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IN SEARCH OF DETERMINANTS OF FDI FORWARD SPILLOVERS: A META-ANALYSIS

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ABSTRACT

Drawing on a unique dataset of 530 estimates from 19 studies on foreign direct investment forward productivity spillovers in China, our prime objective is to investigate determinants of forward spillovers from foreign direct investment using Bayesian Model Averaging based Meta-Analysis. Our results suggest that forward spillovers vary across firm attributes, including the ownership structure of foreign firms, the origin of foreign firms, market orientation of foreign firms, the ownership structure of local firms and the technological levels of local firms. Specifically, wholly-owned subsidiaries yields positive technology diffusion to local firms in upstream sectors while joint ventures negative; both foreign firms from Hong Kong, Macao and Taiwan and other economies create negative spillover effects on local buyers; local-orientated foreign firms are likely to generate positive productivity spillovers while export-orientated foreign firms negative; non-state-owned enterprises are likely to benefit more forward technology spillovers from foreign direct investment than state-owned enterprises; middle-tech local firms tend to obtain more forward productivity spillovers than high-tech local firms and low-tech local firms.

Contribution/Originality: This study contributes in the existing literature on the determinants of forward spillovers from foreign direct investment using Bayesian Model Averaging based Meta-Analysis. The paper's primary contribution is finding that forward spillovers vary across foreign and local firm attributes, such as the ownership structure of foreign firms and the origin of foreign firms.

1. INTRODUCTION

With the rapid development of globalization and labor division, foreign direct investment (FDI) have been accelerating in last decades. One of the primary purposes of attracting foreign investments by host countries is to obtain advanced technology, which is so-called "market for technology" in China. FDI can bring not only abundant capital, modern technology, but also managerial and marketing skills, distribution networks and export contacts (Abraham *et al.*, 2010). More and more worldwide researchers are interested in uncovering the mechanism of FDI and also have done plenty of valuable empirical research to estimate the size of FDI technology spillover effects including horizontal spillovers and backward spillovers as well as forward spillovers. However, the previous results are mixed and inconclusive. To be more specific, the consensus is that FDI backward spillover effect is positive and significant. However, "the estimated size of these spillovers varies broadly" (Havranek and Irsova, 2011). The divergence is the determinants and magnitude of FDI spillover effects. Obviously, it is very significant to investigate the determinants of FDI spillovers for policymakers and academics. However, there are numerous factors affecting empirical results, such as econometric misspecification, firm attributes and so on.

Meta-regression analysis (MRA) provides an effective way to address above problems. Glass (1976) created the term meta-analysis as "the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings"[1]. Stanley and Jarrell (1989) initially introduced this method into the fields of economics and business. MRA approaches are emerging in economics for almost three decades, the examined topics covers the value of a statistical life (Ashenfelter and Greenstone, 2004; Doucouliagos *et al.*, 2012) the effect of common currencies on international trade (Rose and Stanley, 2005) the effect of education on economic growth (Benos and Zotou, 2014) and the effect of FDI on economic growth (Gunby *et al.*, 2017). Disdier and Head (2008) argue the MRA results as "a starting point to indicate objectively the central tendency in the prior literature". Thus, it is appropriate to treat MRA methodology as a quantitative summary of the literature.

There are merely several studies on FDI spillovers using MRA method. Gorg and Strobl (2001) investigate the influences of study design and publication bias on the results by collecting information from a sample of published and unpublished papers. They find evidence of publication bias and that study design may affect the results. Wooster and Diebel (2010) use a sample of 32 studies to determine the effects of study design and data characteristics on the magnitude, significance and direction of spillovers from FDI in developing countries. Mebratie and van Bergeijk (2013) examine the relationship between different firm heterogeneity characteristics and productivity, and argue that exports and R&D are two important sources of results heterogeneity, and find positive and significant effects of labor quality, size and export. Hanousek *et al.* (2011) find that panel studies are likely to find relatively lower spillover effects; the choice of research design, such as definition of firm performance and foreign firm presence matters. The above literature examine the source of heterogeneity of estimated spillover effects. However, the determinants of FDI forward spillovers are still unclear.

In this study we try to quantitatively search for FDI forward spillover determinants in China from the aspects of firm attributes, such as the nature of foreign-invested firms and origin of foreign-invested firms, using Bayesian Model Averaging (BMA) based Meta-Analysis. BMA is an attractive technique to accounting for model uncertainty, and its basic idea is to regress model with many different subsets of variables and make inferences based on a weighted average over model regression.[2]

2. DATA

A majority of previous studies investigates the FDI spillover effects by estimating the so-called FDI spillover regression equation, which regresses the linkages of local firms with foreign firms on their productivity:

$$\begin{aligned} \ln productivity_{ijt} &= e_0^h \cdot Horizontal_{jt} + e_0^b \cdot Backward_{jt} \\ &\quad + e_0^f \cdot Forward_{jt} + \alpha \cdot Controls_{ijt} + u_{ijt}, \end{aligned} \tag{1}$$

Where subscripts *i*, *j* and *t* refer to firm, industry and time. The dependent variable is local firm's productivity in logarithm, which is mostly measured by total factor productivity (TFP). On the right-hand-side of the equation, $Horizontal_{jt}$ is the share of foreign presence in firm i's own sector; $Backward_{jt}$ is the share of foreign presence in firm i's downstream sectors; $Forward_{jt}$ is the share of foreign presence in firm i's upstream sectors;

[1]The terms meta-regression analysis and meta-analysis are interchangeable in the literature.

[2] Zeugner and Feldkircher (2015) offer a brief summary of Bayesian Model Averaging.

$Controls_{ijt}$ is a vector of firm-specific or industry-specific control variables; u_{ijt} is the random error term. The coefficients of $Horizontal_{jt}$, $Backward_{jt}$ and $Forward_{jt}$ can be interpreted as semi-elasticities:

$$\begin{aligned} e_0^h, e_0^b, e_0^f &= \frac{\Delta \ln \text{productivity}}{\Delta \text{foreign presence}} \\ &\approx \frac{\%\text{ change in productivity}}{\text{change in foreign presence}}, \end{aligned} \tag{2}$$

where foreign presence ∈ [0, 1]. For instance, $e_0^f = 0.1$ would indicate that a 10-percentage-point increase in foreign presence can yield a 1% increase in the productivity of local buyers.

To minimize selection bias, we include both English and China empirical studies that report FDI spillover estimates of China. Literature written in English is searched in Google Scholar as Google Scholar has the strong power of full-text search, and literature written in Chinese is searched in National Knowledge Infrastructure (CNKI), which is the most widely used database for Chinese literature. We conduct searches by using the keywords such as "FDI spillovers in China", "FDI horizontal spillovers in China", "FDI vertical spillovers in China", "FDI backward spillovers in China" and "FDI forward spillovers in China". These searches primarily generate a total of more than 200 English studies and 1300 Chinese studies. For Chinese studies, since most of them are unpublished student working papers and theses, we confine our attention to the most cited published Chinese papers for each year if available.

To ensure the comparability of reported estimates across studies in meta-regression analysis, selected studies must satisfy the following three basic criteria. First, the study must report the FDI forward empirical spillover estimates of China. Second, the study must define foreign presences as a share. Third, the study must report the information on the precision of estimates (standard errors or t-statistics). Eventually we identified 19 admissible studies published from 2007 to 2016, among which 15 are English studies and the rest Chinese studies. [3] To control for outliers, we employ the multivariate method by Hadi (1994) to identify outliers in pairs of estimates and the corresponding precisions (the inverse of their standard errors). Consequently, the procedure identifies 25 outliers for forward estimates. In other words, 4.72% of forward estimates are identified as outliers. In this paper our analysis are based on results without outliers.

In this study we use firm attributes and study designs to capture potential sources of determinants of FDI forward spillovers. First, firm attributes include foreign-firm characteristics and local-firm characteristics. Foreign-invested firms can be classified by their ownership structure (wholly-owned subsidiaries (WOS) versus joint ventures (JV)) or by their origin (investors from Hong Kong, Macao and Taiwan (HMT) versus that from other countries (non-HMT)) or by market orientation of foreign-invested firm (local-orientated and export-orientated). Local firms can be divided by their ownership structure (state-owned enterprises (SOEs) versus non-state-owned enterprises (non-SOEs)) or the technological levels of local firms (High-tech, Middle-tech and Low-tech). Second, following Havranek and Irsova (2011) study designs include data characteristics, specification characteristics, estimation characteristics and publication characteristics. Eventually, we collect 43 explanatory variables to capture firm attributes and study designs, among which 11 variables are firm attributes and the rest study designs.[4] In search for forward spillover determinants we focus on the firm attributes in China.

[3] The list of 19 admissible studies can be available on request.

[4] He, Kwan and Fan (2018) offer a detailed description about these 43 variables.

3. METHODOLOGY

Publication bias arises from the preferences of "statistically significant" empirical results or results that are consistent with the conventional theories by researchers or editors. It is widely recognized as a serious issue that will distort statistical inference in empirical research (Card and Krueger, 1995). As guaranteed by random sampling theory, estimates and their associated standard errors will be independent if there is no publication bias (Stanley and Doucouliagos, 2012). On the contrary, there is a systematic pattern between the reported estimates and their corresponding standard errors if there is publication bias:

$$e_i = e_0 + \beta_0 \cdot Se(e_i) + u_i, \tag{3}$$

Where e_i refers to the reported forward spillover effect; e_0 is the publication bias-corrected forward spillover effect; $Se(e_i)$ is the standard error of the reported forward spillover effect, and u_i is random error term. In Equation (3) β_0 measures the extent of publication bias and the term $\beta_0 \cdot Se(e_i)$ can serve as a bias-correction factor. The error term u_i is heteroskedastic by construction because its conditional standard deviation is $Se(e_i)$. Thus, to construct homoscedastic error term, we apply weighted least squares (WLS) by dividing Equation (3) with $Se(e_i)$:

$$e_i / Se(e_i) \equiv t_i = \beta_0 + e_0 \cdot 1/Se(e_i) + \xi_i, \tag{4}$$

Where t_i is the t-statistic of the estimated spillover effect; $1/Se(e_i)$ is the corresponding precision; and the transformed error term $\xi_i = u_i / Se(e_i)$ is by construction homoskedastic. The presence of publication bias and genuine forward spillover effect can be assessed by testing the null hypotheses $\beta_0 = 0$ and $e_0 = 0$, respectively. Our aim is to investigate determinants of forward spillovers, so we rewrite (Equation 4):

$$e / Se(e_i) \equiv t_i = \beta_0 + e_0 \cdot 1/Se(e_i) + \gamma \cdot Determinants + \lambda \cdot Controls + \varepsilon_i \tag{5}$$

Equation (5) is the so-called "multivariate meta-regression" (Stanley and Doucouliagos, 2012). $Determinants$ refers to the 11 potential forward spillover determinants from firm attributes, which should be included in the regression; $Controls$ refers to control variables from study designs, which may be included in the regression. Both $Determinants$ and $Controls$ are those explanatory variables that are divided by the corresponding standard errors.

However, there are 32 control variables in multivariate meta-regression, and it is usually not clear that which control variable matters. According to Moral-Benito (2015) researcher's uncertainty about the value of the estimates of interest includes two levels: the first one is uncertainty associated with the estimate conditional on a given model, which is assessed in each empirical study; the second one is uncertainty with the specification of the empirical model (model uncertainty), which is not fully assessed. Researchers typically get their conclusions from the "appropriate" model based on their subjective choose. However, the conclusions may be sensitive to selected model. In order to address above regression model uncertainty, we employ Bayesian model averaging (BMA) in Equation 5. BMA is an attractive technique to account for model uncertainty, and it has been widely applied in economics (Doppelhofer and Miller, 2004; Tobias and Li, 2004; Blonigen and Piger, 2014) and the field of meta-analysis (Moeltner and Woodward, 2009; Havranek *et al*., 2015). The basic idea of Bayesian model averaging is to regress model with many different subsets of control variables and make inferences based on a weighted average over model regression. In brief, BMA marginalizes over models to derive posterior densities on model parameters that account for model uncertainty, as follows:

$$p(\theta \mid y) = \sum_{m_i} p(\theta \mid y, m_i) p(m_i \mid y), \tag{6}$$

Where m_i are the sets of candidate model. The $p(\theta \mid y)$ is average of posterior distributions under each model considered, weighted by posterior model probability $p(m_i \mid y)$. Posterior model probability for model $m_i \in M$ is:

$$p(m_i \mid y) = \frac{p(y \mid m_i) p(m_i)}{\sum_{j=1}^{I} p(y \mid m_j) p(m_j)}, \tag{7}$$

where $p(y \mid m_i) = \int p(y \mid \beta_i, m_i) p(\beta_i \mid m_i) d\beta_i$ and β_i is vector of parameters in model m_i. Posterior model probability captures how well each regression fits the data, and it is analogous to R-squared or information criteria in frequentist econometrics. Then we can calculate the posterior inclusion probability (PIP), which is the sum of all posterior probabilities of all the regressions including the specific variable as follow equation.

$$PIP_j = \sum_{i:i_j=1} p(m_i \mid y), \tag{8}$$

Where $i_j = 1$ if variable X_j appears in the model, 0 otherwise. The posterior inclusion probability is a ranking measure to see how much the data favors the inclusion of a variable in the regression. If PIP of a variable lies between 0.5-0.75, 0.75-0.95, 0.95-0.99 or 0.99-1, then the variable has an acceptable, substantial, strong or decisive effect (Kass and Raftery, 1995; Havranek *et al.*, 2015). A variable with PIP under 0.5 is considered to be ignorable.

In BMA, we employ a Markov Chain Monte Carlo method called Metropolis-Hasting algorithm, which can go through the most important models with high posterior model probabilities. For all BMA computation we use 1000, 000 burn-ins and 2000, 000 iterations to ensure a good degree of convergence with the *bms* package in R (Zeugner and Feldkircher, 2015). We assign a uniform model prior and the unit information prior on Zellner's g-prior following Fernandez *et al.* (2001) which are quite conservative and reflect unknown true model size and parameter signs. Note that the precision of estimates $1/Se(e_{ij})$ and the 11 potential forward spillover determinants from firm attributes should be included in the regression, while 32 control variables may be included in the regression.

4. RESULTS AND DISCUSSION

Table 1 reports the results in search of determinants of FDI forward spillovers using Bayesian Model Averaging based meta-analysis.

Table-1. Determinants of FDI forward spillovers: Bayesian Model Averaging.

	PIP	Post Mean	Post SD
1/Se	1.000	1.752	0.806
Constant	1.000	1.320	NA
Firm attributes			
Foreign-firm characteristics			
WOS	1.000	0.390	0.116
JV	1.000	-0.169	0.089
HMT	1.000	-0.664	0.208
Non-HMT	1.000	-0.231	0.203
Local-orientated	1.000	0.124	0.100
Export-orientated	1.000	-0.585	0.076
Local-firm characteristics			
SOEs	1.000	0.034	0.059
Non-SOEs	1.000	0.080	0.061
High-tech	1.000	-0.158	0.159
Middle-tech	1.000	0.534	0.160
Low-tech	1.000	0.342	0.171
Study designs			
Data characteristics			
Panel data	0.042	0.019	0.709
Aggregated data	0.153	0.052	0.152
Time span	0.035	0.000	0.001
Average year of data	0.095	0.001	0.005
Specification characteristics			
Both vertical and horizontal	0.055	-0.013	0.086
Both backward and forward	0.068	0.010	0.065
More estimates	0.035	0.000	0.013
Combination of estimates	0.107	-0.014	0.095
Lagged spillover	0.048	-0.003	0.022
Foreign presence in employment	0.408	0.129	0.178
Foreign presence in asset	0.104	-0.001	0.058
Control for foreign presence	0.152	-0.022	0.062
Control for export	0.459	0.136	0.174
Control for absorption capability	**0.780**	**-0.310**	**0.203**
Control for sector competition	0.209	0.036	0.083
Estimation characteristics			
One-step estimation	0.059	0.002	0.011
OLS	0.034	-0.001	0.015
Olley–Pakes or Levinsohn-Petrin	0.036	0.000	0.007
Pooled OLS	0.139	-0.019	0.061
Random effects	**0.999**	**-1.116**	**0.268**
GMM	0.071	-0.012	0.130
Year-fixed effects	**1.000**	**-2.116**	**0.227**
Region-fixed effects	0.243	0.047	0.102
Sector-fixed effects	0.256	0.050	0.109
Estimated in differences	0.248	0.044	0.102
Non-loglin form	0.103	-0.300	1.131
Translog	0.488	0.181	0.213
Publication characteristics			
Published	0.292	0.053	0.093
Publication date	0.416	0.022	0.028
Paper citations	0.139	0.012	0.049
English study	0.172	0.049	0.130
Chinese co-author	0.062	0.011	0.085
N	505		

Notes: A bold font indicates that the corresponding study characteristic type has an estimated PIP larger than 0.5.

Under the columns, "PIP" is posterior inclusion probability which measures the likelihood of including a parameter in the regression; "Post Mean" and "Post SD" report the means and standard errors computed from the full posterior distribution of a parameter. Apart from the firm attributes, we can find only 3 characteristics of study designs impact reported estimates. However, our main purpose is to discover the determinants of forward spillover effects. Therefore, our analysis will focus on the 11 potential forward spillover determinants from firm attributes. It is widely recognized that FDI spillover effects vary with different firm attributes. There are five important firm attributes that are frequently highlighted in prior studies: the ownership structure of foreign firms, the origin of foreign firms, market orientation of foreign firms, the ownership structure of local firms and the technological levels of local firms.

The ownership structure of foreign firms is a widely-discussed determinant of FDI productivity spillovers (Blomström and Sjöholm, 1999; Javorcik and Spatareanu, 2008). The center of discussion is which ownership structure is more beneficial to technology diffusion. Most researchers argue JV facilitates more technology spillovers in several ways (Chang *et al.*, 2007; Javorcik and Spatareanu, 2008; Liang, 2009; Abraham *et al.*, 2010). First, the local partners of JV have much closer contact with advanced technologies. Second, local partners master better knowledge of local conditions, consequently JV has higher tendency to buy local intermediate or sell output to local downstream. However, our results show the posterior mean of WOS is 0.39 while JV -0.169 in Table 1, suggesting that WOS yields positive technology diffusion while JV negative. There are some potential reasons why WOS may facilitate forward technology spillover (Chang *et al.*, 2007; Abraham *et al.*, 2010). First, WOS have incentive to bring more efficient and cutting-edge technology in order to keep technology advantages, thereby WOS can sell products with cutting-edge technology to local buyers. Second, WOS have full control over profits and management, which in turn stimulate them to introduce technology and management skills to obtain persistent competitive advantages.

It is widely recognized that foreign invested firm from Hong Kong, Taiwan and Macau and foreign invested firm from other economies have heterogeneous properties, such as firm size, technological capability, management and productivity level. On one hand, because of same history, same culture, same language and closer geographic position, investments from HMT have more advantages to exploit the market of mainland China as well as technology spillover from HMT multinational enterprises. Tong (2005) also confirms ethnic Chinese networks contribute to cross-border investment. On the other hand, multinational enterprises from non-HMT possess more advanced technology, global production chain and international brand (Lin *et al.*, 2009) and also "employ state-of-the-art technology from heavy investment in R&D to produce innovative and differentiated products" (Buckley *et al.*, 2007). It is interesting to find that the posterior means of HMT and non-HMT are -0.664 and -0.231; suggesting both foreign firms from HMT and non-HMT create negative spillover effects on local buyers. Note that HMT foreign firms generate more negative spillover effects. One explanation is that HMT firms tend to take advantage of lower cost labor and purchase cheaper raw/intermediate materials in China as well as compete with local firms, which may generate larger crowding-out effect than non-HMT firms. Note that FDI from HMT accounted for 70.3% of the total, while the share of FDI from OECD was 13.3% in 2015[5]. The proportion of FDI from HMT is too high to benefit technology diffusion in the short run as well as in the long run. Therefore, it is important to adjust the source structure of FDI for policymakers.

On the market orientation of foreign firms, the posterior means of local-orientated foreign firms and export-orientated foreign firms are 0.124 and -0.585; indicating local-orientated foreign firms tend to result in positive productivity spillovers while export-orientated foreign firms negative, which is accordance with Xu and Sheng (2012). One potential reason is that local-orientated foreign firms tend to supply high-quality and/or lower cost intermediate goods and equipment as well as provide high-standard training and services to local buyers, which improve technological capability of local buyers. On the contrast, export-oriented foreign firms may push up the intermediate price, which increases the cost of related downstream sector and consequently may generate negative effects to local firms in downstream. There are several important heterogeneous characteristics of SOEs and non-SOEs, which may affect their technology absorptive capacity from FDI spillovers. First, market-orientation and market constraint. SOEs are widely recognized as less efficient and less market-oriented as SOEs undertake more

[5] Source: China Statistical Yearbook of 2016.

social and political roles in China. Meanwhile, SOEs face soft budget constraint and they are more likely to receive government support if they encounter financial difficulty. This undermines their incentive to run productively and efficiently (Kornai, 1979). Compared with SOEs, non-SOEs tend to show more learning and imitating initiative. Second, technical capacity. SOEs own typically larger and better technology foundation than non-SOEs. Moreover, R&D expenditure and human resources foundation of SOEs contribute to digest and absorb technology spillovers from foreign invested companies. Third, policy and financial support. China government tends to offer more favorable policies for SOEs as well as financial support. In contrast, non-SOEs (especially private-owned companies) suffer heavily financial constraints because of ownership discrimination in Chinese financial system, which potentially hinder technology absorption and scale economy. However, it is still ambiguous whether there exists different spillover effects of three panels on SOEs and non-SOEs in the literature. In Table 1 the posterior means of SOEs is 0.034 while non-SOEs 0.080. The BMA results indicate that non-SOEs tend to benefit more forward technology spillovers from FDI than SOEs. Under the technological levels of local firms, the posterior means of high-tech firms, middle-tech firms and low-tech firms are -0.158, 0.534 and 0.342, respectively; suggesting that middle-tech local firms tend to obtain more productivity spillovers than high-tech local firms and low-tech local firms. Note that the posterior mean of high-tech local firms is negative. One potential reason is that high-tech local firms lack necessary ability to provide immediate products for high-tech foreign firms as well as absorb the forward spillover effects from FDI. Meanwhile, the international suppliers will follow the high-tech foreign firms entering China market. Their international suppliers own much more advanced technology and management level, such as Japanese automobile firms, which outperform local suppliers. Jeon *et al.* (2013) also have similar findings.

5. CONCLUSION

In this study we conduct a Bayesian Model Averaging based Meta-Analysis of FDI forward productivity spillover effects in China. The prime aim is to search for determinants of forward spillovers from the aspect of firm attributes. That is, the ownership structure of foreign firms, the origin of foreign firms, market orientation of foreign firms, the ownership structure of local firms and the technological levels of local firms.

Our results suggest firm attributes are important determinants of forward spillovers. First, the ownership structure of foreign firms. WOS yields positive technology diffusion while JV negative. Second, the origin of foreign firms. Both foreign firms from HMT and non-HMT create negative spillover effects on local buyers. Third, market orientation of foreign firms. Local-orientated foreign firms are likely to generate positive productivity spillovers while export-orientated foreign firms negative. Fourth, the ownership structure of local firms. Non-SOEs is likely to benefit more forward technology spillovers from FDI than SOEs. Fifth, the technological levels of local firms. Middle-tech local firms tend to obtain more forward productivity spillovers than high-tech local firms and low-tech local firms.

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