Outward FDI: National and Regional Policy Implications for Technology Innovation

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Abstract

Last 20 years' China's economic growth and technological catchup is through their 'go-global' policy promoting investment abroad. This policy developed foundations for establishment of high technology industries and world leading research. We find that across China, the 'go-global' policy needs support from provincial governments in terms of human capital, basic research and infrastructure to ensure that imported technology is effectively absorbed into the local economies. This means a national strategy needs local tuning to the needs of the region. Across all provinces, we find that during the period 2006 to 2016 outward foreign direct investment (OFDI) spillovers have a significant and positive impact on technology innovation as measured by patents. OFDI alone is insufficient and may crowd out local research and development (R&D), as such, those provinces need to get to a threshold of absorptive capacity in basic, applied research supported by human capital and R&D capital stock. When the gap between a province and the rest of the world is large then OFDI could have a crowding out effect without the province supporting basic research. We test for structural changes across all provinces by classifying them by either having large or small frontier technology, the proxy for absorptive capacity. We find that the role of human capital and basic research changes substantially between small gap and large gap provinces indicating that regional policy makers need to ensure that policies are fine tuned to the stage of development in a particular region and will change over time. OFDI effects are diminished as the provinces gap reduces and this may be particularly timely in the face of China being subject to increasing trade and investment pressure internationally.

Key words: Technological innovation, government policy, OFDI spillovers, technology gap, threshold effect, basic research and applied research.

JEL classification: C24, F21, O32, O35, O38

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1 Introduction

In 1999 China unveiled a ‘go-global’ strategy to replace investment driven economic growth with innovation driven growth that would place China at the centre of global economic and political influence. This policy is one of the major institutional push factors for Chinese Outward Foreign Direct Investment (OFDI) as in the following year, OFDI flows grew by 14.27% from $4.036 billion. By 2016, OFDI has overtaken Inward Foreign Direct Investment (IFDI) in China in terms of its value, share of gross fixed capital formation and the share of Chinese national output. As of 2018, 43,000 Chinese OFDI enterprises operated in 188 countries with a staggering investment flow of $143.04 billion (Chinese Ministry of Commerce, 2020).

There are number of pull factors behind the exponential Chinese OFDI growth among which include technology ~~seeking~~, efficiency ~~seeking~~ and asset seeking. Interested readers can consult Acs et al. (2001), Mathews (2006) and Rui and Yip (2008) for more details on these motivations. The Ministry of Commerce and Ministry of foreign affairs established a catalogue which acted as the instrument of OFDI approval. In this catalogue technologically advanced countries in Europe, North and South America and Asia and Pacific were targeted in order to invest in capital and technologically intensive industries. Mathews (2006) described Chinese companies’ participation in these sectors as ‘skilful learning and adoption-cum-adaptation of advanced technologies’.

Paul and Benito (2017) theorizes OFDI using a conceptual framework titled antecedents, decisions and outcomes (ADO). The main outcomes according to the authors are around innovation, knowledge transfer and reverse knowledge transfer. A growing body of literature now looks at the outcomes of OFDI rather than the antecedents and factors (See Hong et al., 2019; Huang and Wang, 2009; Lyles et al., 2014). These studies look at the technology spill over effects of OFDI through the learning channel and technology gap between the home and host country. For instance, Lyles et al. (2014) found that OFDI increases firms’ absorptive capacity. Furthermore, Huang and Wang (2009) found that OFDI is positively related to innovation in China by firms’ patent applications and licensing. Hong et al. (2019) concludes that OFDI in developed countries promotes innovation in regions in China with the technology gap benefits from innovation.

From an Institutional Theory (IT) point of view, national and subnational institutions play an important role in governing firm’s behaviour (See North (1990) for more details). In order for local firms to fully engage and take advantage of China’s ‘go-global’ policy and its ecosystem, the parallel development of national and subnational policies are paramount. However, as documented by Xu (2011), Boisot and Meyer (2008) and Meyer et al. (2009), China suffers from a fragmented domestic economy, regional inequalities, incompatible subnational policies, infrastructure and infostructure. The impact of these institutional policy differences across regions have a significant impact on the levels of OFDI, innovation, technology absorptive capacity of firms and resulting technological spillovers.

This paper empirically investigates the role of OFDI in fostering technological innovation and spillovers for the Chinese economy when regional differences in capabilities exist as a result of national and regional policy differentials. To date empirical work connecting OFDI to technological innovation and technological spillovers are relatively scarce. Through this study, we explore how regional differences in technology absorption thresholds affect the level of technological innovation and spillovers. This study stands out from other existing research in a number of dimensions. First, using regional level data for China, we determine the extent to which OFDI boosts innovation in China. Second, we investigate the extent to which inherent regional differences in the technological absorption threshold affect levels of innovation and technological spillovers from OFDI. Finally, we explore the role of the heterogeneous regional technology gap with the rest of world in influencing the level of OFDI, applied and basic research outcomes.

This paper contributes to the literature by developing an understanding of China’s strategy to importing technological knowhow and so maintain growth across all its provinces. One of the characteristics of China’s strategy is to develop the provinces to such a level as to. Be able to take up technological innovation efficiently. We demonstrate a threshold effect where a foundational level of development is required in the provinces prior to exploiting OFDI channels. Our innovation is that basic research, applied research and OFDI have different joint impacts on technological innovation based regional technology gaps. This influences the political decision making at both provincial and national levels by determining the funding and deployment of foundational applied research. It also determines levels of infrastructure and human capital development required in the provinces.

The structure of this paper is as follows. In section 2 we review the existing literature following the development of the hypotheses in section 3. We then describe our methodological framework in detail with a brief summary of the data sources in Section 4. Section 5 reports the results and their interpretation. Finally, in Section 6 we provide policy implications and conclusions.

2 Literature Review

2.1 Outward foreign direct investment (OFDI) and technological catch-up

One of the key motives for OFDI is to seek technological know-how, referred to in the international business (IB) literature as 'technology-seeking'. Awate et al. (2012) distinguishes between imitation and innovation using the concept of output-catch-up and innovation catch-up. The former relates to closing of the output gap between an EMNE and their advanced country counterparts by learning the technology and processes relating to the currently observable output frontiers while the latter relates to 'enhancement and development of the currently observable product or service' Awate et al. (2012). It can be established that output catch-up is the result of the innovation gaps between the EMNE (both the headquarter and subsidiary) which incentivise the EMNE to mimic in order to achieve parity while the innovation catch-up contributes to the development of applied and basic research enhancing innovation by the EMNE. Under this approach the main strategy used in research and development by Chinese OFDI is competencies creation (Cantwell & Mudambi, 2005, 2011).

The process of knowledge transfers and technological catchup of Chinese enterprises has two channels. The first is through internalisation of technological know-how by firms engaged in OFDI, so that it can transfer this knowledge to domestic headquarters resulting in reverse technology spillovers. The local headquarters are likely to undertake applied research and basic research to strengthen their local and international competitiveness. This creates a wider technology gap locally incentivising firms to react through research and development. The second channel is through local firms learning from their foreign trading partners. As stated by Clegg and Voss (2018) and Hensmans and Liu (2018), local Chinese firm's interaction with foreign firms allows them to leverage the learning achieved through them to become MNEs, thereby increasing the size of Chinese OFDI. Therefore, the level of innovation has a two-way relationship with reverse technology spillovers and the inherent technology gap with foreign partners.

2.2 Absorptive capacity and innovation

Innovation associated with reverse technology spillovers requires OFDI firms to have some degree of absorptive capacity. Absorptive capacity of firms has a direct link to the level of the technology gap that prevails between the EMNE and firms in advanced economies. Hong et. al (2019) describe the technology gap as the 'observed distance of technical efficiency, knowledge or technology level, managerial skills and productivity' between the EMNE and firms in the markets. The channel through which absorptive capacity feeds into innovation is through R&D activities aimed to close the technology gap by integrating foreign technologies. For instance, Japan's technological development had a significant contribution from imported technologies which was absorbed by domestic firms that enhanced the level of innovation. A number of empirical studies have established a link between imported technologies and domestic R&D activities (Pack and Saggi, 1997).

In the literature, there is no consensus on the optimal technology gap required and the technology threshold EMNEs need to reach before the benefits of technology transfer on innovation can be realised. Hausman et al. (2005) stated that for technological transfer to occur, its essential to develop absorptive capacity. Furthermore, Glass and Saggi (1998) advocated that there exists a threshold level in terms of current technology and the human capital firms needs to establish in order for it to benefit from technology spillover effects. The threshold level determines how efficiently firms can manage new knowledge and apply it to innovation.

Edamura et al., (2014) find that at firm level data supports the hypothesis that firms achieve their goals with OFDI whereas Bai (2009) concludes that these reverse spillovers into technological innovations are not significant. In contrast, Li et al. (2016b) identify that there is a significant difference in OFDI spillovers from east to western China, with the effects being more limited in the west. Furthermore, R&D and human capital have much greater effects than OFDI indicating that these are critical channels for China to progress. Another is the OFDI effects in both the short and long run, Yang et al. (2011) identified that the results are regional and relative to the level of development. This view is supported by Bruce and Chang (1991) and Rudy et al. (2016), that the heterogeneous nature of firms and regions in their technology capacities determines if OFDI spillovers are significant.

A technology gap index is the basis for absorptive capacity in IFDI spillover analysis, hence we apply the same index to OFDI. A wide technology gap is most likely to encourage imitation that can lead to a narrowing of the gap and improve absorptive efficiency, hence capacity (Verspagen, 1992; Glass and Saggi, 1998; Girma et al., 2001). Most empirical studies are at a national level (Liu et al., 2005; Buckley et al., 2007). This may lead to variable results due to the limitations in aggregation at a national level that largely compromise any conclusions (Sonnenschein, 1973).

Several empirical papers on Chinese FDI exists in the literature. Table 1 succinctly summarises the most recent literature on FDI and technology spillovers. This empirical paper contributes to the literature by establishing the level of technological threshold the Chinese firms engage with before OFDI is realised and can then benefit from technological innovation.

Table 1 - OFDI and innovation review of the recent literature

Study	Method	Time	Sample	Region	Outcomes
Acs et al. (2002)	OLS	1982	8,074 commercial innovations	125 US metropolitan	Patents are a reasonable proxy for innovation, however, silent economic value to economy.
Borensztein et al. (1998)	2SLS and 3SLS	1970–79, 1980–89	1380	69 Developing countries	For developing countries FDI is an important tool for the transfer of technology and contributes to economic growth in developing countries.
Braconier et al. (2001)	OLS, fixed and random effects	1978 -1994	217	84 Swedish firms	There is a strong positive relationship between OFDI and technology spillover effect.
Buck et al. (2007)	Probit and Tobit	1998-200.	5,861 foreign-invested, 7,697 Chinese firms	China	Technological innovation can be boosted by IFDI with a positive consequence on economic growth.
Coe and Helpman (1995)	OLS and WLS	1976-1989 excl. 1980	4,000 plants	Venezuela	That FDI/FII does not lead to technology spillovers
Comin and Hobijn (2004)	Pooled and fixed effects	1788–2001	23 countries and 25 technologies	23 industrial Countries	Human capital and income have a positive effect on technology adoption.
Lee (2006)	Dynamic OLS	1981-2000	320	16 OECD countries	The IFDI affects international knowledge spillovers.
Li et al. (2016b)	Fixed effects threshold	2003- 2013	290	29 Chinese provinces	OFDI benefits from reverse knowledge spillover when the technology gap between a province and MNEs' host countries. Double-threshold effects of technology gaps.
Pavitt et al. (1987)	OLS	1945-1983.	4000 innovations	UK	U-Shaped relation between firm’s size and innovation output.
Huang et al. (2012)	Fixed effects threshold	1985-2008	696	29 Chinese provinces	Double-threshold effects of regional innovation on productivity spillovers from FDI.

Study	Method	Time	Sample	Region	Outcomes
Tan et al. (2016)	Pooled mean group and mean group	1986-2011	128	8 ASEAN countries	Both IFDI and outward OFDI have a positive impact on the gross domestic investment.
Wang et al. (2016)	Fixed effects threshold	2000 -2011	360	30 Chinese provinces	The FDI technology spillover has two threshold effects of the technology gap in China.
Zhou et al. (2019)	FGLS	2004-2014	341	31 Chinese provinces	The relation between OFDI and domestic innovation is positive in developing countries but negative in emerging markets.

3 Hypotheses, theoretical framework and methodological approach

3.1 Hypothesis 1 (H1): Chinese OFDI boosts domestic technological innovation

The ability of Chinese transnational firms to absorb all the technology and use it to increase innovation depends on the infrastructure, current technology levels, human capability and, willingness to learn and develop (Bitzer and Kerekes, 2008; Li et al., 2016a). While many of these studies have concluded that significant technology gaps are likely to moderate the effects of OFDI (Wang et al., 2016; Li et al., 2016a), the data used in these studies are dated and potentially less useful in establishing the heterogeneity of provinces. Intuitively, one needs to consider the role of regional development in terms of both human and technological capital for technological absorption.

To establish the relationship between OFDI and domestic technological innovation, one needs to observe a measure for technological advancement. Following Griliches (1979), Hall and Ziedonis (2001) and Acs et al. (2002) and the general trend in the literature, we use as a proxy the intellectual property (IP) measure (authorized patents). A core driver for IP is domestic R&D (RD) supported by human capital development (HC) and the three channels for international spillovers: IFDI, imports (IM) and exports (EX) (van Pottelsberghe and Lichtenberg, 2001; Li et al., 2016b; Filippetti et al., 2017; Zhou et al., 2019). We take logs of all variables to form the linear model:

$$IP_{it} = \gamma_i + \alpha_1 RD_{it}^{s} + \alpha_2 IFDI_{it} + \alpha_3 IM_{it} + \alpha_4 EX_{it} + \alpha_5 HC_{it} + \beta OFDI_{it} + \epsilon_{it} \quad (1)$$

where the dependent variable is IP_{it} which is the number of authorised patents in province i at time t, $OFDI_{it}$ is the total inward foreign direct investment to China, EX_{it} is the total exports, IM_{it} is the total imports, $IFDI_{it}$ inward foreign direct investment from country i to China, HC_{it}

is the human capital level and RD^s_{it} is the stock of R&D investment, $OFDI_{it}$ is the total outward foreign direct investment from China.

As stated already, we use the flow of authorised patents as the proxy for the flow of technological development following Griliches (1979), Li et al. (2016a), Hong et al. (2019) and Zhou et al. (2019). This could be somewhat problematic in that patents are not necessarily of the same technological benefit nor do they cover all development (Griliches, 1990; Arundel, 2001; Cuddington and Moss, 2001). The alternative is R&D expenditure which measures only the resources put towards development which may not account for beneficial outcomes. Furthermore, accounting practices may differ across firms and lead to inconsistent results. Although IP is potentially problematic as a proxy, it is from a primary source which is not reliant on differences in reporting. It is likely to understate the level of development, thus amplifying the effect of the inputs. Many of these criticisms are overcome by Li et al., (2016a) and overall it is accepted in the literature as a reasonable proxy.

When it comes to R&D, then we use the depreciated stock of all accumulated R&D investments in a province at time t. Treating R&D as an inventory, we write the equation for motion of R&D using Coe and Helpman (1995) and Coe et al. (2009) as:

$$RD^s_{it} = (1 - \delta)RD^S_{i,t-1} + RD^e_{i,t} \tag{2}$$

where RD^s_{it} is the R&D inventory in province i at time t, δ is the R&D depreciation rate and RD^e_{it} is the R&D expenditure in province i at time t. We normalise all R&D to 2006 prices. This implies that for a province to grow R&D inventory then $\delta RD_{it-1} < RD^O_{it}$. This presents a problem, although we know the investment per period, we do not know the R&D stock. Again following Coe and Helpman (1995), we use the calculated present value of R&D stock at $t = 0$ by:

$$RD^s_{i,0} = \frac{RD^e_{i,0}}{(g+\delta)} \tag{3}$$

where the growth rate in R&D expenditures are calculated by $g = \left(\frac{RD^e_{i,T}}{RD^e_{i,0}}\right)^{1/T}$ and then rolling forward (3) above to calculate every year’s total R&D investment stock. By summing the provinces per period it provides the Chinese total level of R&D investment stock, formally:

$$RD^s_t = \sum_{i \in I} RD^S_{i,t} \tag{4}$$

We construct OFDI using the two step process set out in van Pottelsberghe and Lichtenberg (2001), Hong et al. (2019) and Zhou et al. (2019). Firstly, the domestic OFDI related R&D capital stock is obtained:

$$OFDI_t = \sum_j \frac{OFDI_{jt}}{GDP_{jt}} RD_{jt}^s \tag{5}$$

where $OFDI_t$ is the R&D stock China obtains from its OFDI towards country j in year t and GDP_{jt} is the GDP of country j in year t. We translate nominal into real by dividing $OFDI_{jt}$ by P_{jt} . The RD_{jt}^s is the R&D stock of the country j at the time t, it can be obtained using the same method as above:

$$RD_{jt}^s = (1-\delta)RD_{j,t-1}^S + RD_{j,t}^e \tag{6}$$

where RD_{jt}^s is the R&D inventory in country j at time t, δ is the R&D depreciation rate and RD_{it}^e is the R&D expenditure in country j at time t. Then the OFDI of the province is calculated by using the proportion of province OFDI stock relative to the domestic one.

$$OFDI_{it} = OFDI_t \times \frac{OFDIstock_{it}}{\sum_i OFDIstock_{it}} \tag{7}$$

3.2 Hypothesis 2 (H2): That OFDI spillover is dependent on an absorptive capacity threshold

The absorptive capacity constrains the effectiveness of FDI. Absorptive capacity is a function of R&D investment stock and human capital (Cohen and Levinthal, 1990; Dussauge et al., 2000; Glass and Saggi, 1998; Mowery and Oxley, 1995). In equation (1), we control for the heterogeneity by the fixed effects model. If the OFDI's coefficient for a province is significant and positive, then OFDI has an impact on technological development. To resolve this, we need to employ a threshold model to understand if thresholds exist and at what level. Equation (8) sets a threshold (TH) and determines the OFDI coefficient below and above that threshold. If a threshold exists and is significant in both coefficients then we check for two thresholds and so on (Wang, 2015; Li et al., 2016b). We employ the fixed-effects threshold model described in Hansen (1999, 2000).

$$IP_{it} = \gamma_i + \sum_{m \in v} \alpha_{m,i,t} v_{m,i,t} + \sum_{k=1}^{K+1} \beta_{k,i,t} TH_{i,t}(\theta_{k-1} < TH_{i,t} \leq \theta_k) + \epsilon_{it} \tag{8}$$

$$IP_{it} = \gamma_i + \sum_{m \in v} \alpha_{m,i,t} v_{m,i,t} + \beta_{i,t} OFDI_{i,t} \times TH_{i,t}(\theta_1 > TH_{i,t}) + \beta_{k,i,t} OFDI_{i,t} \times TH_{i,t}(\theta_1 \leq TH_{i,t}) + \epsilon_{it} \tag{9}$$

$$v_{i,t} = \{RD_{i,t}, HC_{i,t}, IFDI_{i,t}, IM_{i,t}, EX_{i,t}\}$$

$$TH_{i,t} = \{PG_{i,t}, HC_{i,t}, RD_{i,t}\}$$
$$\theta = \{-\infty, \theta_1, \dots, \infty\}$$

where $K+1$ is the length of set θ, elements θ_1 ... are threshold parameters, PG is the productivity gap and TH is the threshold variable computed following the Hansen methodology. Note that if RD or HC is the threshold variable then it does not appear in the linear part of the model. We use the three proxies to represent the technology gap - productivity gap, human capital and R&D stock. For the productivity gap (PG), we follow Kokko (1994), Castellani and Zanfei (2003) and Hong et al (2019), which involves the use of real GDP. For human capital, we follow Glass and Saggi (1998), Zahra and George (2002), Comin and Hobijn (2004), and Zhou et al., (2019) to measure the absorptive capacity. Meanwhile, the R&D effort, spending on training and the ability to hire a well-educated labour force indicates the resources that a firm has (Cohen and Levinthal, 1990; Glass and Saggi, 1998; Mowery and Oxley, 1995). We apply the productivity gap, R&D stock and human capital to observe if technological absorptive capacity has a threshold effect.

This treatment on ‘clustering’ similar firms in geographical regions mirrors what has been observed throughout the industrial age. Prior empirical studies do not take into account the ‘threshold’ level for absorptive capacity which lays the ‘foundations’ for development. The following hypothesis describe the motivation for the use of the threshold level.

3.3 Hypothesis 3 (H3): Regional differences in research and OFDI impact levels of technological innovation

Our approach is to utilise the thresholds from H2 to classify provinces into two groups based on the technology gap - large and small technology gap. This allows us to study causation between absorptive capacity and OFDI spillovers in greater depth. Furthermore, this causal relationship influences the technological innovation incentive effect of basic research. A non-significant threshold does not necessarily imply thresholds have no effect. Instead, we should expect that a small technology gap would lead to lower acquisition of technology spillovers suggesting that the absorptive capacity is not being fully utilised (Cohen & Levinthal, 1989; Martínez-Senra et al., 2015).

Salter and Martin (2001) identify that scientific research including applied and foundational or basic research is core to moving technological innovation forward. As in Nelson (1959), the difference between applied research, focusing on practical inventions and product development, and basic research in its effects on absorption and innovation capacity indicates that basic research is the foundation for absorptive capacity. Therefore, as these two forms of research have different but joint effects and there is little in the way of recent research on these effects, we need to consider the relative roles of applied and basic research, so we add a subsidiary to this hypothesis to clarify the distinct and joint impacts.

Foundational or basic research tends to be riskier, more expensive and lengthy than applied research thus governments tend to conduct or fund this type of research with the intention of producing spillovers into the private sector[2] (Nelson, 1959). The government is able to take on much greater risks and deploy greater resources to attain research objectives. Therefore, the private sector tends to focus on applied research that it can turn into marketable intellectual property and profitable products arising out of the work of government.

We utilise the Arrow (1972) and Park (1998) model extended by Cassiman et al. (2002), Henard and McFadyen (2005) and Gulbrandsen and Kyvik (2010) to explore the impact of applied and basic research on knowledge creation and technological spillovers. The model specifies the interaction between applied and basic research, the models include the provincial government (state) investment, measures of infrastructure development (road pavement) and per capita GDP to determine the province's technological development. We specify the model thus:

$$IP_{it} = \rho_{11} + \rho_{11}A_{it} + \rho_{12}A_{it} \times B_{it} + \rho_{13}H_{it} + \rho_{14}OFDI_{it} + \rho_{15}State_{it} + \rho_{16}pGDP_{it} + \rho_{17}pInf_{it} + u_i + v_t + e_{it} \tag{10}$$

where IP_{it} and $OFDI_{it}$ are as before, A_{it} and B_{it} are the applied basic research respectively. Basic Research is research that tries to expand the already existing scientific knowledge base largely on a theoretical basis whereas applied research solves real-life problems using scientific study, that is by developing practical solutions to real-world problems. The interaction term $A_{it} \times B_{it}$ represents the incentive innovation effect of basic research. We control for the number employed (H_{it}), provincial government investment in fixed assets $(State_{it})$, the per capita real GDP (GDP_{it}), and as a proxy for infrastructure the paved roads area $(pInf_{it})$ following Higón (2016). The u_i is the provincial fixed effect and the v_t is the time fixed effect.

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[2] Examples are in Space exploration where governments took the lead and eventually, we will observe the commercialisation by the private sector. This also include military research stemming back to the basics of radar, sonar, GPS providing the foundations for much applied research. Much foundational medical research is government funded particularly in the areas of vaccines and genetics.

However, we need to determine the level of applied research A_{it}, we do this by the process developed by Nelson (1959) by estimating the equation:

$$A_{it} = \rho_{21} IP_{it} + \rho_{22} B_{it} \times OFDI_{it} + \rho_{23} H_{it} + \rho_{24} OFDI_{it} + u_i + v_t + \mu_{it} \qquad (11)$$

and $B_{it} \times OFDI_{it}$ indicates the absorptive effect of OFDI spillovers of basic research. Note that IP_{it} and A_{it} occur in both 10 and 11 creating an endogeneity problem that we solve by using three stage least squares (3SLS).

4 Methodology and data

4.1 Econometric approach

To the existing empirical framework, we introduce methodological innovations to capture the technology spillover effects and extend the Chinese Provincial panel dataset (in Appendix A) to test the three hypotheses outlined above.

We collect additional data from various sources and merge them into a panel dataset with the same timeframe and provinces. Appendix A reports summary statistics and other tests on the dataset for validation. We use unit root tests such as Levin et al. (2002), Im et al. (2003), Fisher ADF and Fisher PP, Maddala and Wu (1999) and Choi (2001), to test for stationary in the panel data for each series. We then determined the lag length to be used to test the hypotheses using the Akaike Information Criterion (AIC).

Starting with H1, we test for the direct impact of OFDI on technological innovation in a province with and without lags. As this is a panel, we use the Hausman test, as suggested by Wu (1973), and Hausman (1978), to exclude pooled and random effects. If this is the case, then this implies that H1 is more suited to the fixed effects analysis.

Moving next to H2, where thresholds are important to our analysis, we apply the Hansen (1999, 2000) method to identify any threshold effects with their confidence bands for the threshold parameter. This provides a method for endogenously estimating the threshold level and its significance in a non-linear specification. The determination of thresholds begins with identifying the first significant threshold then finding the second significant threshold and so on until there are no more significant thresholds.

Finally, as H3 involves simultaneous equations, it poses an endogeneity problem that can lead to over identification. To overcome this, we used 3SLS. An F-test on the first stage identifies if it addresses the issue of endogeneity. For consistency we expect an F-stat of greater than 10.

We separate the provinces into two groups, namely, large and small technology gaps[3] as identified from H2. We expect basic and applied research to have lagged effects. We introduce controls for the one period and two period lagged values of applied and basic research respectively. In addition, we control for differences in the provincial and national economic factors, to control for the individual fixed effect and time fixed effects. We add to this hypothesis a subsidiary hypothesis to further explain the dynamics.

4.2 Data

We utilize a panel of 31 Chinese provinces covering the time period 2006 to 2016 including all the above variables sourced principally from the Chinese year book. We add in the controls such as employment, government investment, output and infrastructure. We normalize all prices to 2006 international US dollars. Prior to 2006 data for some provinces such as Xinjiang and Tibet is somewhat limited so not included. Furthermore, this extends and updates the studies by Hong et al. (2019), Xia et al. (2016) and Li et al. (2016b) by using a more comprehensive dataset with significant methodological extensions. For a detailed analysis of the data sources and issues refer to the Appendix A.

5 Results

We report the results from our empirical analysis of the three hypotheses here in the same order as specified in the methodology section above.

5.1 Panel data tests and results

The results of the unit root test and the AIC determined lags tests are reported in Table 2. The results rule out the presence of a unit root in the data. Furthermore, results indicate lags between 1 and 3 are the most relevant for dynamic equation analysis.

Table 2- Unit Root and AIC results

Variable	**Levin, Lin & Chu**	**Im, Pesaran and Shin W-stat**	**ADF - Fisher Chi-square**	**PP – Fisher Chi-square**	**Lags**
IP	-12.25^{***}	-1.51^{***}	97.31^{***}	132.02^{***}	3
RD	-24.77^{***}	-11.89	244.36^{***}	292.60^{***}	1
$IFDI$	-5.74^{***}	-0.87	69.78	57.63	1
IM	-9.10^{***}	-0.35^{***}	93.72^{***}	144.50^{***}	1
EX	-27.86^{***}	-6.38^{***}	169.34^{***}	102.18^{***}	3

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[3] The Technology gap is a measure of the level of technological development as benchmarked with the rest of the world, particularly the main trading partners.

$OFDI$	-31.18	-5.11***	138.31***	153.75***	3
A	-21.36***	-11.28***	231.99***	275.67***	1
B	-23.11	-11.52***	234.62***	323.18***	1
GAP	-39.91***	-27.66***	418.05***	417.22***	1
HC	-6.39***	-1.82**	87.87**	35.83	1

Note: ***, ** and * indicate the level of significance at 1%, 5% and 10% respectively.

5.2 OFDI spillovers boosts technological innovation

Table 3 reports the OLS regressions, fixed effects and random effect models that test H1. We observe that the Hausman test confirms that the fixed effects model is preferable to the OLS/pooled and random effects models. R&D is the main driver of technological innovation as one would expect. Regarding OFDI, this is both positive and significant in both the level and lag models indicating that OFDI has both an immediate and lasting effect on technological innovation, albeit small compared to R&D. This effect is observed across all provinces indicating that the Chinese government strategy of 'go-global' to the private sector has a materially positive impact on domestic innovation. Note that in the lagged OFDI models where OFDI plays a more significant role than the R&D role, it is about 12% less indicating that OFDI is more important than R&D. This would lead us to conclude that some level of R&D needs to be present for OFDI to be effective. We will explore this further in the next hypothesis.

Significance levels reported in Table 3 reinstate the hypothesis that R&D and OFDI are the most significant determinants of regional innovation. When discussing innovation, one needs to be cautious that imitation of a technology does not necessarily equate with innovation. While IFDI builds the technological base through imitation, OFDI through direct investment, joint ventures and partnerships facilitates transfer of knowledge and hence innovation. Our findings on OFDI as the mechanism that enhance knowledge transfer and innovation align with Piperopoulos et al. (2018).

As described in the introduction, for OFDI to feed into domestic innovation there is a subsequent time lag. The dynamic panel regression reported in Table 3 columns 4 to 8 explores this structure which incorporates one period and two period lags into the estimation. We note that in Table 3 the first and second lags individually (t-1 and t-2) are significant and positive and the lagged coefficients are increasing with time. Combining both lags into a single regression rules out the significance of the OFDI effect on innovation during present and lagged periods. However, a joint hypothesis test with two lags in Table 4 reveals joint significance indicating that OFDI has to be sustained over time to have a marked effect on domestic innovation. The policy implication is that the government needs to have a sustained consistent outward investment policy over many years for the Chinese economy to benefit from innovation associated with OFDI.

Table 3 - China's provincial effects on Innovation and OFDI

Variable	OLS	RE	FE (level)	FE (t-1)	FE (t-2)	FE (t,t-1)	FE (t,t-2)	FE (t,t-1,t-2)
RD	1.06***	0.90***	0.60***	0.64***	0.53***	0.60***	0.50***	0.50***
$IFDI$	0.10	0.05	0.05	0.04	0.05	0.04	0.05	0.05
IM	-0.15*	-0.11	-0.08*	-0.05	0.003	-0.05	-0.001	-0.01
EX	0.05	0.03	0.06	0.05	0.04	0.06	0.04	0.05
$OFDI$	0.05**	0.04**	0.11***			0.05	0.02	0.04
$OFDI_{-1}$				0.09***		0.05		0.04
$OFDI_{-2}$					0.11***		0.11***	0.12***
HC	-1.36***	-0.38	-0.38	-0.21	-0.29	-0.31	-0.32	0.26
C	-0.64	-2.37***	1.47	-0.15	0.83	0.67	1.26	0.50
R^2	0.91	0.90	0.98	0.89	0.87	0.88	0.86	0.87
$F-statistic$	691.21***	679.48***	109.92***	337.24***	257.35***	290.31***	219.91***	192.14***
$Hausman\ Test^1$			17.91***					
$Hausman\ Test^2$			30.92***					

Note: ***, ** and * indicate the level of significance at 1%, 5% and 10% respectively. OLS= Ordinary Least-squares, FE= Fixed effects, RE= Random effects, Hausman Test^1= FE VS RE and Hausman Test^2= FE to OLS.

Table 4 - Joint significance test results

Wald Test	FE(t,t-1)	FE(t,t-2)	FE (t,t-1,t-2)
$F-statistic$	7.26***	7.65***	5.24***
$\chi^2-statistic$	14.51***	15.29***	15.73***

In Table 4, we observe that R&D is significant in all cases. However, if we take into account the level and lagged OFDI, then the magnitude of the coefficient decreases indicating that OFDI has a role over time of about one quarter of that of domestic R&D. This supports the normative approach that both domestic R&D and sustained OFDI need to be present to increase domestic innovation.

IFDI and exports have little impact on innovation outcomes leading us to believe that foreign controlled investment and exports use productive capacity rather than innovative capacity.

They have little domestic benefit other than the streams of income from exports cause the labour force employment to increase (Wei, 2010). As our focus is on OFDI, we shall leave that issue for other studies. Likewise, the coefficient on imports is negative but insignificant indicating little impact from imports on innovation. Although local firms can observe, study, imitate and upgrade imported products (Coe and Helpman, 1995; Liu and Buck, 2006), its spillover' effects on technological innovation are also influenced by absorptive capacity (Eaton and Kortum, 1996; Liu and Buck, 2006). This may contradict some political viewpoints that China's imitation and acquisition of foreign IP through these channels are the main drivers for their own innovation. Rather this activity may boost exports providing a flow of funds to domestic firms that they can employ into OFDI and R&D, this again is a subject for further investigation.

Finally, with human capital (HC), one would expect that human capital, in part, drives innovation output. Surprisingly, in the presence of OFDI our finding contradicts this regardless of lag length. While there are many studies which establishes the role of that domestic human development in innovation (Lai et al., 2006; Huang et al., 2012; Zhou et al., 2019), in order for domestic innovation outputs occur a base level of education, knowledge and knowhow to engage with R&D needs to be established. This implies some form of threshold of human development as a prerequisite for R&D, exploitation of repatriated technology and innovation outputs. We will discuss this under the threshold model next.

5.3 The technology absorptive capacity threshold effect

Our interest now turns to the capability of Chinese provinces to absorb technology and whether there is a threshold level applying to the productivity gap, human capital and R&D stock. If thresholds exist, then we should observe different innovation performances as a province crosses a threshold.

Table 5 reports the results of our single and double threshold tests. Following on from H1 and comments on human capital, we find that there is a single threshold indicating that there is some minimum level of human development necessary for effective absorption of technology from outside sources confirming H1. The existence of one threshold imply that China needs to upskill domestic population's human capital though education and training for technology spillover to happen. One could deduce that any developing country attempting to absorb foreign technology needs to attain some level of human development to exploit the technology effectively. This implies that government policy needs additional impetus towards education, training, knowhow retention and skills development to ‘jump start’ innovation (Li et al., 2016a; Zhou et al., 2019).

R&D also has a threshold indicating that there needs to be a level of R&D investment activity in prior years to build R&D capability. This implies that R&D tends to a critical mass where ideas, knowhow and people interact in networks to becomes efficient in producing innovative outputs. We observe this effect throughout history with clustering in such places as Silicon Valley (US) for Computational technology, Detroit (US) in the 1930’s and the Midlands UK for vehicle development and Ruhr and Rhine valleys (Germany) for Heavy industry in the early part of the 20th century.

Table 5 – Thresholds Test Results

Threshold Variable	Threshold	θ_i	95% CI	F-statistic
Productivity Gap	1st	13.85	[13.19, 13.89]	18.53
	2nd	8.17	[7.550, 8.23]	8.29
Human Capital stock	1st	6.70	[6.69, 6.71]	59.09^{***}
	2nd	6.25	[6.07, 6.57]	21.99
Research and Development Stock	1st	9.05	[8.67, 9.14]	57.04^{***}
	2nd	13.60	[13.60, 13.62]	33.37

Notes: **, *** and * show significance at 1%, 5% and 10% levels respectively. 95% CI = 95% confidence interval.

In Table 6 we report the results from the interaction of a threshold variable with OFDI using the first threshold reported in Table 5. As before, R&D is a substantial contributor to the innovative outputs whereas IFDI, IM and EX are not. Although the threshold may not be significant the coefficients on either side imply these form a transitional curve. When the productivity gap is wide, OFDI make up the shortfall to gain the necessary research outputs to increase productivity. We will discuss the potential for OFDI to crowd out innovation later. If the productivity gap is small, OFDI has served its purpose in accelerating development to the developed country standards. However, this relationship has a breakpoint where OFDI has much less effect on output, with a diminishing improvement in innovation as the gap is closed.

This naturally raises the question, is there a similar threshold for human capital stock and R&D as suggested by Table 5 when there is an interaction with OFDI? We observe a threshold in both cases (Table 6). Human capital has a pronounced difference in the coefficients indicating that OFDI has double the effect when human capital development is low compared to being high. Likewise, with R&D, although there is an effect, it is more limited. Note that both human capital and R&D coefficients are significant and in the case of HC, particularly pertinent in the presence of the R&D threshold. We can imply that both human capital and R&D are significant contributors to innovation when OFDI is present. Therefore, OFDI policy play a significant role in developing intellectual capacity and knowhow when appropriate human capital development and R&D activities are in place. As the domestic HC and R&D matures OFDI effects tail off and China becomes more self-reliant on its own capabilities. We observe this with the maturing of Chinese corporations now directly competing in innovation with developed nations. Exploiting this channel has and continues to be somewhat of a ‘leg-up’ for Chinese innovation.

Table 6 - The estimates of OFDI technology spillovers for single-threshold

Variable	**TH=Productive gap**	**TH= Human capital**	**TH=R&D**
RD	0.55^{***}	0.53^{***}	
$IFDI$	0.05	0.05	0.06^{*}
IM	-0.07	-0.05	-0.01
EX	0.02	0.08	0.09^{*}
HC	-0.26		1.17^{***}
$OFDI \times TH\ (TH \leq \theta_1)$	0.11^{***}	0.20^{***}	0.36^{***}
$OFDI \times TH\ (TH > \theta_1)$	0.10^{***}	0.12^{***}	0.22^{***}
Constant	1.96	-1.23^{**}	-4.69^{***}
R^2	0.86	0.85	0.23
$\boldsymbol{F-statistic}$	354.83^{***}	501.88^{***}	$4.76.27^{***}$

Notes: ***, ** and * show significance at 1%, 5% and 10% levels respectively.

5.4 OFDI, basic and applied research and the innovation technology gap.

Using the results from H1 and H2, we divide the provinces into groups with large technology gap and small technology gap in order to describe how technology gap affects innovation. In Table 7, we report the results of running 3SLS for each province clusters to consider separately role of applied and basic research and total research, that interaction between applied and basic research in explaining technology gap. In addition, we consider OFDI separately and its interaction with basic research.

Table 7 – Role of applied research: 3SLS analysis of the grouping in the frontier technology distance

	Large				**Small**			
	Separate		**Interaction**		**Separate**		**Interaction**	
Dependent	$\boldsymbol{IP}$	$\boldsymbol{A}$	$\boldsymbol{IP}$	$\boldsymbol{A}$	$\boldsymbol{IP}$	$\boldsymbol{A}$	$\boldsymbol{IP}$	$\boldsymbol{A}$
$\boldsymbol{IP}$		0.26^{*}		0.55^{***}		-0.03		-0.35^{***}
$\boldsymbol{A}$	-0.45^{**}				-0.71			

B	0.94^{***}				0.92			
$A \times B$			0.29^{***}				0.09^{***}	
$OFDI$	-0.03	-0.89^{***}	0.01	-0.72^{***}	-0.02	-0.90^{***}	-0.002	-0.99^{***}
$B \times OFDI$		0.83^{***}		0.65^{***}		0.89^{***}		0.99^{***}
H	1.01^{***}	0.10	0.69^{***}	-0.13^{***}	1.29^{***}	0.27^{***}	1.22^{***}	0.66^{***}
HC	-0.56^{***}	1.03^{***}	-1.10^{***}	0.95^{***}	0.37^{***}	1.04^{**}	-0.11^{***}	2.72^{***}
$STATE$	-0.88^{**}		-0.83^{**}		-0.49		-0.51	
$pGDP$	0.52^{***}		0.35^{***}		0.31^{***}		0.30^{***}	
$pINF$	-0.04^{***}		-0.04^{***}		-0.01		-0.01	
C	-0.00	-6.66^{***}	4.03^{*}	-4.65^{**}	-0.00	-8.96^{**}	-1.09	-19.22^{**}
R^2	0.93	0.94	0.95	0.93	0.88	0.94	0.94	0.93
χ^2	60511^{***}	2182^{***}	2959	1948	3136^{***}	68675^{***}	60510^{***}	1930^{***}

Notes: ***, ** and * show significance at 1%, 5% and 10% levels respectively. Large and small are separate data sets classified by the gap being either wide and narrow between the current Chinese technology and the world. Separate and interaction indicates that Applied and basic research are either separate variables with coefficients or they are combined into one interaction term with one coefficient. IP and A indicate that the dependent variable is IP – intellectual property and A is applied research. C is the intercept or constant.

In this simultaneous equation models, we consider the effect of the dependent variables IP and A on each other first. With large gaps, IP negatively depends on A which is not the same with small gaps. On the contrary, A is positively enhanced by IP with large gaps and negatively with small gaps when we do not consider the rest of the research (B or A × B). We could infer that when the gap is large then possibly imported IP, that is locally registered is then exploited for applied research. The more applied research activity there is the less that imported IP is needed and firms focus on improving their processes and knowhow in production. This theory could possibly be further enhanced if one considers that basic research in large gaps is a significant contributor to IP and this is the mechanism that drives more applied research (Nelson, 1959). Somewhere there may be an equilibrium growth path in research and its outputs that affect the interaction between IP and applied research. Although moderate in comparison, the interaction between applied and basic research has a positive outcome on IP. If a small gap is a situation where all research has matured, then the production of IP from the combination of applied and basic research is moderated inferring that it becomes increasingly harder to find new innovations that warrant IP and the focus becomes more on taking basic research through to its application and then into production. Possibly, the negative driver that IP has on applied research is that research is not as important when the gap is small.

Moving next to OFDI, such investment has a negative impact on applied research regardless of technology, however little impact on IP. However, when we take into account basic research, this negative impact turns positive indicating that basic research is a significant driver of applied research regardless of the technology gap. This result lead us to devise additional an additional hypothesis regarding basic and applied research with regard to OFDI and IP which we will explore later.

Next, accounting for the labour force and human capital, the role of the state and the state of the economy. An interesting observation is that employment (H) has a positive effect on IP in both large and small gap scenarios (approximately 30% more influence in small gaps) and contributes to small gap applied research. In contrast, human capital is negative in large gap contributions to IP and positive with applied research suggesting and possibly reinforcing the view that the large gap provinces largely import IP and then apply it though applied research. Once the domestic economy develops and the gap is small then human capital and employment contribute to both IP and applied research reinforcing the view that basic research has a material need for human capital development when the gap is wide (Kim, 1998; Girma et al., 2001; Hermes and Lensink, 2003).

Finally, considering the state and economy's role in the development of IP and applied research. As one would expect, growing GDP would have a positive influence with both large and small gaps, inflation only in large gaps. The result that contradict with the norm is that state investment has a negative impact when there is large gaps while there is no impact with small gaps. This seems to imply that the state somehow displaces new developments. However, if the theory that IP is imported holds when the gap is large, then the state could be involved in developing the basic and applied research capacity, which might go some way to explain the dynamics. When the gap is small then the state's role becomes irrelevant, again theorising, research capacity is most likely self-sustaining rather than needing government intervention relative to how it might have been done in large gap provinces.

5.4.1 Applied and basic research, their roles in the technology gap

Extending H3, we consider the role of basic research as the instrument rather than applied research. We report the results in Table 8.

Table 8 - Role of basic research: 3SLS analysis of the grouping in the frontier technology distance

	Large		Small	
	Separate	**Interaction**	**Separate**	**Interaction**

Dependent	IP	B	IP	B	IP	B	IP	B
IP		0.05		0.85***		0.05		0.47***
A	-0.71***	0.53***		0.37***	-7.41	0.76***		0.70***
B	1.61***				9.71			
$A \times B$			0.29***				0.14***	
$OFDI$	-0.11***		0.08***		-0.26		0.003	
$A \times OFDI$		0.01***		-0.002		0.001		0.001
H	0.71***	0.02	0.64***	-0.67***	0.29	0.02	1.15***	-0.54***
HC	-0.45	-0.57**	-0.95***	-0.70**	-15.78	1.70***	-0.26	-0.42
$STATE$	-1.20**		-1.44***		0.79		0.44	
$pGDP$	0.42***		0.14**		0.14		0.25***	
$pINF$	-0.05***		-0.03**		0.07		-0.02	
C	-0.92	6.16***	3.20	8.73	100.16	-10.78***	-1.22	-4.92
R^2	0.89	0.93	0.95	0.89	-3.35	0.95	0.87	0.93
χ^2	2137***	2032***	2912***	1441***	329***	3463***	1300***	3069***

Notes: ***, ** and * show significance at 1%, 5% and 10% levels respectively. Large and small are separate data sets classified by the gap being either wide and narrow between the current Chinese technology and the world. Separate and interaction indicates that applied and basic research are either separate variables with coefficients or they are combined into one interaction term with one coefficient. IP and B indicate that the dependent variable is IP – intellectual property and A is applied research. C is the intercept or constant.

When compared with Table 7, results in Table 8 shows that IP effect magnifies while employment and human capital effects are moderated without interactions. When the instrument is basic research and is the dependent variable, then applied research, OFDI and human capital play a significant positive role whereas IP does not. Basic research has a significant role in developing IP (first column) and the mechanism for enhancing OFDI and human capital in IP development is though basic research. This potentially reinforces the argument that governments should encourage OFDI spillovers into the local economy and human capital development in the provinces to develop their economy and close the gap. Considering the interaction between applied and basic research, this is a driver for IP activity and IP with applied research has a significant positive impact on basic research. Contrary to Table 7, when the gap is large, human capital has a negative impact on basic research. This presence a policy conundrum where when provinces focus resources on applied research but it has a negative impact on IP and basic research. As basic research is the core driver of IP and gap, it is not supported by human capital development. One could surmise that the specialist nature of basic research involves such a small part of the working population that the effects would be minimal.

5.4.2 Research analysis and discussion

When productivity gap is small human capital play no role in IP development however, it becomes significant in affecting basic research. Moreover, one could question the role of IP there is no causation and does not contribute to basic research. This implies that there is a structural change in the dynamics of the provincial economies suggesting that the threshold is likely to uncover differences. Taking the interaction model, IP and applied research have a significant positive impact although the magnitude depends on the level of technology gap with smaller gap having limited impact. To theorizes this finding we consider the following scenario: a province with a large gap might find that human capital development is detrimental to basic research and decide to limit the investment. Such a decision will affect both applied research and growth and as the technology gap narrows and the demand from basic research for human knowhow will increases. There are substantial policy implications in the support of R&D with the effects from the underpinning resources to support both applied and basic research in a growing economy.

Some explanation of this basic research impact could come from Higón (2016). Although his was for the Spanish economy, there are some parallels in product pioneering in low to medium technology sectors. A developing country with a large gap may not have the necessary ‘infrastructure’ to conduct cutting edge high-tech research as compared with developed nations. This creates opportunities for developing countries to develop new products by undertaking pioneering research on low-tech industries.

We concur with Czarnitzki and Thorwarth (2012) that basic research leads to other R&D, however we find that if applied research comes to the fore, then this has a detrimental effect on IP development. Furthermore, importing knowhow may not be good for IP development (Higón 2016). We observe that ‘importing’ (OFDI) has a negative effect on applied research as in Table 7 across the board, whereas if interacted with basic research then there is a positive contribution. In Table 8, we observe that OFDI has a negative impact on IP (separate) and positive in the interaction model. These effects are somewhat more limited that in Table 7. In all cases basic research is fundamental to driving technological innovation and not OFDI or applied research. This is most evident when the technology gap is large. Note however, that applied research is instrumental in driving basic research although it is detrimental to technological innovation.

As with Cassiman et al. (2002), we support the view that basic research with the *addition* of OFDI contributes to applied research and that applied research enhances basic research. This potentially complements the results of Henard and McFadyen (2005). Applied research is greatly enhanced by human capital in contrast to basic research and technological innovation, that human capital affects in a detrimental way. One could conjecture that Stern's (2004) view that lower salaries in basic research are less attractive. We may suggest that those best placed for basic research may seek alternatives with applied research when the gap is large. Maybe basic research is in its infancy when the gap is large. When the gap is small then basic research benefits from the human capital stock implying that the demand for highly skilled researchers needs to be matched with an equivalent supply for there to be gains in research output. As with Cassiman et al. (2002), the investment decisions of a firm in applied or basic research or, IP have a direct effect on the absorptive capacity. We find that the interaction between basic research and OFDI is the catalyst that drives both applied research and technological innovation. Policies that support firms conducting basic research in conjunction with a 'go-out' OFDI policy are more likely to benefit provincial, as well as national, growth.

6 Conclusion and policy implications

Our findings are that OFDI has both a national and provincial potential to contribute to improvement in technological innovation with appropriate regional policies. Although national governments may have an overall strategy, it can only work if regions (or provinces as in China) are able to adapt to the local conditions and circumstances. As such, regions will close the gap at different rates depending on policies expanding on the ideas set out in Piperopoulos et al. (2018). OFDI, by itself, has a negative effect on regional technological innovation. As such, repatriation of knowhow is reliant on the ability of the provincial, regional and national economy to absorb such knowledge and skills. Our conclusion is that for OFDI to be effective, it needs basic research to be the key channel through which absorption enters into the local economy and policy makers need to put in place necessary motivations and environment to connect OFDI with technology spillovers. Failure to do so could lead to OFDI crowding out research.

An aspect of IP, OFDI and R&D is that they do not form a linear relationship. Instead, there is a base level of provincial R&D and human capital which creates absorptive capacity required for efficient and effective uptake of repatriated knowhow. This constraints policy makers in their investment into human capital and R&D to a maximum level as any higher will saturate the market and crowd out productive activities. As noted in the additional H3.1, applied and basic research have different demands on human capital and R&D depending on the threshold and distribution of research between applied and basic. Therefore, policies must be balanced between motivating domestic firms to ‘go-global’ with an OFDI strategy to appropriate technology knowhow whilst encouraging domestic R&D and supporting human capital development. OFDI must not be motivated to crowd out local development as we might observe in some of the provinces. Our threshold model enhances the viewpoints of Phene and Almeida (2008) with the addition of a regional perspective and thresholds.

Further to this it is necessary to consider the impact of OFDI spillovers and scientific research on technological innovation according to different absorptive capabilities. We demonstrate that technological absorptive capacity relies on the level of regional technological development, frontier technological distance and resources such as human capital and R&D stock. Policies need to account for regional variation. Our policy recommendations are that for large gap provinces, they should focus more on the investment into basic research to improve their technology levels and technology absorptive capability to ensure further development and better use of OFDI for technology spillovers. Provinces in the small technology group should consider the optimal allocation of resources for applied research, basic research and OFDI. Their technological development levels are initially relatively high, indicating their previous successful efforts in basic research. Therefore, they can try to find the balance between applied research and basic research to facilitate an efficient use of resources; they should not ignore the important role of basic research for long-run technological development and its positive impact on OFDI spillovers because it strengthens the absorptive capacity. Firms from those provinces should also be rational when considering conducting OFDI. They are supposed to comprehensively analyse the joint effects of basic research, applied research and OFDI spillovers according to their own development levels and conditions although it is difficult to do so, especially when the government is encouraging OFDI because it boosts overall technological progress.

As to the domestic policy regarding infrastructure, education, human development and R&D capability, we demonstrate that there are different thresholds where, at a provincial level, the ability to absorb efficiently is compromised when one or more elements is below that threshold. This is cogent with the view expressed in Baskaran and Chaarlas (2012), as policy makers need to consider the pre-existing R&D intensity (that includes human capital) to fully assimilate OFDI technologies. We add to the policy view in that policy makers must consider if their province or region is above or below the threshold. It could be quite feasible that a policy maker would progressively change their strategy, altering the disposition of ‘investments’ as they progress. As with China, and drawing parallels into the Indian sub-continent, such ‘investments’ need not only consider the national perspective, we demonstrate that policy makers need to account for regional differences in capability and not a ‘one-size fits all’ approach to OFDI and its supporting policies.

Although OFDI policies in China have been successful in short-cutting the route to developing world capabilities, it has drawn much criticism and resentment. Complaints about foreign ownership, state controlled commercial spying and IP theft to name a few. Recent trade restrictions imposed by America and others may have a long-term attenuating effect on OFDI and the ‘go-out’ policy. This may give other developing nations time to ‘catch up’ and exploit the opportunities that China has developed. One cannot separate international politics from domestic policy when it comes from trade and foreign investment. We leave that matter for future research.

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