient. Drukker (2003) shows that this test has good size and power properties in reasonable sample sizes. In our test, the test statistic is 0.008 with a p-value of 0.93, and hence we conclude that there is no first order autocorrelation at 5% significance level.

The dependent variable in Equation (4) is the value added in the industry, which is very different across industries in the manufacturing sector as some industries tend to have big value added while other industries tend to have small value added. So there is potential heteroskedasticity problem. To test for this, a procedure suggested by Wiggins and Poi (2003) is adopted. Firstly, the Equation (4) is estimated using iterated generalized least square (GLS) estimator by allowing for panel-level heteroskedasticity and by assuming homoskedasticity respectively. Then these two estimations are compared with each other to see whether there is significant difference. The likelihood ratio test can be adopted to test this as the estimation assuming homoskedasticity is nested within the estimation allowing for panel-level heteroskedasticity. The test statistic we obtained, which is chi-square distributed with degree of freedom of 22, is 115.73 with a p-value of 0. Hence we reject the null hypothesis of homoskedasticity at 5% significance level. In the fixed effect estimation, we also conduct a modified Wald test for groupwise heteroskedasticity, and obtained a test statistic of 5601.92 with a p-value of 0. Hence at 5% significance level we reject the null hypothesis of homoskedasticity.

Assuming the exogeneity of FDI, Equation (4) is estimated using the fixed effect estimator and random effect estimator separately, with robust standard errors computed to account for heteroskedasticity of arbitrary form. In the fixed effect estimation, the *F* test statistic for the significance of fixed effect, namely the joint significance of industry dummies, is 6.72 with a p-value of 0, which rejects the null hypothesis of no fixed effects. For the fixed effect and random effect estimator, if the fixed effects (or the unobserved industry heterogeneity) are uncorrelated with the regressors, then the random effect estimator is more efficient than the fixed effect estimator, however if they are correlated the random effect estimator will be inconsistent. Under the assumption of conditional homoskedasticity and no autocorrelation, this can be tested by Hausman test. However due to the presence of the heteroskedasticity which is accommodated by computing the robust standard errors, the Hausman test is invalid. To determine whether the fixed effect estimator or the random effect estimator is appropriate, we conduct an "omitted variables" version of the Hausman test, which is asymptotically equivalent to the Hausman test. We first compute the time demeaned explanatory variables, the quasi-time demeaned explanatory variables and dependent variable, and then regress the quasi-time demeaned dependent variable against both the time demeaned and quasi-time demeaned explanatory variables. Under the null hypothesis that the fixed effects are uncorrelated with the explanatory variables, namely the random effect estimator is appropriate, the coefficients of time demeaned explanatory variables shall be jointly insignificant, i.e. if the random effect estimator is appropriate, the time demeaned explanatory variables shall have no explaining power. Hence a joint significance of the coefficients will reject the random effect estimator in favor of fixed effect estimator. The F statistic for the joint significance of the time demeaned explanatory variables in our test is 13.12 with a p-value of 0. Hence we conclude that the fixed effect estimator is appropriate at 5% significance level.

Up to now, the FDI is assumed to be exogenous. However, it is possible that FDI is endogenous in Equation (4), which will make the fixed effect (FE) estimation inconsistent and biased. The endogeneity problem can happen if there is a reverse causality, for example FDI tends to flow into industries that are growing more quickly, or FDI is correlated with some unobserved and uncontrolled factors that also have impact on the industry's output, for example the Chinese government's industrial policy may cause FDI to self-select into quickly growing industries. This kind of endogeneity of FDI will make three terms, $\log A_{f,it} \times \log rA_{it}$, $\log A_{f,it} \times \log rK_{it}$, and $\log A_{f,it} \times \log rL_{it}$, correlate with the idiosyncratic error term in Equation (4), which can not be eliminated by the panel data estimation technique. Hence, with the endogeneity of FDI, our estimation using FE estimator will be biased and inconsistent. To resolve the endogeneity problem of FDI, we employ the instrumental variable (IV) estimator. The key point of IV estimator is to identify the instrument of FDI that is correlated with FDI, namely the relevance of instruments, and uncorrelated with the error term, namely the validity of instruments. Conventionally the lagged endogenous variable is a good instrument. So in our IV estimation, we use the one-period lagged $\log A_{f,it}$, which is interacted with $\log rA_{it}$ (the log of technology gap), $\log rK_{it}$ (the log of relative factor intensity), and $\log rL_{it}$ (the log of relative labor supply), and the number of firms in the industry as the instruments.

The IV estimation is carried out using Schaffer (2007) procedure. In the estimation, we first test the relevance and validity of instruments. As discussed in Baum et. al. (2003), the relevance of instruments can be tested by examining the fit of the first stage regressions, for which there are three statistics, namely the Bound et al. (1995) partial R-square, the Shea (1997) partial R-square, and the F statistic for joint significance of the lagged variables and the number of firms. Table 4 presents the test statistics, which confirms that the instruments are all relevant as both the R squares are high and the F statistics are significant. For the validity of instruments (overidentifying restriction), as we have more excluded instruments than endogenous variables, we are able to test it using Hansen's (1982) *J* statistic, which is asymptotically chi-square distributed with degrees of freedom equal to the number of overidentifying restrictions. The *J* statistic we obtain is 1.441 with a p-value of 0.2299. Hence we conclude the instruments are valid at 5% significance level.
<insert Table 4 here>

As we find evidence of heteroskedasticity in the estimations assuming FDI being exogenous, it is reasonable to suspect the existence of heteroskedasticity in the IV estimation. Pagan and Hall (1983) statistic is thus computed to test the heteroskedasticity. The statistic obtained is 60.603 with a p-value of 0.0005, and hence we reject the null hypothesis of homoskedasticity at 5% significance level. Thus, the robust standard errors are computed in the IV estimator and the feasible efficient two-step generalized method of moments (GMM) estimator which is more efficient than the IV estimator if there is heteroskedasticity (Baum et. al., 2003).

The last step in our estimation process is to determine whether the IV/GMM estimators or the FE estimator is more appropriate, which is done by an endogeneity test. The endogeneity test is carried out using the *C* statistic (Hayashi, 2000, Eichenbaum et. al., 1988, discussed in Baum et. al., 2003), which tests the orthogonality of endogenous variables and is chi-square distributed. The *C* statistic we obtain is 2.951 with a p-value of 0.3992, and hence we fail to reject the null hypothesis of orthogonality of endogenous variables at 5% significance level, namely there is no endogeneity problem, which is consistent with the finding of Liu (2002). So we conclude the FE estimator is most appropriate to estimate Equation (4).

7.2 Testing for Existence of Technology Spillovers

Table 5 presents the estimation results. Columns one to five are the coefficient estimation using the FE estimator, feasible efficient two-step GMM without instruments, IV estimator, feasible efficient two-step GMM estimator with instruments, FE estimator with the dependent variable (value added), the capital and labor being the industry average respectively. In general, the estimated coefficients are robust in the sense that most of the estimate is generally within one or two

standard deviation of another estimate. Compared with the FE/IV/GMM estimations, the IV/GMM with instruments estimations get bigger point estimate of coefficients of the relative labor supply and relative factor intensity terms and smaller point estimate of the coefficient of the technology gap terms. However, as described in the above estimation strategy, we conclude that the FE estimation in the column one presents the most appropriate estimation of Equation (4). Hence, the following test for existence of technology spillovers will be based on the FE estimation in column one. In addition, compare the FE and GMM without instruments estimations, there is only negligible difference.
<insert Table 5 here>

The estimated coefficients for the capital and labor inputs are both statistically significant (0.4164 for the capital input with *t* statistic of 2.58, 0.4818 for the labor input with *t* statistic of 2.85), and the magnitude is consistent with the findings of Chow (1993), Liu (2002), and Chow & Lin (2002). The coefficients for the nonlinear time trend are both individually significant (*t* statistics for the *t* and t^2 are 6.03 and -6.03 respectively) and jointly significant (*F* statistic is 18.25 with a p-value of 0). The negative coefficient for t^2 and positive coefficient for *t* show an inverse U-shaped time trend, which implies that the manufacturing sector as a whole has experienced a positive productivity growth after the capital, labor and FDI factors are conditioned out, but this exogenous productivity growth is subject to a decreasing speed.

As described in the above, testing for the existence of technology spillovers from FDI follows two steps: first test the joint significance of coefficients δ_1, δ_2, and δ_3. The *F* statistic obtained is 61.33 with a p-value of 0, which indicates the three coefficients are jointly significant at 5% significance level. Secondly plug the estimated coefficients δ_1, δ_2, and δ_3 in to Equation (5), the technology transfer elasticity, and evaluate it at different industries' value of technology gap, relative factor intensity, and relative labor supply in different periods. If the evaluated elasticity is positive, then the technology transfer by FDI has positive impact on domestic productivity growth, namely there exists technology spillovers from FDI. Table 6 presents the evaluated elasticity across time and industries.
<insert Table 6 here>

In Table 6, a positive figure indicates the FDI has positive impact on domestic industry's productivity, and hence there exists technology spillovers. In contrast, a negative figure shows the domestic industry actually suffers from FDI's presence. Table 6 shows that a few industries actually suffer from the FDI's presence. On

average, the elasticity is -0.1114, which indicates that 1% increase in the technology transfer by FDI will decrease domestic productivity by 0.1114%. Nevertheless, Table 6 also presents several interesting dynamic patterns on the impact of technology transfer by FDI. Firstly, there are more and more industries that have positive elasticity. In 1995, there is only one industry, namely the tobacco processing industry, has positive elasticity. In 1996, 1997, 1999, 2000, 2001, 2002, and 2003, the number of industries with positive elasticity increases to 3, 3, 3, 4, 4, 7, and 20 respectively. Secondly, most industries' elasticity is increasing over time (please see figure 4 for detail), which reflects the learning effect of domestic industry. Thirdly, from 1999 to 2000, most industries' elasticity decreases, except the tobacco processing industry, the smelting and pressing of ferrous metals industry, the electric equipment, machinery, electronic and telecommunications industry, and the petroleum processing and coking industry. The decrease of elasticity in this year may come from the adverse impact of 1997-8 Asian financial crisis.
<insert Figure 4 here>

The driving force for our different estimates of technology transfer elasticity across different industries in different time periods is the technology gap, relative factor intensity, and relative labor supply. As we already show, we expect the technology gap to play a negative role, namely the higher the technology gap, the lower the spillovers will be, the relative factor intensity to play a positive role, namely the higher the relative factor intensity the higher the spillovers will be. Our estimation confirms the prior expectation. For the technology gap, the coefficient estimated is -0.2027 with a t statistic of -13.43, which is significant at 5% level and indicates that for a 1% increase in the technology gap the technology transfer elasticity will decrease by 0.2027%. For the relative factor intensity, the coefficient is 0.052 with a t statistic of 1.7, which is significant at 10% level and indicates that a 1% increase in the relative factor intensity will promote the elasticity by 0.052%. For the relative supply, our estimation shows it has positive and significant impact on the elasticity, with 1% increase in the relative labor supply promoting the elasticity by 0.0681%.

7.3 Discussions

We empirically test the technology spillovers of FDI and their determinants in China's 23 industries from 1995 to 2003. Compared with previous studies, we allow for the FDI's impact on domestic industry to vary across time and industries. We find that for most of time the FDI inflow in China has a negative impact on domestic industries, however as time goes by domestic industries are handling FDI's challenge better and better. In 2003, 20 out of all the 23 industries benefit from the FDI's presence. Furthermore, we also confirm that the technology gap and relative factor intensity play a negative/positive role in the happening of spillovers respectively.

However, is this result driven by the aggregation of industry level data? To find whether our result is sensitive to this, we re-estimate Equation (4) by FE estimator using a dependent variable of log of average industrial value added which is equal to value added divided by the number of firms in the industry, the log of average industrial capital and labor inputs which are equal to the capital and labor inputs divided by the number of firms in the industry respectively. Column (5) of Table 5 presents the estimation result. Compared with column (1), the capital and labor coefficients are smaller, but are still within reasonable range. For the three interaction terms of technology transfer, the estimated coefficients display no significant difference in the sense that they are within one standard deviation of each other. The evaluated elasticity, which is not reported but is available upon request, also displays no significant difference. Hence we conclude our estimation result is robust to the data aggregation.

In Equation (2), the domestic technology accumulation in the industry is only affected by FDI flowing into the industry, not by FDI that flows into the other industries. This means that we are only testing the intra-industry technology spillovers of FDI, not the inter-industry technology spillovers. Besides, we are also not able to distinguish horizontal FDI and vertical FDI. For these two types of FDI, the FDI-invested firms will have different power of technology control and in turn will generate different magnitude of spillovers.

8. Conclusions

In this study, we try to estimate the technology spillover effect of FDI in China and its determinants with an eight-year balanced industry level panel data. To do so, we first propose an analytical framework from which the empirical model is derived and estimated. Compared with previous studies, our study allows for the impact of FDI to vary across time and industries, and moreover we are able to empirically test the determinants by further decomposing the spillover parameter in Equation (2) into three general factors: the technology gap, relative factor intensity, and relative labor supply.

Our empirical estimations find that the FDI inflow in China in different industries generates different impact on the domestic industries' productivity. On average the FDI exerts a negative impact on domestic industry, and for a 1% increase in the technology transfer by FDI, domestic industries' productivity will decrease by 0.1114%. However, through learning, domestic industries are doing better and better. In 1995 only one industry benefits from the FDI's presence, while in 2003 there are 20 industries that benefit from the FDI's presence. Moreover even for industries that never benefit from the FDI's presence in our sample periods, the negative impact from FDI gets smaller and smaller from 1995 to 2003. This finding hints the necessity of designing specific industrial policy for FDI that suits the specific requirements of different industries in China. We also test the determinants of technology spillovers of FDI, and find the technology gap plays a negative role in the happening of technology spillovers, the relative factor intensity and relative labor supply play a positive role, which is consistent with the theoretical expectation.

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