Location Determinants of China’s Outward Foreign Direct Investment
Shujie Yao, Fan Zhang, Pan Wang, Dan Luo*

Abstract

Compared to inward foreign direct investment, outward foreign direct investment (OFDI) from China is a relatively new phenomenon. However, the volume of China’s OFDI increased rapidly from 2004. There has been an increasing amount of literature on the motivations of China’s OFDI, but few studies have focused on its location determinants. The present paper aims to fill this gap in the literature by focusing on two important location factors, natural resources and technology, which are the most important determinants of China’s OFDI. We use a large panel dataset comprising 132 countries over the period 1991–2009 and the Tobit as well as the Heckman models to establish the relationship between the two location factors and China’s OFDI. The empirical results suggest that although China’s OFDI has been driven by the country’s desire for a secure supply of natural resources and to attain advanced technology from the developed world, China’s technology is also a critical attraction for the host developing economies.

Key words: China, location factors, OFDI, resource seeking, technology seeking

JEL codes: F21, O53

I. Introduction

Complementing the magnificent success in attracting inward foreign direct investment (IFDI), China’s outward foreign direct investment (OFDI) has increased rapidly over the past decade.1 In 2016, China was the second largest source country of OFDI, equating to approximately US$180bn, or US$50bn more than the country’s IFDI (Figure 1).

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1From this point onward, China refers to Mainland China.
Despite its massive expansion, China’s OFDI has attracted limited little attention from researchers due to the relatively small amount of investment in the early stages (Cheung and Qian, 2008) and limited data availability (Buckley et al., 2010). Most extant studies focus on the pattern, regulation and policy implications of China’s OFDI (Cai, 1999; Wu and Chen 2001; Wong and Chan, 2003; Voss et al., 2009), and few studies pay attention to the determinants of China’s OFDI (Cheung and Qian, 2008; Zhang, 2009; Buckley et al., 2010). The present paper aims to make a new contribution to the literature focusing on two important location factors, natural resources and technology, which have played a critical role in explaining China’s OFDI behavior.

The rest of this paper is organized as follows. Section II summaries the development of China’s OFDI and reviews the literature on economic incentives for investing in natural resources and technology. Section III describes the models and addresses some data issues. Section IV interprets the empirical results and Section V presents robustness tests. The final section concludes.

II. Literature and Hypothesis

In 1978, China launched its “open-door” policy to facilitate both IFDI and OFDI. By 1983, China had established over 100 joint ventures, which was rationalized as an effective way to secure the supply of scare natural resources, to accelerate technological advancement and to penetrate overseas markets (Guo, 1984). However, despite the introduction of a more transparent and decentralized approval regime by the central
government, China’s OFDI during this initial period was limited due to the shortage of foreign exchange and the lack of investment experience (Voss et al., 2009).

The second stage of OFDI development was stimulated by Deng Xiaoping’s “South Tour” in the early 1990s. An increased number of overseas projects were approved and the Ministry of Commerce (MOFCOM) was restructured to provide more comprehensive guidance and assistance on foreign trade and investment-related activities.

Later, along with China’s accession to the WTO and the launch of the “Go Global” policy, internationalization activities were greatly stimulated among Chinese firms. The MOFCOM and the National Development and Reform Commission (NDRC) jointly announced the Country and Industry Catalogue of Outward Foreign Direct Investment, officially shifting the Chinese Government’s focus from policy guidance and application approval to investment supervision and assistance. In the meantime, a series of financial subsidies were introduced to encourage state-owned enterprises to invest overseas (Xiao and Sun, 2005; Yao and Sutherland, 2009; Yao et al., 2010).

As shown in Figure 1, despite a slowdown in China’s economic growth since 2011 and a decline in global investment activities, the flow of OFDI from China maintained a double-digit growth rate, except in 2015.

Facing complex and volatile international conditions, the Chinese Government proposed the “One Belt and One Road” Initiative in 2014 to further facilitate domestic firms becoming more globalized. According to the 2015 World Development Report, by the end of 2014, the flows and total stocks of China’s OFDI were approximately 9.1 and 3.4 percent of the world’s total, respectively. In 2016, the amount of OFDI rose more than 50 percent to surpass the level of IFDI for the first time in history.

Unlike the OFDI from the developed nations, China’s OFDI mainly comprises equity investments rather than reinvested earnings. For instance, in April 2015, China signed an agreement to invest approximately US$45.6bn in Pakistan over the next few years to support the development of the country’s electricity and transportation infrastructure (UNCTAD, 2015). In terms of geographical location, investment from China is highly imbalanced, with almost 70 percent of the investments directed to Asia.

In the past decade, China also invested heavily in developed economies, including the USA, the EU and Australia. China’s OFDI to the developed world reached US$23bn in 2014, up by 72.3 percent from a year earlier. The motivation of OFDI in the developed economies may be to seek technology and resources (Liu et al., 2015).

Over the past two decades, the global extractive industry has experienced two major changes. One is the rapid rise of mineral prices and the other is the increased market concentration of the sector. Along with a few mega mergers and acquisitions, the metal
and mining industry is now dominated by a few multinational corporations (MNCs). For example, in 1995, the world’s 10 largest metal mining companies jointly accounted for 26 percent of the global non-energy mineral value; the share increased to 33 percent in 2006. Similarly, for the oil industry, it was also highly concentrated, with the 10 largest companies controlling approximately 77 percent of the world’s total oil reserves in 2005. Such a high concentration places substantial pressure on countries like China, which relies heavily on external supply of resources.

Along with the rapid economic expansion, industrialization and urbanization, China’s demand for energy surged. In 2010, total energy consumption in China reached 3.2 billion tons of coal equivalent (TCE), accounting for approximately 20 percent of the world’s total and overtaking the USA for the first time to become the world’s largest energy consumer. Despite a sharp slowdown of its economic growth in 2015, China still consumed 4.2 billion TCE in that year, placing increased pressure on energy supply and security. Since 2007, over half of China’s oil demand has been met by imports (Figure 2). If such high dependency on external supply continued, it would inevitably expose China to serious energy security problems, and this partially explains why in recent years the country has been trying hard to diversify its resource supply to more stable countries, like Brazil and Australia.

Resource seeking has long been identified as a key motivation driving international capital flows (Dunning, 1993). In particular, when a resource-abundant country has neither the capital nor the technical skills required for resource extraction, investments...
are more likely to occur. For example, the IMF estimates that for Azerbaijan, approximately 75–82 percent of total FDI was invested in the oil and gas industry (Tondel, 2001), and for Kazakhstan, the majority of capital inflows were also directed toward the natural resource sector. A similar picture has emerged for China’s OFDI destinations. Among the 15 largest recipients of China’s OFDI in 2014, many of them were resource-abundant countries, including Australia, Russia, Kazakhstan and South Africa. This leads to our first hypothesis.

**Hypothesis 1:** China’s OFDI is driven by a motivation to seek natural resources (oil and metals).

In addition to securing the supply of natural resources, another reason for China’s investments into resource-abundant countries is to ensure price stability. Figure 3 depicts the co-movements between China’s OFDI flows and changing oil and mineral price indices. In the early 1990s when the mineral and oil prices were stable, OFDI from China was limited. Later, from the 2000s when resource prices rose sharply, China’s OFDI caught up quickly. The growing reliance on external supply of nature resources has made China vulnerable to price volatilities. As a result, to lock in prices and to secure the future supply of resources, the Chinese state-owned energy companies actively pursued overseas equity investment opportunities (Lieberthal and Herberg, 2006).

![Figure 3. Price Indices of Petroleum and Metals and China’s Outward Foreign Direct Investment (OFDI) Flow, 1992–2015](image)


Notes: The crude petroleum index accounts equal weight for the following oil prices measured by US dollar per barrel: Dubai, Brent and Texas. The base point for the price indices is 2000 = 100.
Compared with the conventional OFDI theory which regards firms’ overseas investments as a way to explore ownership advantage, less profitable Chinese SOEs’ acquisition of foreign energy giants suggests that such behaviors could mainly be driven by political and financial concerns (Houseer, 2008; Yao and Sutherland, 2009). The relatively low efficiency of the Chinese MNCs is compensated by cheaper bank loans and government support and, in this way, the long-run interests of the country can be secured (Morck et al., 2008; Ongena et al., 2015). This leads to the development of our second hypothesis.

Hypothesis 2: China’s OFDI is driven by the motivation to ensure price stability of natural resources imported from the host countries.

In terms of the technological effect on China’s OFDI decision, it is found to polarize the country’s investments. Both poorer developing countries, such as Pakistan and Thailand, and developed nations, like the USA and the UK, are consistently among the largest recipients of the country’s investments. This is explained by two distinct motivations: importing advanced technologies from the developed nations through “learning by doing” and transferring “appropriate technologies” to the less developed countries (Brezis et al., 1993; Haddad and Harrison, 1993).

The large amount of capital flow from developing countries to developed nations is explained as the “latecomer advantage,” which allows the latecomers to use the same technology at lower cost and to catch up with the market leaders in a more time-efficient manner (Brezis et al., 1993). Similar conclusions have also been reached in other published studies (e.g. Fosfuri and Motta, 1999; Niosi, 1999; Love, 2003), in which it is argued that the technology-sourcing OFDI could be expressed as a process through which technologically weak countries seek advanced technologies by locating subsidiaries in technologically strong countries. Subsidiaries effectively become carriers and transfer the acquired technology from the host country to the home country through technology spillovers.

Because technological advancement generally requires large capital inputs, China, as a latecomer, may fuel this catching-up process by investing directly into knowledge-intensive industries in developed nations (Matthews, 2002). In this way, the advanced technologies could be disseminated to China in a more cost-effective manner. Partners in host countries may provide staff training and technical support to facilitate the technological transfer process (Kokko, 1994). Chinese investors may learn from their foreign partners first, and then imitate and innovate later (Wang and Blomstrom, 1992). Consequently, the leakage of advanced technology from technically superior
foreign companies could encourage domestic endogenous innovation and accelerate the technological advancement process of the whole industry. Nowadays, a large amount of China’s OFDI is directed to developed nations, which leads to our third hypothesis.

**Hypothesis 3:** *China’s OFDI to the developed world is partly driven by advanced technology seeking.*

In addition to the developed nations, countries from Latin America, Africa and Asia are also popular destinations for China’s OFDI. This might result from the mutual benefits that can potentially be enjoyed by both parties (Walz, 1997). For the Chinese MNCs, setting up subsidiaries in less developed regions may lead to additional cost savings, while companies in host countries may obtain access to more advanced technologies and, hence, the domestic industrial upgrading process would be accelerated. In contrast, China has directed an increased amount of technology-embodied OFDI to emerging countries in recent years. The key argument behind this is that companies from developing countries are more interested in absorbing appropriate technologies rather than the most sophisticated technologies, in particular when financial and human capital constraints are taken into account. Compared with the most advanced technologies developed by Western companies, those developed by Chinese MNCs tend to be easier to learn and cheaper to adapt. There has always been a trade-off between the best and the most suitable technologies as far as the host countries are concerned. The positive impact of technology spillovers tends to decrease along with a widened technological gap, which explains why technology transferred from Chinese firms tends to be a better fit for emerging economies (Haddad and Harrison, 1993; Kokko et al., 1996). Similar economic conditions of two countries may speed up the technological diffusion process and, in turn, enable both companies to benefit from improved total factor productivity of the host country (Kokko, 1994). This leads to our fourth hypothesis.

**Hypothesis 4:** *China’s OFDI to the developing world is partly driven by its relatively superior and more appropriate technologies to the host countries.*

### III. Methodology and Data

The investigation of the determinants of bilateral trade and FDI is analogous to Newton’s law of gravitation. Tinbergen (1962) first applied the gravitation model to an international trade study. However, the gravitation model has been challenged due to the lack of theoretical foundation, even though it works well empirically. Various theories
have emerged thereafter to explain this empirical success, with one group focusing on the non-trade theory aspect and the other on the trade theory aspect. Regarding the first group of studies, the general equilibrium framework (Linnemann, 1967), the differentiated goods framework (Anderson, 1979), the utility maximization framework (Nijkamp, 1975) and the microeconomic foundations framework (Bergstrand, 1985) have all proved to be applicable. In terms of the second group of studies, the Ricardian trade framework (Evenett and Keller, 2002), the Heckscher–Ohlin trade framework (Bergstrand, 1989) and the new trade theory framework (Helpman, 1987; Hummels and Levisohn, 1995) are generally used to explain the theoretical derivation of the gravity model. It has been commonly applied to empirical studies on FDI. Braconier et al. (2002) empirically tested the vertical FDI theory by adopting Brainard’s (1997) log-linear gravity specification and chose the same control variables as Carr et al. (2001).

Head (2003) sketched a formal derivation of the gravity model and proposed a simplified version. The major difference is that the constant term $G$ was replaced by a non-constant, $R_j$:

$$F_{ij} = R_j \frac{M_i M_j}{D_{ij}^\theta}, \quad (1)$$

where $F_{ij}$ is the bilateral FDI, $M_i$ and $M_j$ are economic masses, and $D_{ij}^\theta$ is the FDI friction.

We apply this specification and define $F_{ij}$ as the OFDI from China ($i$) to a host country ($j$). $M_i$ and $M_j$ are economic masses of China and the host country, respectively; they are used to control the host country’s time-variant market size variables, including GDP, the GDP growth rate and income. $D_{ij}^\theta$ is a function of resistance factors. It controls time-invariant gravity-type variables, including distance ($Distance$), common language ($ComLang$), contiguity ($Contiguity$) and Special Administration Region ($SAR$) dummies. The non-constant item $R_j$ extends to a set of variables that have effects on $F_{ij}$, such as a host country’s natural resource endowment and the technology level. These variables can be classified into two categories: one is our main variables of interest, and the other is a range of control variables. Therefore, the efficiency of revealing the locational determinants of China’s OFDI depends on these two categories of variables.

To verify the first hypothesis which states that China’s OFDI is driven by a motivation to seek natural resources (oil and metals), we include the abundance of natural resources as the main variable of interest. Exports and trade openness are chosen as control variables. For the purpose of consistency, we add the main variable of interest and control variables into the multiplier $R_j$ in Equation (2) and then we have the following new expression:

$$R_j = f(\text{Resources, Exports, Trade Openness}). \quad (2)$$
The fixed-effect (FE) estimation technique specifies a country dummy to capture all the time-invariant country-specific effects besides the items in $D^0_j$, therefore integrating Equation (1) with Equation (2) and then converting it into Equation (3). It includes the main variable of interest ($Resources$) and the control variable ($Control$):

$$OFDI_{jt} = \alpha_0 + \alpha_j (Resources)_{jt} + \beta Control + \epsilon_{jt}, \text{ where}$$

$$Control = (GDP, GDP\ Growth\ Rate, Income, Export, Openness, Time, v_i), \quad (3)$$

where $j$ and $t$ denote host country $j$ and year $t$. For the subsample period 2003–2009, $j$ and $t$ denote host country $j$ ($j = 1, 2, \ldots, 132$) and year $t$ ($t = 2003, 2004, \ldots, 2009$). For the subsample period 1991–2003, $j$ and $t$ denote host country $j$ ($j = 1, 2, \ldots, 131$) and year $t$ ($t = 1991, 1992, \ldots, 2003$). We divide the entire sample into two subsamples because China’s OFDI behaviors in these two subperiods are distinctively different due to the shifting capability and motivations of OFDI.

Here, $OFDI$ is the current value of China’s OFDI and it is expressed in logarithmic form. $Resources$ is the abundance of natural resources and is specified by two subcategories, one using the share of oil’s production in GDP to measure the oil abundance ($Oil$) and the other using the share of metals’ exports in total exports to measure the metals abundance ($Metal$). $Control$ includes a set of time variant and invariant control variables. $GDP$ is logged real GDP. $GDP\_Growth$ is the growth rate of real GDP. $Income$ is a set of income dummies which include high income ($HIncome$), upper-middle income ($UMIncome$), lower-middle income ($LMIncome$) and low income ($LIncome$). $Export$ is China’s exports to a host country in logarithmic form. $Openness$ is the trade openness defined as trade/GDP ratio. $Time$ is a time FE dummy and $v_i$ is a country FE dummy. A detailed description of variables and data resources is available on request but not presented here.

The first hypothesis states that natural resources ($Resources$) has a positive effect on the dependent variable. The validity of this hypothesis depends on whether the statistical test on the coefficient of $Resources$ is positively significant. The control variables, such as $GDP$, $GDP\_Growth$ and $Export$, are expected to be positive.

The effect of the control variable $Openness$ is indecisive. On the one hand, $Openness$ reflects the host country’s level of openness. A higher level attracts foreign investment and has a positive effect on China’s OFDI. On the other hand, $Openness$ is negatively related to trade barriers of the host country. China conducting OFDI in a country with high trade barriers might be for the purpose of “tariff-jumping,” implying that a host country’s openness may have a negative effect on China’s OFDI. The net effect of $Openness$ depends on the interaction of these two counteractive forces.

The effect of the control variable $Income$ is indecisive, too. On the one hand, income
may reflect the quality of domestic labor because high income usually implies high productivity. On the other hand, income may reflect higher cost for OFDI because high domestic income implies high wages, which have a negative effect on OFDI (Zhou and Song, 2016). The net effect of \textit{Income} depends on the interaction of these two opposite effects.

To verify the second hypothesis which states that China’s OFDI is driven by a motivation to stabilize the prices of imported resources, an interaction term of natural resources and mineral prices is introduced. In addition, considering that mineral prices may have moved in a certain way, an interaction of natural resources and a time trend (\textit{Trend}) is also introduced. The interaction term Resources*Price and natural resources (Resources) are used as two main variables of interest. We include the interaction term Resources*Trend as an additional control variable together with the previous control variable (Control). Equation (3) is extended below:

\[
OFDI_{jt} = \alpha_0 + \alpha_1 (\text{Resources})_{jt} + \alpha_2 (\text{Resources}*\text{Price})_{jt} + \alpha_3 (\text{Resources}*\text{Trend})_{jt} + \beta\text{Control} + \varepsilon_{jt},
\]

where the change in mineral prices is defined by the annual growth rate of the price index. Analogically, Resources*Price has two expressions. One is the interaction (Oil*Price) of oil’s abundance (Oil) and the oil price index growth rate (Price\_Oil); the other is the interaction (Metal*Price) of metals’ abundance (Metal) and metals’ price index growth rate (Price\_Metal). Similarly, Resources*Trend has two expressions: one is the interaction (Oil*Trend) of oil’s abundance and a time trend; the other is the interaction (Metal*Trend) of metals’ abundance and a time trend.

The second hypothesis states that the interaction term Resources*Price and the abundance of natural resources (Resources) have positive effects on the dependent variable. The additional control variable Resources*Trend is expected to have a positive effect and all the other control variables are expected to have the same effects as before.

To verify the third hypothesis, which states that China’s OFDI is driven by a motivation of seeking advanced technology, subject to data availability,\(^2\) we use the share of high-technology exports in manufacturing exports as a proxy for advanced technology. Hence, Technology is included as the main variable of interest, but Resources is treated as an additional control variable together with the previous control variable (Control). Equation (3) is extended below:

\[
OFDI_{jt} = \alpha_0 + \alpha_1 (\text{Technology})_{jt} + \alpha_2 (\text{Resources})_{jt} + \beta\text{Control} + \varepsilon_{jt}.
\]

\(^2\)We tried using R&D expenditure as a proxy for the technology ability, but missing values significantly reduced the explanation power of regressions.

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It is expected that *Technology* has a positive effect on the dependent variable and *Resources* also has a positive effect. All the control variables are expected to have the same effects as before.

The fourth hypothesis states that China’s OFDI is driven by a motivation of seeking advanced technology in the developed countries but is attractive to the developing economies because China has more advanced and appropriate technology to be transferred to the latter group. To test this hypothesis, we need to clarify the following arguments. First, income level (*Income*) is a meaningful instrument to measure a country’s development level. The World Bank (2010) classifies all countries into four groups: high income, upper–middle income, lower–middle income and low income. This classification is a good alternative to using GDP per capita to measure a country’s development level in this context. Our primary concern is to capture two opposite technology-related OFDI motivations that are conditional on development differences.

GDP per capita is an appropriate measurement to reflect the level of economic development. However, China’s technology-related OFDI crucially depends on the relative effect of a host country’s development level. The fourth hypothesis states that China seeks technology from countries with a higher development level and transfers technology to countries with a lower level of development.

A country’s income level implicitly reflects its technological capability. Therefore, a positive difference in income levels implies technology superiority but a negative difference in income levels implies technology inferiority. A smaller income difference implies a smaller technology gap. The implication of the fourth hypothesis is twofold. On the one hand, China’s OFDI in high-income countries is driven by the positive income differences between the host countries and China. It mirrors the technology superiority of the host countries. In contrast, China’s OFDI in low income countries is driven by the positive income differences between China and the host countries.

For comparison purpose, we select the lower–middle income countries as the control group. As a result, three interactions of *Technology* and income levels (*Income*) are introduced to represent countries in the high income, upper–middle income and low income groups (*Tech*HIn, *Tech*UMIn and *Tech*LIn), respectively. These three interactions together with *Technology* are used as the main variables of interest. *Resources* is added as an additional control variable together with all the other control variables. Equation (3) is extended below:

\[
OFDI_{jt} = a_0 + a_1 (Technology)_{jt} + a_2 (Tech*HIn)_{jt} + a_3 (Tech*UMIn)_{jt} + a_4 (Tech*LIn)_{jt} \\
+ a_5 (Resources)_{jt} + \beta \text{Control} + \epsilon_{jt}.
\]

It is expected that *Tech*HIn and *Tech*UMIn will have positive effects and *Tech*
$L_{In}$ will have a negative effect on the dependent variable, and all the control variables are expected to have the same effects as before. The positive effects of $Tech \times H_{In}$ and $Tech \times UM_{In}$ are easy to understand as the technologies in the high and upper-middle income countries are attractive for Chinese OFDI. The negative effect of $Tech \times L_{In}$ should be interpreted indirectly. China’s income level is in the range of the upper-middle and lower-middle income categories during the data period, which implies that its technology should be superior compared to that in low-income countries. As a result, the negative effect of $Tech \times L_{In}$ on the dependent variable (i.e. China’s OFDI) means that instead of being attracted by the technology in the low-income countries, China’s technologies appear to have been attracted to the low-income countries through OFDI.

Data used for the empirical models are extracted from MOFCOM’s annual publications. We divide the whole sample period into two subsamples, one from 1991 to 2003 and the other from 2003 to 2009, due to changes in statistical standards and the surge of OFDI activities among Chinese firms since the 2000s. Data for the early period are extracted from the *Almanac of China’s Foreign Economic Relations and Trade* and are recorded under China’s own approved definitions and standards, whereas data for the latter period are obtained from the *Statistical Bulletin of China’s Outward Foreign Direct Investment* and are recorded under the OECD and IMF compatible standards. Similar to other statistical data on China, the reliability and accuracy of the data are questionable and, therefore, a series of adjustments are made before they are used for empirical analysis.

The following four steps are undertaken for data cleaning: (i) we exclude tax havens and offshore financial centers; (ii) we delete observations with negative values; (iii) we eliminate observations which account for the smallest 1 percent of the total OFDI flow for both sample periods and eliminate observations which account for the largest 1 percent; and (iv) we remove random host countries.

After cleaning, the new subsamples comprise 82.5 and 61.79 percent of the original sample observations for the two respective subperiods. For 1991–2003, there are 131 countries and regions and for 2003–2009, there are 132 countries and regions.

On average, approximately 80 percent of China’s OFDI was directed to Asia and approximately 6 percent to Africa and Europe, respectively. Latin America only attracted 1 percent of the total investments as the exclusion of capital flows to the tax havens and offshore financial centers has greatly reshaped the landscape of China’s OFDI. During the entire sample period, investments received by every

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1The geographical breakdown for the two cleaned datasets is not presented but is available on request.
continent remained relatively stable, with the exception of 2008 when significant adjustments were made after the global financial crisis.

IV. Empirical Analysis

Summary statistics for the key variables and detailed regression results are not presented for all the models but are available on request. Tables 1–3 present the key regression results based on the FE models for two sample periods. The four hypotheses are verified, although the levels of significance vary with model specifications and sample periods.

For the 2003–2009 period, oil (one variable for resources) is significant at the 5-percent level in the base model (Table 1). The interaction of oil and oil price’s growth has the expected sign but is not significant. The interaction of oil and time trend is significant at the 5-percent level. Metals (the second variable for resources) is significant at or below the 5-percent level depending on the inclusion of control variables in the base models (Table 2). The interaction of metals and its price growth is significant at the 5-percent level in the augmented model and the interaction of metals and time trend is significant at the 5-percent level. Technology is significant at the 5-percent level in all the base and augmented models except in one case in the base model (Table 3).

Table 1. Regression Results for the Motivation of Oil Seeking

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<tbody>
<tr>
<td></td>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>Oil</td>
<td>2.351</td>
<td>3.930*</td>
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<tr>
<td></td>
<td>(1.853)</td>
<td>(1.846)</td>
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<tr>
<td>Oil*Price</td>
<td>1.477</td>
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<tr>
<td>Oil*Trend</td>
<td>0.413*</td>
<td>0.353</td>
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<tr>
<td>Control</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>706</td>
<td>664</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.689</td>
<td>0.698</td>
</tr>
</tbody>
</table>

Notes: All models include time fixed effects. Robust standard errors are in parentheses. AM, augmented model; BM, base model. Augmented models include the interaction of oil’s abundance and the oil price index’s growth rate and the interaction of oil’s abundance and time trend. * represents significance at the 5-percent level.
Table 2. Regression Results for the Motivation of Metal Seeking

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<tbody>
<tr>
<td></td>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>Metals</td>
<td>2.446*</td>
<td>3.371**</td>
</tr>
<tr>
<td>Metals*Price</td>
<td>2.270</td>
<td>2.405*</td>
</tr>
<tr>
<td>Metals*Trend</td>
<td>0.379*</td>
<td>0.309</td>
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<tr>
<td>Control</td>
<td>No</td>
<td>Yes</td>
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<tr>
<td>Observations</td>
<td>538</td>
<td>516</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.733</td>
<td>0.727</td>
</tr>
</tbody>
</table>

Notes: All models include time fixed effects. AM, augmented model; BM, base model. Augmented models include the interaction of oil’s abundance and the oil price index’s growth rate and the interaction of oil’s abundance and time trend. Robust standard errors are in parentheses. * and ** represent significance at 5 and 10 percent, respectively.

Table 3. Regression Results for the Motivation of Technology Seeking

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<tbody>
<tr>
<td></td>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>Technology</td>
<td>2.908*</td>
<td>1.798</td>
</tr>
<tr>
<td></td>
<td>(1.450)</td>
<td>(1.679)</td>
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<tr>
<td>Tech*HIn</td>
<td>0.758</td>
<td>−2.463</td>
</tr>
<tr>
<td></td>
<td>(3.599)</td>
<td>(5.164)</td>
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<tr>
<td>Tech*UMIn</td>
<td>−3.014</td>
<td>−3.772</td>
</tr>
<tr>
<td></td>
<td>(2.535)</td>
<td>(3.370)</td>
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<tr>
<td></td>
<td>(3.308)</td>
<td>(3.757)</td>
</tr>
<tr>
<td>Resources</td>
<td>2.986**</td>
<td>4.008**</td>
</tr>
<tr>
<td></td>
<td>(1.050)</td>
<td>(1.118)</td>
</tr>
<tr>
<td>Control</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>511</td>
<td>497</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.723</td>
<td>0.727</td>
</tr>
</tbody>
</table>

Notes: All models include time fixed effects. AM, augmented model; BM, base model. Augmented models include the interaction of oil’s abundance and the oil price index’s growth rate and the interaction of oil’s abundance and time trend. Robust standard errors are in parentheses. * and ** represent significance at 5 and 10 percent, respectively.
The interactions of technology and income levels are all insignificant except for the negatively significant interaction of technology and low income in the two augmented models (Table 3). This negative effect is insensitive with the control variables.

For the 1991–2003 period, oil is found to be positively significant at the 5-percent level in both the base and augmented models (right-hand panel in Table 1). Metals are found only to be significant at the 5-percent level in the augmented model (right-hand panel in Table 2). Apart from oil and metals, technology is insignificant in the base and augmented models (right-hand panel in Table 3).

The empirical results confirm our hypothesis in general, suggesting that the diversification of China’s OFDI since 1991 has mainly been driven by the following four factors. First, natural resources (oil and metals) are demonstrated to have driven China’s OFDI in both periods. The elasticity of oil ranges from 3.930 to 6.475 and the elasticity of metals from 2.446 to 4.208. This could be interpreted as a 1-percent increase in oil and metal abundance potentially leading to China’s OFDI rising by up to 6.5 and 4.2 percent, respectively. The motivation of seeking natural resources was more obvious in 2003–2009 than in 1991–2001. These findings are in line with the conclusions reached in Figure 2 that seeking and securing a supply of natural resources are key impetus that have driven China’s OFDI, particularly after the 2000s when economic expansion in China accelerated.

The growing concern over energy security forced Chinese MNCs to diversify the sources of energy supply and to invest in resource-abundant countries. This explains why countries like Russia and Australia could constantly attract large OFDI from China.

Second, China’s OFDI is also driven by the desire to ensure price stability of imported natural resources such as oil and metals. This was particularly so in the second subperiod 2003–2009 when global commodity prices rose rapidly. For decades in the 20th century, China’s reserves of iron ore were plentiful and prices were stable. With limited steel production capacity, China relied on the direct import of iron ore to meet its additional demand. However, things changed in the early 2000s when China’s huge steel needs transformed iron ore into the “unobtainium” of the global market. Prices surged, making the country highly vulnerable to price volatilities. To ensure price stability, China increased OFDI towards the sector to achieve direct control over market prices. Based on the empirical results, a 1-percent rise in metal prices would lead to an additional 2.4-percent increase in China’s OFDI. Such a finding also reflects the awkward position of China in the international price negotiation process. Chinese steel mills, represented by China’s Iron and Steel Association, have fought for years to gain the upper hand in iron ore price negotiations with the world’s top iron ore miners, including BHP Billiton and Rio Tinto, but little has been achieved. As a result, to protect
domestic interests and to improve the transparency in global price setting, several Chinese state-owned mining giants have expanded their operations overseas through acquisitions and strategic alliances. This is consistent with our second hypothesis that China’s OFDI is stimulated by an effort to secure the supply of iron ore at reasonable prices.

Third, it is confirmed by the statistical significance and positive coefficient of “Technology” in the base model in 2003–2009 that China’s OFDI was driven by the motivation of technology seeking (left-hand panel in Table 3). A 1-percent rise in the host country’s technology level would lead to a nearly 3-percent increase in China’s OFDI. This positive impact only became significant in 2003–2009. Since China entered the WTO, a series of structural transformations have been initiated and the deployment of advanced technology for productivity enhancement has attracted increased government attention at all levels. A series of preferential policies were proposed to encourage technological advancement through firms’ genuine R&D activities and through foreign investments and collaborations. This has directly triggered China’s OFDI to the developed nations because it is considered as an effective way to accelerate technology transmission, allowing China to climb up the technology ladder in a more cost-effective and time-effective manner.

Fourth, the coexistence of technology seeking and transfer motivation was found to exist exclusively in the latter period, 2003–2009. The positively significant coefficients of “Technology” in the augmented models and one in the base model confirm the dominant purpose of technology seeking among China’s OFDI (columns 1, 3 and 4 in Table 3). In general, a 1-percent rise in technology abundance would lead to an approximate 3–6 percent increase in China’s OFDI. In addition, the insignificant coefficients of Tech*HIn and Tech*UMIn, together with the base income dummy, lower-middle income, address a positive net effect of technology-seeking motivation, and this effect is not conditional on income levels. In other words, China may seek technology transfer from any country as long as the income level of the host country is not lower than that of China’s. The insignificant effects of these variables jointly confirm the domination of the advanced technology-seeking motivation in relation to China’s OFDI, but it seems that the country has no apparent preference over high-income countries for technology-seeking purposes. Such an assertion will be further investigated in our robustness tests below.

China’s intention to transfer its technology to the developing countries through OFDI is confirmed by the negative but significant coefficients in the augmented models (columns 3 and 4 in Table 3). The positive coefficients for the variable Technology range from 5.819 to 6.188 and the negative coefficients for the variable Tech*Lin range from
6.807 to 8.782, suggesting a net negative effect in the range of 0.619 to 2.963. These results suggest that China has a strong interest in transferring technologies to countries with lower income levels and inferior technologies. However, developing countries are also willing to embrace China’s investments as the technology embedded in such OFDI is considered to be at the appropriate level, and would be easier and cheaper to learn, and to be able to adapt to and to diffuse to the domestic market. Such a conclusion is further confirmed by comparing the statistical results between the two subsample periods. In the earlier period 1991–2003, as a low-income country, the comparative advantage of technology processed by Chinese firms was limited, hence leading to the insignificant statistical results for variables in the base and augmented models (right-hand panel in Table 3). Later, along with China’s fast economic expansion, the country moved to the middle-income level and achieved significant technological advancements. As a result, its technology has become appealing to lower-income countries, resulting in the statistically significant negative coefficients for the variable \( \text{Tech} \times \text{Lin} \). Therefore, it could be concluded that China’s technologically-embedded OFDI are closely related with the income level of the host countries. Chinese MNCs may import more advanced technologies from the developed nations and simultaneously export less sophisticated but more appropriate technologies to lower-income countries.

V. Robustness Tests

1. Tobit Model

The Tobit model has been applied to international trade (Carr et al., 2001) and FDI (Razin and Sadka, 2007) studies. The Tobit model in the context of China’s OFDI is shown as Equations (7) and (8):

\[
Y_{jt} = \begin{cases} 
Y_{jt}^* & \text{if } Y_{jt}^* > 0 \\
0 & \text{if } Y_{jt}^* \leq 0
\end{cases},
\]

(7)

where

\[
Y_{jt}^* = X_{jt} \beta + u_{jt}.
\]

(8)

Here, \( j \) and \( t \) denote host country \( j \) and year \( t \). \( Y_{jt} \) is the observed OFDI value. \( Y_{jt}^* \) is the latent OFDI value. \( X_{jt} \) is a vector of explanatory variables. The censoring value is 0. China’s OFDI is only observable when the value surpasses the threshold 0 (\( Y_{jt} = Y_{jt}^* > 0 \)); otherwise it is unobservable and marked as 0 (\( Y_{jt} = 0 \)). For verifying our hypotheses, we follow the same argument as for FE in Section V.

The detailed regression results of the Tobit models are not presented but are available on request. For the period 2003–2009, the Tobit estimations have similar
findings in FE except for the significant role of metals prices. For the period 1991–2003, the Tobit estimations extend the FE findings by providing additional significance of metals and technology in the base models at or below the 5-percent level. No evidence of oil seeking is found. Two unexpected significant results are found: one is the negatively significant oil seeking in the augmented model and the other is the negatively significant technology-seeking interaction in the augmented model. However, these unexpected results become insignificant once the control variables are included.

2. Heckman Model

The Tobit model was a conventional estimation technique when the dependent variable was censored at zero (Sigelman and Zeng, 1999). Compared with the Heckman model, Tobit’s interpretations face a dilemma. Tobit’s estimation relies on observable latent values ($Y^*_j > 0$) which are merely part of the whole sample; it is not convincing to explain unobservable latent values ($Y^*_j \leq 0$) by implying estimation results based on observable latent values, because these unobservable latent values are intrinsically excluded from the Tobit estimation. Razin and Sadka (2007) further indicate that the Tobit model is a special case of the Heckman model when the selection equation and flow equation are perfectly correlated.

In interpreting China’s OFDI under the Heckman model, we consider whether China engages in FDI or not, and how much China invests. The two-stage Heckman selection model explains China’s OFDI from a new dimension. It is applied to overcome the drawbacks of the Tobit model and to correct biased data resulting from the sample selection problem. Heckman (1979) illustrated two reasons for sample selection bias: one was the self-selection bias and the other the sample selection bias. The sample selection bias in the current context refers to the endogenous OFDI decision subject to unobserved effects (Damijan et al., 2003). Bias arises from the non-random selection, which means that OFDI is only observable if it surpasses a certain threshold which is closely related with the unobservable effects. The observable value was not randomly selected and the neglect of zero OFDI values made the dependent variable no longer endogenous.

Heckman (1979) managed the selection bias problem by using a two-stage procedure: a selection equation in the first stage and a flow equation in the second stage. The sample selection bias in the selection equation is converted to an omitted variable bias in the flow equation through introducing the inverse Mills ratio (IMR).\(^4\) Estimated individual probabilities from the probit model in the first stage are used to calculate the IMR, which is an additional explanatory variable in the second stage. This two-stage

\(^4\)IMR is the ratio of the probability density function over the cumulative density function.
mechanism improves the explanatory power by taking into consideration of China’s OFDI that are not available \( (D^*_j \leq 0) \), because some unobserved effects may affect China’s OFDI.

Assume a Heckman model specified as:

First stage: selection equation

\[
D_j = \begin{cases} 
0 & \text{if } D^*_j \leq 0 \\
0 & \text{if } D^*_j > 0 
\end{cases} ,
\]

where

\[
D^*_j = Z_j \delta + e_j.
\] (10)

Second stage: flow equation

\[
Y_j = \begin{cases} 
Y^*_j & \text{if } D^*_j > 0 \\
0 & \text{if } D^*_j \leq 0 
\end{cases} ,
\] (11)

where

\[
Y^*_j = X_j \beta + u_j.
\] (12)

\[e_j \sim N(0, \sigma)\] (13)

\[u_j \sim N(0, 1)\] (14)

\[\text{corr}(e_j, u_j) = \rho_{eu}.\] (15)

Here \( j \) and \( t \) denote host country \( j \) and year \( t \). \( D^*_j \) is a latent value of the selection equation (10). This binary dependent variable can be estimated by a probit model to assess the probability of China making OFDI conditional on \( Z_j \). \( Z_j \) is a vector of explanatory variables which includes both the main variables of interest and control variables.

\( D_j \) is a decision dummy, \( D_j = 1 \) represents China conducting OFDI in country \( j \) at time \( t \) and \( D_j = 0 \) represents China not conducting OFDI. The selection equation (9) illustrates that China makes OFDI if and only if a certain threshold is surpassed. \( Y^*_j \) is the latent value of the flow equation (12). \( X_j \) is a vector of explanatory variables to estimate the magnitude of China’s OFDI. \( X_j \) include all the explanatory variables in \( Z_j \) together with an additional selection criteria \( D\_OFDI \).

The continuous dependent variable \( (Y_j) \) in flow equation (12) is no longer randomly selected in the Heckman selection model \( (Y_j = Y^*_j, \text{if } D^*_j > 0) \). Systematically neglecting censored OFDI leads to a sample selection bias. \( Y^*_j \) is only observable when China makes OFDI in country \( j \) at

\[\text{We choose a dummy (D\_OFDI) for the 1-year lagged OFDI flow to represent the selection criteria. D\_OFDI = 1 if China invested in a host country in the last year, and 0 otherwise. A similar choice is illustrated by Razin and Sadka (2007).}\]
time $t$ if $D^*_{jt} > 0$, but $Y_{jt}$ is unobservable if China does not invest irrespective of the small positive latent value $Y^*_{jt}$. This non-observability biases the estimation by non-randomly excluding latent $Y^*_{jt}$ if $D^*_{jt} \leq 0$. An ordinary regression will generate biased results if the correlation ($\rho_{eu}$) between selection equation (10) and flow equation (12) is significantly different from zero.

Detailed regression results for the Heckman model for two sample periods are not presented but are available on request. For the time period 2003–2009, the $\rho$-value is significantly different from zero for all models when excluding the control variable; it is significant only for oil and oil price models after including the control variables. For the period 1991–2003, the $\rho$-value is significant for all models. The significance of the $\rho$-value ensures that the Heckman estimations are reliable except in considering the effect of the control variable when metals and technology are investigated for 2003–2009. For the period 1991–2003, the significant $\rho$-value indicates that the unobserved effect is significant for China’s OFDI. Three specific implications are notable. The first implication is the coexistence of symmetric and asymmetric effects of the same independent variable on the dependent variable in both the selection and flow equations. The second implication is the sensation of the commercial risk in the oil sector. The third implication is the preference for technology seeking in the high-income countries.

(1) Asymmetric Effects from a Two-stage Mechanism
Symmetric and asymmetric effects mirror the two-stage specificity, which allows the same independent variable to have the same or a different effect on the dependent variable in the selection equation and flow equation, respectively. A symmetric effect implies that the same independent variable simultaneously affects the dependent variable in both the selection and flow equations. Oil abundance provides a good example of the symmetric effect. In 2003–2009, the oil-seeking motivation is significant at the 1-percent level in the base selection and flow equations. An asymmetric effect implies that the same independent variable can only have a significant impact in either the selection or the flow equation, but not in both.

In the period 2003–2009, the metal-seeking motivation is positively significant at the 1-percent level in the base flow equation. The technology-seeking motivation is positively significant at the 5-percent level in the base flow equation. The oil-seeking motivation is positively significant at the 5-percent level in the augmented flow equation. The technology-seeking motivation is positively significant at the 1-percent level in

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6 The insignificance of $\rho$ for 2003–2009 under metals and technology may be a result of fewer missing and zero values of the dependent variable.
the base selection equation. A cross-comparison of technology seeking in the entire ample period reveals a more significant change. In the early subperiod 1991–2003, host countries’ highly-advanced technology exclusively increases the possibility of China’s OFDI for technology-seeking purposes in the selection equation, but does not have any effect on the magnitude of OFDI. In sharp contrast, in the subperiod 2003–2009, host countries’ highly-advanced technology exclusively increases the magnitude of China’s OFDI in the flow equation but does not have any effect on the possibility of China engaging in OFDI.

(2) Commercial Risk in Extractive Industries

In the period 2003–2009, a negative correlation is found between oil prices and China’s OFDI in the selection equation. The two-stage mechanism reveals the asymmetric effects of high oil prices in the sense that this commercial risk only reduced SOEs’ possibility of investing, but after SOEs made a decision to invest in the oil sector, the magnitude of OFDI did not affect oil prices. This commercial risk is widely acknowledged as expropriation. It is a common risk in the extractive industry. It is closely related to the rise of prices and it frequently arises when raw material prices increase.

Duncan (2006) defines three acts of expropriation, including the seizure of MNCs’ capital, compelled sales of MNCs’ shares and increasing tax on MNCs’ profits. He points out that the rise in mineral prices is a significant factor triggering expropriation. Expropriation has a higher likelihood in extractive industries than others and this likelihood increases with the rise of mineral prices (Truitt, 1970; Jodice, 1980; Kobrin, 1980; Hajzler, 2012). This happens not only in developing countries, but also in developed countries. For example, the UK Government raises the tax rate on the North Sea oil when oil prices rise. Expropriation occurred frequently in the 1960s and 1970s (Truitt, 1970; Kobrin, 1984) and from the mid-1990s onwards (Hajzler, 2012). A rise in mineral prices increases profits of investors relative to the income in host countries and the expectation of higher prices inevitably increases the risk of expropriation (Hajzler, 2012). Using a probit model, Duncan (2006) confirms the positive correlation between the possibility of expropriation and mineral prices.

Expropriation is a concern of the Chinese Government and SOEs. Lieberthal and Herberg (2006) indicates that the Chinese Government carefully selects national oil companies to invest in host countries after carefully calculating the commercial risk. CNPC is selected to invest in controversial countries while CNOOC invests in less controversial countries. According to Houser (2008), CNPC and Sinopec have operated risky projects under government-related parent companies but have selected less risky projects underlisted subsidiaries. China’s major OFDI participants in extractive
industries are SOEs that are heavily controlled by the central government, but participants also include public listed companies (Chinalco, CNOOC, CNPC and Sinopec). Chen (2008) indicates that China’s oil companies have dual goals. Their international expansions are driven by the central goal of maximizing profits as listed companies. They also seek national oil security. This dual role implies that Chinese SOEs have to maximize national interest and minimize commercial risk at the same time.

(3) Preference for Advanced Technology in Developed Countries
In the period 2003–2009, the interaction of high income and advanced technology (Tech*HIn) is found to be positively significant at the 1-percent level in the base flow equation. This implies that China has a strong incentive to acquire technology in high-income countries. The two-stage mechanism reveals asymmetric effects to confirm this preference. This interaction is insignificant only in the selection equation, which means that developed countries do not have a higher possibility of receiving investment before China makes the OFDI decision for technology-seeking purposes.

This indifference may be the root of insignificance under the FE estimation. However, if the decision is made to invest, developed countries would receive more investments because they possess the technologies that China needs. This finding confirms our early discussion in Section V. A country’s income level implicitly reflects its technological capability. Therefore, a positive difference in income levels implies technological superiority. As discussed in Section III, advanced technology is the key to promoting productivity growth and improving competitiveness. As an important source of late-comer advantages, China can use these technologies advanced by developed countries. Sophisticated technologies are expensive and time consuming to develop (e.g. general purpose technologies). However, the leapfrogging theory suggests that developed countries may not have strong incentives to utilize them due to high labor costs. This implies that lagging countries that take the opportunity to utilize new technology and boost economic growth eventually may take the lead from other countries. China’s rapid expansion of high speed rail and nuclear power are just two examples.

VI. Conclusion

China’s recent surge in OFDI has attracted media and political attention from various

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7Chen (2008) also illustrates the contradiction of the goals between Chinese oil companies and the government.
perspectives due to several significant buyouts. This study provides a formal empirical examination by focusing on two important location determinants, natural resources and technology.

We use two separate but connected datasets for China’s OFDI in two time periods: 132 host countries in 2003–2009 and 131 host countries in 1991–2003. The datasets provide the richest information that can be used to explain China’s OFDI behavior. The empirical results from the traditional FE regression technique provide a good benchmark. The specific features of China’s OFDI enables this study to use sample selection econometric techniques, the Tobit and Heckman models, to reveal results that are not possible to attain through the traditional techniques. Estimations from sample selection techniques provide consistent and informative results, which are in line with theoretical expectations and our hypotheses.

The outside world has typically argued that China’s OFDI presents a threat rather than an opportunity for other countries to prosper. For example, some people argue that China’s large-scale buyouts in natural resources will harm the interests of host countries. It is also argued that China’s generous investments in developing countries are not based on economic incentives but on the country’s political needs.

There are four key motivations for China’s OFDI: to seek natural resources to secure a stable supply of such resources; to stabilize mineral prices to maintain an acceptable price level; to seek advanced technology; and to transfer appropriate technology to developing countries to increase the market share of Chinese goods and services. Chinese OFDI is clearly driven by host countries’ natural resource endowments in oil and metals. A rise in metal prices would also increase China’s OFDI.

The recently booming mineral prices have increased the commercial risk, especially the expropriation risk, which is a major problem for extractive industries. China is aware of the commercial risk of OFDI in the oil sector and explicitly takes this into account in the decision-making process. China’s OFDI is driven by host countries’ advanced technology to enhance its ownership advantage. China has a preference for seeking the most advanced technology in the most developed countries, because these sophisticated technologies provide late-comer advantages to China.

High labor costs in the host economies constrain their ability to utilize technology. China can take this opportunity to realize the so-called leapfrogging bypass. The acquisition of these advanced technologies from developed countries would enable China to grow faster than the host countries in question. Provision of appropriate technology is the key to the popularity of China’s OFDI in the developing world, because it is easier and cheaper for them to adopt compared with the more sophisticated and, hence, more expensive technologies imported from the developed world.
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