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Foreign direct investment among developing markets and its technological impact on host: Evidence from spatial analysis of Chinese investment in Africa

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ABSTRACT

This paper investigates the technological impact of foreign direct investment (FDI) among developing markets on the host economy, as the distinctive features of FDI from developing countries may induce stronger technology-enhancing effect on the host developing nations than that of FDI from developed economies. Adopting the context of Chinese FDI in a set of 24 African nations during 2006–2017, we first separate structural change from total factor productivity (TFP) to obtain the technological progress series. We then account for spatial dependence in technological progress across countries by employing various spatial models; of these, the Spatial Durbin Model is found to best describe our data. We find that, first, both structural change and technological progress have contributed positively to TFP in Africa. Thus, the latter captures the pure technological change more accurately than TFP does. Second, Chinese FDI in Africa has had a positive and significant effect on the region's technological progress, whilst non-Chinese FDI (mainly from developed countries) has not, substantiating our expectation of stronger technological benefit for developing economies when FDI is from other developing nations. Finally, there had been negative spatial technological dependence across countries, implying a competitive rather than cooperative relationship among African nations.

1. Introduction

Foreign direct investment (FDI) inflows are often regarded as an important driver for economic growth in host countries. FDI can enhance economic growth not only by increasing capital stock and improving its efficiency (Li and Liu, 2005; Suyanto and Salim, 2010), but also through technological spillovers from the more developed home country to the less developed host country (Borensztein et al., 1998). Many studies have already examined the magnitude of the positive effect that FDI might have on economic growth (e.g., Borensztein et al., 1998; Hermes and Lensink, 2003; Mallick and Moore, 2008; Azman--Saini et al., 2010; Alguacil et al., 2011; Okada and Samreth, 2014; Slesman et al., 2015; Malikane and Chitambara, 2018; Tanna et al., 2018; Tchamyou, Asongu and Odhiambo, 2019).

Compared with the large body of FDI-growth literature, much less attention has been devoted to investigating how FDI inflows have contributed directly to productivity growth. According to Easterly and Levine (2001), Klenow and Rodriguez-Clare (2005) and Parente and Prescott (2005), productivity growth contributes more to economic growth than the traditionally emphasized capital accumulation does, and is the main reason why countries have different income levels and rates of growth. Therefore, productivity growth presents a more important indicator of a country's potential for long-term economic growth (Easterly and Levine, 2001; Kose et al., 2009; Li and Tanna, 2018). Moreover, recent evidence has shown that productivity in developing countries can rise as a result of FDI inflows, through technology transfer (Djulius, 2017), the introduction of new processes and managerial experiences (Marcin, 2008; Li and Tanna, 2018), as well as a process of technological catch-up among domestic firms due to competitive forces (Suyanto and Salim, 2010; Liu, et al., 2016).

As such, our study examines the relationship between FDI and *productivity*, rather than growth. Our investigation focuses specifically on FDI between developing economies and its impact on technological progress in the host economies. In the past two decades, outward FDI

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from developing countries has grown significantly. This trend has altered the traditional view that the role of FDI source countries are often played by developed economies and the developing nations are only at the receiving end. According to the Global Investment Competitiveness Report 2017/2018 (World Bank, 2017a), outward FDI from developing countries accounted for one-fifth of global FDI in 2015, up from just 4% in 1990. Fig. 1 highlights developing markets as an increasingly important origin of FDI, accounting for over 40% of global outward FDI in 2018. However, previous literature on the FDI-host productivity relationship often takes a generic view of FDI, without differentiating between investments from developing countries and those from developed economies (e.g., Djankov and Hoekman, 2000; Yudaeva et al., 2003; Javorcik, 2004; Driffield and Love, 2007; Liu, 2008; Bitzer and Görg, 2009; Woo, 2009; Suyanto and Salim, 2010; Liu et al., 2016; Djulius, 2017; Li and Tanna, 2018). As such, these analyses provide only limited insight on the technological effect of outward FDI from developing economies.

More importantly, when both the host and origin economies are themselves developing nations, FDI flows are likely to have a more profound technological impact on host developing nations than when FDI comes from developed economies. Inward FDI can generally enhance host countries' technology through direct technology transfer (Djulius, 2017; UNIDO, 2004), inducing more competition on the local market (Driffield, 2001; Suyanto and Salim, 2010), and passing on new operational processes and managerial experiences (Chueng et al., 2003; Marcin, 2008) (see Section 3.1). As illustrated in Section 3.2, in addition to these well-established channels through which FDI enhances host countries' technology, technological spillovers between developing markets are likely to be more effective precisely because the technology gap between them is smaller (Cheng, 1984; Gelb, 2005; Amighini and Sanfilippo, 2011; Malikane and Chitambara, 2018). Furthermore, developing economies are generally characterised by institutional voids (Khanna and Palepu, 1999; Ricart et al., 2004; Acquaah, 2007). While this factor often deters investment from industrialised nations, it does not seem to discourage FDI from developing countries (Dixit, 2012; Darby et al., 2013), as developing investors are more accustomed to and more capable of adapting to weak institutions (Rui, 2010). Finally, technological spillovers are dynamic processes that are more likely to be successful over a longer time horizon (Caves, 1974, Rodriguez-Clare, 1996; Javorcik, 2004; Liu, 2008; Havranek and Irsova, 2011). Enabled by their foreign exchange reserves accumulated over the years, a number of export-oriented developing nations are capable of carrying out longer-term overseas investment without the strict financial constraints that many developed economies face. Thus, given these unique features of investment from developing economies, developing-to-developing FDI presents a key research area which can inform the important issue of the host-country technological implications of FDI between developing markets.

Over the past few decades, the economic centre of gravity has inexorably been moving toward developing economies, and there has been a remarkable upsurge in cooperation among developing countries (Singh Puri, 2010). Such South-South cooperation has been recognised as a vital means of implementing the 2030 Agenda for Sustainable Development, especially through enhancing access to science, technology and innovation internationally (United Nations, 2019)[1]. Investment among developing nations, an important form of South-South cooperation, offers significant development opportunities for the host economies (World Bank, 2017a). Yet we lack a deeper level of analysis and understanding of the technological impact of developing-to-developing FDI on the host economy to inform national and regional policies on how best to utilise rising FDI from developing nations to enhance local technological progress. Against this backdrop, the main purpose of this study is to examine the technological effect of FDI among developing markets on the host nations, as the distinctive features of FDI from developing countries (discussed in Sections 3.1 and 3.2) may trigger stronger technology-enhancing effects on the host developing nations than those of FDI from developed economies.

Our study contributes to the literature on technology spillover (e.g., Djulius, 2017; Malikane and Chitambara, 2018; World Bank, 2019) by contending that developing-to-developing FDI, a surging engine to promote technology transfer globally, can better induce technological progress in the host economies than FDI from developed nations. Our study also offers new insights into the international business literature (e.g., Bonaglia et al., 2007; Keen and Wu, 2011; Cieślik and Hien Tran, 2019). Building upon the widely acknowledged notion that the internationalisation of developing economies has different characteristics from those of developed nations, this study further proposes that these unique features can generate technological progress for the local developing economics to a level that is over and above what can be induced by investment from developed markets. Furthermore, our analysis expands upon prior research on the 2030 Agenda for Sustainable Development (e.g., Fabrizio et al., 2015; United Nations, 2018; You et al., 2020) by considering developing-to-developing investment as a more effective means of global partnership for sustainable development through enhanced technology and knowledge sharing (see the Technology section under Sustainable Development Goal 17) compared with developed-to-developing investment.

The second contribution of our paper stems from our method of separating structural change from total factor productivity (TFP) in order to obtain the pure technological progress series. One of the central insights of the literature on economic development, the notion of structural change, describes the rise of overall productivity and incomes generated by labour and other resources moving from less productive activities (such as agriculture) to more productive modern economic activities (McMillan and Rodrik, 2011). Unless this structural change component is stripped out, then using TFP gains as a proxy for technological progress is bound to overestimate actual technological advancement. Therefore, in our study we will first estimate pure technological progress by filtering out structural change effects, to then examine whether the developing-to-developing FDI has a positive technological impact in the host region.

Third, we account for spatial dependence in our analysis. Technological advances in one region will affect its neighbouring regions through the spillover effect (Naveed and Ahmad, 2016). For a panel of OECD countries, Madsen (2007) finds that knowledge spillovers are an important contributing factor to total factor productivity convergence within the group. Both Fischer et al (2007) and Elhorst (2010) investigate the spatial aspect of technology and find that a region's TFP depends not only on its own knowledge capital, but also on cross-regional knowledge. Elhorst (2010) finds that the latter factor may even be more important than the former. Thus, our study employs several alternative spatial models to account for spatial dependence in technological progress across our sample of host countries.

For the empirical context, we select Chinese outward FDI to a group of African nations over the twelve-year period from 2006 to 2017. Our choice is grounded in a number of factors. Firstly, in the past fifteen years, China has been the driving force of the aforementioned global trend of rising investment between developing economies. In 2017, China alone made up over a quarter of developing economies' total outward FDI stock (World Investment Report 2019). Meanwhile Africa, the world's least developed region, has experienced drastic changes in terms of its FDI source countries. France has traditionally been the largest investor in Africa. However, France's total FDI stock in Africa was not significantly different in 2017 from the 2013 figure (World Investment Report 2019). Investment in Africa from both the United States (US) and the United Kingdom (UK) has decreased over the same period as a result of divestments and profit repatriations. In sharp contrast, the

[1] Cooperation/Investment between developing economies is sometimes referred to as 'South-South' cooperation/investment (e.g. Gelb, 2005; Amighini and Sanfilippo, 2011; UNCTAD, 2019).

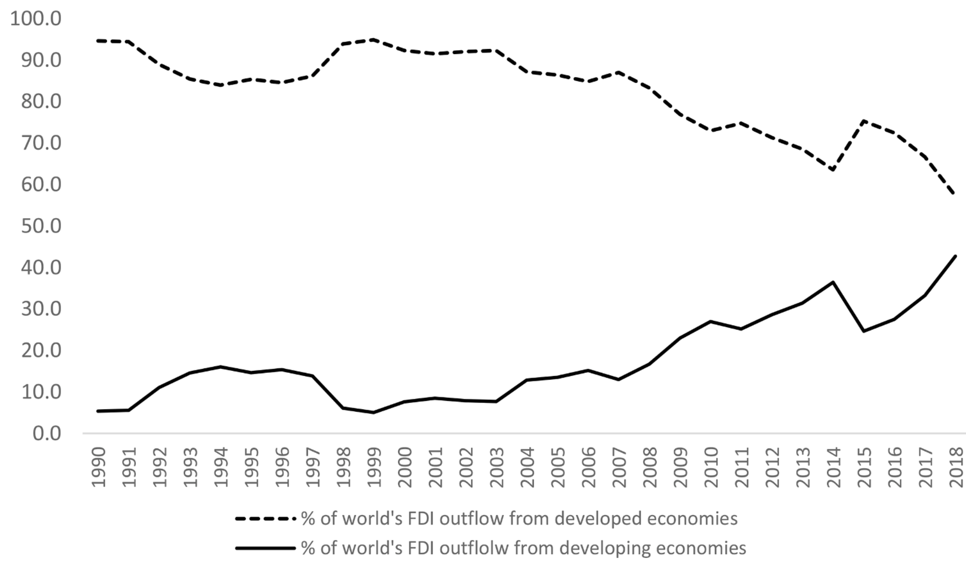


Fig. 1. Global FDI outflows from developed and developing economies (%).
Data source: World Investment Report, UNCTAD.

stock of China's FDI in Africa increased by more than 50% from 2013 to 2017. From an FDI flow point of view, China was Africa's largest investor between 2014 and 2018, investing more dollars in the continent than France and the US combined (EY Attractiveness Program Africa September 2019). As such, while developed economies remain the main investors in Africa, emerging partners, especially China, are playing an increasingly important role. Finally, technology plays a central role in driving economic development (Schniederjans, 2017), and potential technological transfer from FDI presents an important opportunity for developing countries (Liu, 2008; Bengoa and Sanchez-Robles, 2003). In the case of Africa, technology can positively transform its economy in numerous ways including alleviating poverty (Amankwah-Amoah and Sarpong, 2016; You et al., 2020), improving business opportunities (Amankwah-Amoah et al., 2018) and fostering local innovation (Amankwah-Amoah, 2019). Therefore, Chinese investment in Africa represents a context that is ideally suited for developing-to-developing FDI analysis. Our findings would have wider implications regarding the technological effect that investment between developing economies can have on the host country.

The rest of the paper is organised as follows. Section provides an overview of China's outward FDI to Africa. This is followed by a discussion on the theoretical underpinnings in existing literature of how FDI can influence technological development, along with a review of relevant empirical literature, in Section 3. Section 4 outlines the methodology, including the production function that filters structural change out of TFP and the spatial models. Section 5 discusses the data and the empirical results. The final section concludes.

2. An overview of China's outward FDI to Africa

Over the past two decades, developing markets have become a strong and growing force of global investment. As shown in Fig. 1, by the end of 2018, only 55% of FDI originated from developed countries, while FDI from developing countries covered over 40% of the world's total investment outflows. In 1990, these two figures were 95% and 5% respectively. Amidst this phenomenon, China has risen to become one of the most important FDI source countries, accounting for over 10% of the world's outward FDI flows (and for over a third of Asia's) between 2014 and 2018 (based on UNCTAD data).

2.1. *Chinese investment in Africa – from China's perspective*

It should be duly noted that Africa has not been a major destination for China's overseas investment. As shown in Table 1, according to the Statistical Bulletin of Chinese Outward FDI from the Ministry of Commerce of China, since reaching a peak of 4.8% in 2008, China's FDI stock in Africa averaged 3.5% of the nation's global stock from 2009 to 2017, not only far below investment in Asia (69.2%), but also behind Latin America (13.9%), Europe (6.4%) and North America (4.2%). However, these figures need to be put into perspective. Pairault (2014) suggests that given that it is impossible to trace the actual destinations of investments that go through tax havens, the focus should be on non-tax haven investment only. Following Wolf and Cheng (2018), we adopt the definition of tax havens used by Hines and Rice (1994) and adjust the statistics to focus on non-tax haven destinations. The adjusted figures in Table 2 show that the importance of Africa as the host market of China's outward FDI has risen to an average of 11.4% of the total in 2009–2017, surpassing Latin America (3.4%) and Oceania (8.7%), and only a slightly lower portion than Europe (15.2%).

It is often perceived that China's investment in Africa has a strong resource-seeking motive (Renard, 2011; Ross, 2015). Indeed, many studies have highlighted that the Chinese government has placed significant importance on securing natural resources strategically in order

Table 1
Destinations of China's outward FDI stock (as % of total).

	Asia	Africa	Europe	Latin America	North America	Oceania
2003	80.1	1.5	1.5	13.9	1.7	1.4
2004	70.1	1.9	1.4	17.3	1.9	1.1
2005	71.6	2.8	2.2	20.0	2.2	1.1
2006	63.9	3.4	3.0	26.3	2.1	1.3
2007	67.2	3.8	3.8	20.9	2.7	1.6
2008	71.4	4.2	2.8	17.5	2.0	2.1
2009	75.5	3.8	3.5	12.4	2.1	2.6
2010	71.9	4.1	5.0	13.8	2.5	2.7
2011	71.4	3.8	5.8	13.0	3.2	2.8
2012	68.5	4.1	7.0	12.8	4.8	2.8
2013	67.7	4.0	8.0	13.0	4.3	2.9
2014	68.1	3.7	7.9	12.0	5.4	2.9
2015	70.0	3.2	7.6	11.5	4.8	2.9
2016	67.0	2.9	6.4	15.3	5.6	2.8
2017	63.0	2.4	6.1	21.4	4.8	2.3

Source: Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance.

Table 2
Destinations of China's outward FDI stock (% of total), excluding tax havens.

	Asia	Africa	Europe	Latin America	North America	Oceania
2009	21.0	13.6	8.9	2.7	44.6	9.3
2010	21.1	13.1	9.9	3.1	44.2	8.6
2011	21.6	12.2	13.0	2.9	41.3	9.0
2012	23.8	12.1	15.5	3.9	36.3	8.4
2013	22.2	11.1	18.0	4.0	36.6	8.1
2014	22.6	10.9	18.1	4.2	35.4	8.8
2015	21.1	9.8	21.4	3.4	35.2	9.1
2016	19.1	8.6	16.7	2.9	44.4	8.2
2017	15.4	6.4	13.1	2.2	56.6	6.2

Note: Tax havens are identified as per the definition in Hines and Rice (1994). See Wolf and Cheng (2018) for a similar way of excluding tax havens for FDI calculations.

to satisfy China's growing demand for energy and raw materials (e.g., Zhan, 1995; Morck et al., 2008; Cheng and Ma, 2009). Nevertheless, we can provide a more balanced, evidence-based view using data on the sectoral distribution of Chinese FDI in Africa. In 2011, investment in the mining industry accounted for 30.6% of China's total investment stock in Africa (Wolf and Cheng, 2018). Albeit a high percentage, this is actually lower than the overall global level reported by UNCTAD (2015): as of 2012, 35% of total FDI in sub-Saharan Africa (SSA) went to the mining industry. More recent data from the Chinese Ministry of Finance provided in Table 3 shows that in 2017, the share of investment headed for the mining industry fell to 22.5% of China's total investment in Africa, similar to that in Europe (20.3%) and much lower than that in Oceania (over 50%). Construction has overtaken mining to become the sector with the highest portion of Chinese FDI stock in Africa, with the financial services and manufacturing sectors taking third and fourth place, respectively.

2.2. *Chinese investment in Africa – from Africa's perspective*

From the perspective of Africa, investment from China has been growing rapidly in the past fifteen years (Fig. 2). The average annual growth rate of China's FDI stock in Africa from 2003 to 2008 was an astonishing 74.0%. Since the 2008 global financial crisis, this growth has slowed down, but the annual average was still a robust 21.4% from 2009 to 2017.

China has thus become Africa's largest developing nation investor and as important as Africa's major investors from the developed world. Table 4 shows Africa's top seven investors in 2017 and their investment amounts from 2013. In contrast to France, US and the UK, whose FDI stock in Africa has either declined or stagnated in recent years, China's investment in Africa has risen steadily and substantially, reaching the fifth largest stock level in 2017, almost on par with the UK.

Fig. 3 further demonstrates the magnitude, from Africa's point of view, of China's FDI flows to the continent from 2003 to 2017. FDI inflows from China peaked in 2008 in terms of both the amount and proportion of total FDI flows to Africa. Despite being adversely affected by the 2008 crisis in subsequent years, flows have recovered gradually since 2009; in 2017, Chinese investments accounted for 9.9% of Africa's total FDI inflows.

3. Theoretical underpinnings and literature review

3.1. *The host country technological impact of inward FDI: channels of influence*

Inward FDI can have positive technological effects on the host economy through various channels. The main and most direct channel is technology transfer (Djulius, 2017), which in its general form refers to the mechanism by which the accumulated knowledge developed by a specific entity is transferred wholly or partially to another, allowing the receiver to benefit from such knowledge (UNIDO, 2004). In the context of FDI, technology can be transferred from home to the host economy via the demonstration effect, when local firms copy technologies of foreign firms by learning with the practice of foreign entities (Cheung and Lin 2004; Lin and Chuang 2007). Foreign firms may initiate the transfer of technology and know-how to local suppliers in order to improve the quality of inputs (Rodriguez-Clare, 1996). Local enterprises can also benefit from foreign peers' firm-specific knowledge (Fosfuri et al., 2001) when hiring workers trained by foreign affiliates (Blomström and Kokko, 1998; Jacob and Christopher, 2005). Such transfers among workers can occur within the same industry as well as across different industries (Sjöholm, 1999).

FDI can also influence technological progress more indirectly, by inducing more competition in the host market (Suyanto and Salim, 2010). Stronger domestic market competition not only forces local firms to use their resources more efficiently (Pessoa, 2007), but also compels domestic firms to update production techniques and to search for new technologies in order to become more productive (Blomström and Kokko, 1998). On the other hand, Driffield (2001) points out that intensified competition following foreign entry is likely to increase the exit rates of local enterprises, raising the average productivity of an industry as the local firms that survive the foreign competition tend to be more amenable to new technology and more efficient than their local competitors.

An additional channel of influence is that FDI can extend positive technological externality through new operational processes and managerial experiences (Marcin, 2008). More effective management skills and production processes make foreign firms more productive than local firms (Chung et al., 2003). The training that local workers receive and the skills they learn when observing new operations developed in multinational firms constitute an important means by which the host country improves its human capital (Loungani and Razin, 2001; Alfaro et al., 2004). It further raises the capacity that the local labour force possesses to adopt new technologies in their own country (Forte and Moura, 2013). By imitating managerial and organisational innovations, domestic enterprises may also become more productive (Wang and Blomström, 1992). Linking this to the first channel, local personnel who receive managerial training from foreign companies may then be hired by local firms to help establish their operations and utilise their entrepreneurial capabilities in seeking out investment opportunities (Lall and Streeten, 1977; Kurtishi-Kastrati, 2013).

3.2. *The host country technological impact of FDI between developing nations and the China-to-Africa route*

From the host economy's perspective, investment from other developing nations can potentially generate a greater positive technological impact than investment from developed countries can do, for several reasons. First, technological spillovers between developing markets might be more effective given that the technology gap between them is narrower (Gelb, 2005; Amighini and Sanfilippo, 2011). Employing a dynamic game-theory model, Cheng (1984) shows that a change in technological leadership is more likely to occur when there is a *smaller* initial technological disparity between countries. In the case of Africa, Malikane and Chitambara (2018) find that the failure of many African countries to fully adopt foreign technologies has been due to their relative backwardness (i.e., technological gaps being too wide). Given that the Africa-China technological gap is likely to be narrower than the gap between Africa and other developed nations, technology transfer between China and Africa could be more effective.

Second, in sharp contrast to developed economies, developing nations are generally characterised by institutional voids such as corruption, political instability, lack of transparency and bureaucracy (Khanna and Palepu, 1999; Ricart et al., 2004; Acquaah, 2007). Whilst institutional voids discourage investment from industrialised countries, investors from developing countries are often less concerned about the

Table 3
Distribution by sector of China's outward FDI stock in Africa – top 5 sectors (as % of total).

Sector	2013	Sector	2014	Sector	2015	Sector	2016	Sector	2017
1	26.4	2	24.7	1	27.5	2	28.3	2	29.8
2	26.1	1	24.5	2	27.4	1	26.1	1	22.5
3	14	3	16.4	4	13.3	4	12.8	3	14
4	13.4	4	13.6	3	9.9	3	11.4	4	13.2
5	5.1	5	4.2	5	4.2	5	4.8	6	5.3

Note: 1 = Mining; 2 = Construction; 3 = Financial Services; 4 = Manufacturing; 5 = Scientific Research and Technical Services; 6 = Leasing and Business Services. Data based on the Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance.

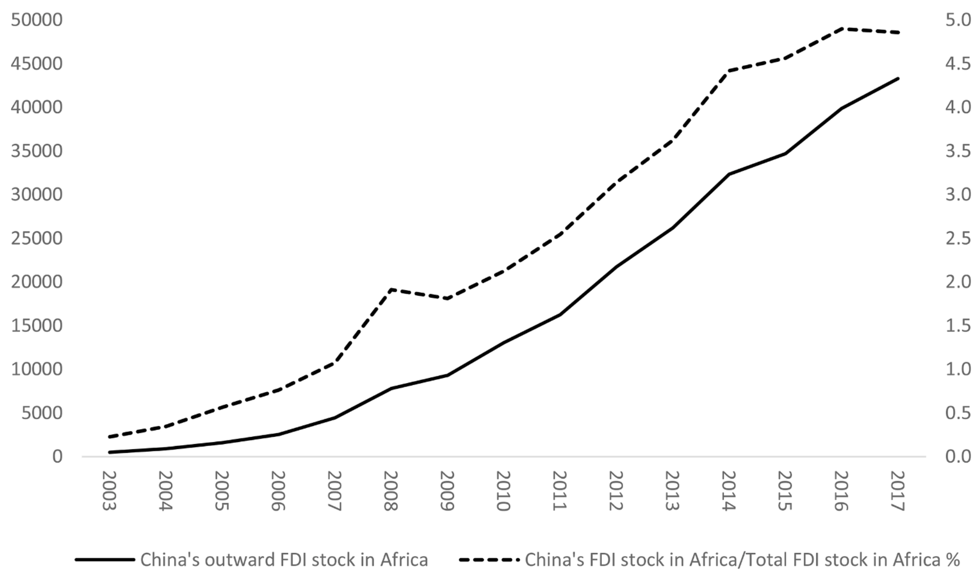


Fig. 2. China's FDI stock in Africa, in value (million USD, left scale) and as % of total FDI stock in Africa (right scale).
Data source: Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance

Table 4
Top Investors in Africa by FDI stock (in billion USD).

	2013	2014	2015	2016	2017
France	64	52	54	49	64
Netherlands	20	n.a.	n.a.	n.a.	63
US	61	64	54	57	50
UK	60	66	58	55	46
China	26	32	35	40	43
Italy	19	19	22	23	28
South Africa	22	26	22	24	27

Source: based on data collected from the World Investment Report, UNCTAD

institutional quality of host economies (Dixit, 2012; Darby et al., 2013). Rui (2010) demonstrates that developing countries' outward FDI can make positive contributions to economic development in developing host countries, particularly because the strategies and mindsets deployed are more adaptable to the host country's development needs and institutional environment. Donou-Adonsou and Lim (2018) confirm that FDI from China to Africa has not been deterred by poor host country institutional quality. Morck et al. (2008) postulate that, perhaps because they are more experienced in dealing with governments and more accustomed to operating in countries with weak institutions, Chinese firms can perform better than other foreign firms in host environments with inefficient institutions. Many African nations with weak institutional quality also are the ones that could benefit most from capital injections, especially in the infrastructure sector. High up-front capital costs and limited end-user financing schemes have indeed constrained technological progress in Africa (Amankwah-Amoah, 2015). He and Zhu (2018) point out that as a relative latecomer in Africa, Chinese capital tends to choose underinvested, relatively less stable countries, precisely to avoid competition with investors from the advanced economies. FDI from developing countries, especially from the 'BRIC' nations, is often accompanied by infrastructural improvements (Mlachila and Takebe, 2011; UNCTAD, 2012); in other words, FDI from other developing countries is more likely to provide capital to African countries in the areas where they need it most.

Finally, a recent study by the World Bank (Farole and Winkler, 2014) points out that when the time horizon is limited, the potential of FDI for generating technological spillovers is also limited. Knowledge spillovers to the local economy are not a static aspect of FDI, but rather dynamic processes that evolve over time (see e.g. Caves, 1974; Rodriguez-Clare, 1996; Javorcik, 2004; Havranek and Irsova, 2011). Liu (2008) shows that there is a time component in FDI's technology spillover impact: FDI is more likely to help increase productivity growth in the long run, as a consequence of increasing opportunities to research new products. Compared with developed nations, Chinese firms are subject to a lower degree of financial constraints to invest abroad thanks to supportive government policies and ample foreign exchange reserves; these factors could positively impact the average length of time of their FDI in Africa (Wolf and Cheng, 2018), thereby raising the potential for stronger technological spillover effects on African nations. Also, Yao et al. (2010) report that Chinese firms are backed by Chinese government's low-cost credit, which allows them to take on riskier overseas projects that their developed rivals will not consider.

3.3. *A brief review of empirical literature*

Despite the various theoretical channels mentioned above through which FDI inflows *can* raise the productivity of host economies, there

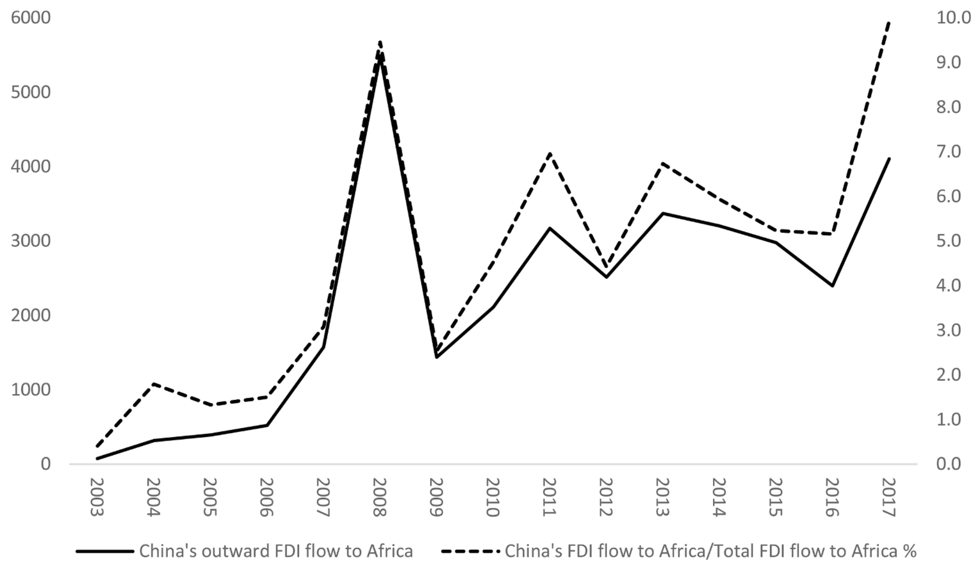


Fig. 3. China's FDI flows to Africa, in value (million USD, left scale) and as a % of total FDI flows to Africa (right scale).
Data source: Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance

does not seem to be a consensus in the existing empirical literature on whether FDI actually *does* raise productivity[2].

There are certainly numerous findings in the theory's favour. Liu et al. (2000) examine intra-industry productivity spillovers from inward FDI for the UK manufacturing sector. Their results suggest that FDI has a positive spillover impact on the productivity of UK-owned firms. Based on firm-level data from Lithuania, Javorcik (2004) also finds evidence supporting positive productivity spillovers from FDI. Using a large panel of Chinese manufacturing firms, Liu (2008) reveals that an increase in FDI lowers the productivity level in the short term, but raises it in the long term. Using both industry- and country-level data for a group of OECD countries, Bitzer and Görg (2009) discovers that on average, productivity benefits from inward FDI. Woo (2009) investigates the effect of FDI inflow on host TFP growth in a large sample of countries in 1970–2000 and find that FDI has a positive and direct effect on TFP growth. Employing firm-level data from China, Liu et al. (2016) confirm that FDI inflows have increased productivity in the electronics industry. For a large group of developing countries, Li and Tanna (2018) show that a robust FDI-induced productivity growth response is dependent on the absorptive capacities in the host countries captured by of human capital and institutions.

In contrast, however, Aitken and Harrison (1999) find that foreign investment had a negative effect on the productivity of a panel of domestically-owned plants in Venezuela. Djankov and Hoekman (2000), who employ firm-level data in the Czech Republic from 1992 to 1996, showed that joint ventures and FDI appear to have a negative spillover effect on firms that do not have foreign partnerships. For Russian firms, Yudaeva et al. (2003) report that FDI has positive horizontal technology spillovers but negative vertical technology spillover effects on domestic firms. Using firm-level data from three central and eastern European economies, Konings (2001) discovers that foreign FDI led to negative technology spillovers on domestic firms in Bulgaria and Romania and had no spillover effects in Poland, suggesting that a negative competition effect undermined any positive technology transfer effect. Focusing on the Indonesian electrical machinery and food-processing industries, Suyanto and Salim (2010) find that the technology spillovers of inward FDI are positive in the former but negative in the latter. Their findings highlight that productivity gains may be industry-specific.

Meanwhile, some studies have found that FDI inflows do not have any significant impact, positive or negative, on the host economy's productivity. For instance, Girma et al. (2001) find no aggregate evidence of intra-industry spillovers from foreign to domestic firms in the manufacturing industry in the UK. Using country-level data, De la Porterie and Lichtenberg (2001) find that a country's productivity increases if it invests in R&D-intensive foreign countries, but not if it receives foreign R&D-intensive FDI inflows. Driffield and Love (2007) develop a taxonomy that relates FDI motivation (technology-based and cost-based) to its anticipated effects on host countries' domestic productivity. Employing FDI inflows to the UK, their results suggest that inward FDI motivated by technology-sourcing considerations has no productivity spillovers.

Regardless of whether supportive evidence is found for a technological impact from FDI, the studies cited above do not seem to make a distinction between FDI sourced from a developing or a developed economy. As such, their insight may be limited regarding the technological influence of FDI on host economies specifically when both origin and host are developing markets.

In the particular case of African nations as the host economies of inward FDI, some studies that empirically examine the macro-level impact of FDI on African countries' productivity have surfaced in recent years, but they are still quite rare. These studies include Ng (2007), Senbeta (2008), Roy (2016), Ssozi and Asongu (2016a) and Malikane and Chitambara (2018)[3]. Using causality analysis, Ng (2007) examines the linkage between FDI and productivity in 14 sub-Saharan African (SSA) countries but finds such linkage does not exist. Using a similar sample of 22 SSA nations, Senbeta (2008) employs fixed effect and the dynamic panel models and observes a positive effect of FDI inflows on TFP, but only in the long run. Applying a threshold regression technique for a group of Latin American and African countries, Roy (2016) finds that the impact of FDI on TFP growth would be negative unless the initial distance of a country from the technology frontier exceeds a threshold. Ssozi and Asongu (2016a) reveal a positive association between FDI and TFP for a group of SSA nations from 1980 to 2010 using a two-step system generalised method of moments (GMM) approach. More recently, Malikane and Chitambara (2018) employ the

[2] See Li and Tanna (2018) for a recent review of literature examining the relationship between FDI inflows and host economic growth.

[3] Both Baltabaev (2014) and Li and Tanna (2018) have included a few African countries in their full sample and hence may be less representative for the African nations on the inward FDI and host productivity relationship.

fixed effects and two-step system GMM methods for a group of 45 African countries over the 1980–2012 period. Their results suggest a generally positive but weak effect of FDI on productivity growth but do not support the convergence theory that relative backwardness would result in higher productivity growth via the adoption of foreign technologies.

Again, the above country-level studies on Africa do not seem to emphasise which countries the FDI originated from, so they do not shed light on how FDI from developing markets in particular might affect the technological progress of African nations[4]. In addition, although China has risen to become the largest developing investor, to a degree almost on par with Africa's major investors from the developed world, very few studies have empirically examined the technological impact of FDI from China to Africa. The very few attempts to address this issue include Elu and Price (2010) and Seyoum et al (2015), both of which focus on manufacturing firms in Africa[5].

Employing data from manufacturing firms from five SSA countries, Elu and Price (2010) consider whether FDI from China to SSA and trade between them result in productivity-enhancing technology transfers from the former to the later. Their GMM estimates suggest that while Chinese investment does have a positive effect on SSA's TFP growth, increasing trade openness with China does not. Seyoum et al (2015) analyse the technological impact of Chinese FDI on Ethiopian manufacturing firms. Employing the ordinary least squares (OLS) and instrumental variables two-stage least squares (IV 2SLS) procedures, they find that domestic firms with higher absorptive capacity experience positive technology spillovers, while those with lower absorptive capacity experience negative spillovers.

3.4. Considerations arising from the literature and our contributions

Our review of the existing literature gives rise to the following three issues in relation to our investigation. First, previous analyses do not differentiate between developed and developing FDI source countries, while studies specifically investigating the technological impact of FDI from China to Africa are quite rare and contain firm-level analysis only (e.g. Elu and Price, 2010; Seyoum et al., 2015). This is surprising, especially given that developing-to-developing economy FDI has become an increasingly significant global phenomenon (as outlined in Section 2). More crucially, as demonstrated in Sections 3.1 and 3.2, FDI from developing countries has different characteristics from FDI from developed economies – characteristics that may help induce stronger technological progress in the host developing nations. In the case of Chinese FDI in Africa, Africa's technological gap to China is narrower than to its most advanced investor nations such as France and the US; furthermore, Chinese investors are less concerned about institutional quality, are less financially constrained and hence more likely to make stable, longer-term investments, and are more willing to take on riskier projects. As discussed in Section 3.2, these special characteristics of Chinese FDI lead us to expect that Chinese FDI in Africa could have a stronger local technology-enhancing effect. Therefore, this study investigates the technological effects of FDI among developing markets on the host economies through a country-level analysis on how Chinese FDI has influenced technological progress in Africa. Our study will extend the technology spillover and international business literature by linking various unique features of FDI from developing countries to technological progress of the host economies which are also developing nations. We then empirically examine the local technological effect of such developing-to-developing FDI, an important form of global partnership promoted under the 2030 Agenda for Sustainable Development.

The second key issue is that the macro-level studies mentioned previously often estimate TFP based on the Cobb-Douglas production function (e.g. Li and Tanna, 2018; Baltabaev, 2014; Malikane and Chitambara, 2018; Roy, 2016; Bitzer and Görg, 2009; Woo, 2009) or apply the TFP data from the World Productivity database of UNIDO (e.g. Ng, 2007; Senbeta, 2008). However, none of these measurements of TFP account for structural change. When labour and other resources shift from less productive sectors (especially agriculture) to more productive sectors (e.g. industry), the TFP of the whole economy rises even without technological progress in any individual sector. Structural change is a particularly relevant factor for Africa: given that labour productivity in traditional sectors like agriculture is low at early developmental stages, a shift in the labour force from agriculture into the service or industrial sector will lead to greater structural change than would be the case for a more advanced economy (Lewis, 1954; Kuznets, 1966; Chenery and Taylor, 1968; Szirmai, 2015). Although at varied rates, African countries have experienced noticeable structural change in recent years. For instance, according to data from the World Bank, in Cameroon, the share of agricultural labour fell from 61% in 2006 to 45.7% in 2017. Namibia, a relatively more developed country in Africa, has seen its labour share in agriculture further decrease from 30.5% to 19.9% over the same period. Several recent studies have found evidence to support the hypothesis that this structural change is contributing to TFP growth in Africa (e.g., McMillan et al, 2014; Mensah et al., 2018; Diao et al., 2019). If instead we want to observe the *pure* technological progress of an economy, this structural change 'bonus' needs to be separated from the overall TFP. Therefore, in our study, we construct a structural change factor following McMillan and Rodrik (2011) and account for it in the Cobb-Douglas production function. Doing so enables us to estimate more precisely the impact of Chinese FDI on Africa's technological progress without the interference of the structural change effect.

The third point to consider is that the technological progress performance of any given country may be related to its geographic proximity and economic relationships with other countries (Morrill et al., 1988). While many studies have been dedicated to identifying spatial dependence in the estimation of growth regression (see Esiyok and Ugur (2018) for a recent literature review in this strand), such spatial relations in technological spillovers have received far less attention. For Africa, Lukongo and Rezek (2016) test for spatial dependence in TFP growth in the agriculture sector from 1965 to 2009. Their estimates for a group of African countries reveal that the growth shocks from one country affect the TFP growth rates of other countries. Employing firm-level data in Ethiopia and Nigeria, Owoo and Naudé (2017) find that the productivity of non-farm enterprises in rural Africa can be associated with the productivity of other spatially proximate non-farm enterprises. Focusing on South African firms and using a spatial autoregressive model, Amusa et al. (2019) find that firms that cluster with other firms have a stronger influence on productivity than do market conditions and firm-specific characteristics. Although there is evidence for spatial dependence in productivity in Africa, it remains an under-studied area, especially at the country level. With this factor in mind, our study employs several spatial models (see Section 4.2) to account for possible technological dependence in our sample of African countries. This facilitates more accurate estimates of the technological impact on Africa that is due to Chinese FDI in the region.

4. Methodology

4.1. Production function and structural change

Following You and Sarantis (2013), McMillan et al. (2014) and Diao et al. (2019), we decompose TFP into two elements: pure technological

[4] Dunne and Masiyandima (2017) focus on FDI between South Africa and other developing countries in the region but they analyse the relationship between FDI and income convergence. Ssozi and Asongu (2016b) find that international remittance, an alternative source of external finance flows to FDI inflows, raised TFP for 31 SSA countries in 1980–2010.

[5] Both Baltabaev (2014) and Li and Tanna (2018) have included a few African countries in their full sample and hence may be less representative for the African nations on the inward FDI and host productivity relationship.

progress and structural change. The latter captures TFP growth induced by labour reallocation between economic sectors. Given that Africa is at an earlier stage of development and thus labour productivity in traditional sectors such as the agricultural sector is low (Lewis, 1954; Kuznets, 1966; Chenery and Taylor, 1968; Szirmai, 2015), structural change is captured by labour moving out of the agriculture sector to the more productive industrial and service sectors (see You and Sarantis (2013) for a similar measurement). We then incorporate structural change into the Cobb-Douglas production function as follows:

$$y = TFPk^{\alpha} = (e^{\beta t})k^{\alpha} \tag{1}$$

$$y = TFPk^{\alpha} = (PTP)(SC^{\gamma})k^{\alpha} = (e^{\beta t})(SC^{\gamma})k^{\alpha} \tag{2}$$

where y and k denote output per labour and capital stock per labour respectively, while α is the capital share of income. Eq. (1) is the standard Cobb-Douglas production function, while in Eq. (2), TFP is separated into pure technological progress (PTP) and structural change (SC). PTP is captured by $e^{\beta t}$ where β measures the effect of technological progress, and γ measures the effect of SC on TFP. Taking logarithm of the above gives:

$$\ln y_{it} = c + \beta t + \alpha lnk_{it} + \gamma lnSC_{it} + u_{it} \tag{3}$$

Eq. (3) is used in the empirical estimations in Section 5.

4.2. Spatial models

That an observation in relation to a geographic location varies with observations in other locations gives rise to the possibility of three types of spatial interaction effects: endogenous interaction effects, exogenous interaction effects and correlated effects (Elhorst, 2010). In the context of technological progress, an endogenous interaction effect refers to a change in technological progress in a country caused by changes in technological progress in neighbouring countries. In other words, there is a spatial dependence in technological progress across countries. Exogenous interaction effects are observed when the explanatory variables of technological progress in neighbouring countries influence the technological progress in a given country. Correlated effects are related to unobserved and similar environmental factors across countries that affect technological progress in a similar way but are not observed; therefore, the errors are correlated across space. A model that incorporates all the spatial interaction effects takes the form of:

$$y_{it} = \rho \sum_{j=1}^{N} W y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W X_{jt}\theta + \mu_i + \delta_t + \epsilon_{it}, \quad i,j = 1, \ldots..N. \tag{4}$$

$$\epsilon_{it} = \lambda W_{jt} + \upsilon_{it} \tag{5}$$

$$-1 \le \rho \le 1 \quad -1 \le \lambda \le 1, \tag{6}$$

where subscripts i and t denote spatial units (countries) and time, respectively. y_{it} refers to technological progress in country i at time t, ρ measures the impact of technological progress in countries other than country i on technological progress in country i. W is an N*N non-negative matrix specifying the spatial arrangement of countries. X_{it} includes our main variable of interest (FDI) and a list of control variables which include financial development, human capital, trade openness, institutional index and infrastructure in country i at time t (see Section 5.1 for more information about these control variables). θ includes parameter estimates of the exogenous interaction effects (i.e. FDI and control variables), in other words the spatially lagged independent variables. μ_i and δ_t represent country and time fixed effects. Finally, λ is the spatial autocorrelation coefficient.

It is technically possible to estimate the model above that accounts for all three spatial interaction effects, but this poses a problem for interpreting the result, as the endogenous effects cannot be separated from the exogenous effects (Elhorst, 2010). This limitation is reflected in the maximum number of spatial interaction effects that spatial models include simultaneously. Capturing the endogenous and exogenous interaction effects by incorporating a spatially lagged dependent variable and several spatially lagged independent variables in a regression (the first and the third term in right hand side of Eq. (4), respectively), the Spatial Durbin Model (SDM) leaves out the correlated effects, while the spatial auto combined (SAC) model excludes only spatially lagged independent variables in estimations but includes ρ and λ. There are two other commonly used models that include only one type of spatial interaction effect, namely spatial autoregressive regression (SAR) and the spatial error model (SEM). The former is used when spatial dependence exists only in the dependent variable and the latter is appropriate if spatial interaction effects are limited to correlated error terms across countries.

The omission of either one of the endogenous and exogenous effects or both of them (by assuming ρ=0 and θ=0) leads to biased and inconsistent estimates, while the less severe consequence of ignoring the presence of correlated effects results in loss of efficiency in estimations. On these grounds, Le Sage and Pace (2009) suggest excluding the spatially auto-correlated error term and points to the SDM from alternative candidates of spatial models. By the same token, Elhorst (2012) indicates that the SDM yields unbiased coefficient estimates even if the true data generation process is a SEM, SAC or SAR.

The SDM model nests the SEM and the SAR; in other words, the SEM and SAR are the special cases of the SDM. Therefore, one can start with a general model and then test whether θ=0; if this is the case then the SAR is the appropriate model provided that ρ is different from 0, and if not, then the SDM is the preferred model. Non-rejection of the common factor hypothesis θ+βρ=0 leads to acceptance of the SEM as the true model. Both the likelihood ratio (LR) and the Wald tests can be used to test these hypotheses after the estimation of the SDM. As the SDM and the SAC are non-nested, the model that produces lower Akaike Information Criteria (AIC) is accepted as the most appropriate model.

Estimating Eq. (4) by the OLS will produce inconsistent estimates due to the violation of one of the main assumptions of the OLS that the explanatory variables are orthogonal to the error term. We can rewrite Eq. (4) by dropping subscripts as follows:

$$y = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}\epsilon \tag{7}$$

The presence of the spatial multiplier $(\mathrm{I} - \rho \mathrm{W})^{-1}$ indicates that the spatial dependent variable (Wy) depends on the error term of other countries and thereby leading to a correlation between Wy and the error term. In contrast to the OLS estimation, in this setting the maximum likelihood (ML) estimation provides consistent and efficient parameter estimates (Anselin, 1988). Furthermore, the bias correction procedure by Lee and Yu (2010) ensures the consistency of fixed effect estimations of panel models.

The two-stage least square (2SLS) and GMM estimators, while used less commonly than the maximum likelihood estimators, have the advantage of being able to accommodate more than one endogenous right-hand side variable other than the spatially lagged dependent variable. On the other hand, obtaining a coefficient estimate on ρ greater than unity is a possibility, which is regarded as a disadvantage associated with 2SLS and GMM estimators.

Based on Eq. (7), the SDM model implies that an impact of a change in an explanatory variable in a spatial unit influences not only technological progress in that unit but also technological progress in other spatial units. The former is termed as direct effects while the latter is defined as indirect effects. Furthermore, impacts brought by a change in an explanatory variable in a spatial unit pass through other countries and they come back to that spatial unit. These are called feedback effects and explain the differences between the coefficient estimates of the SDM model and direct effects.

The choice of weight matrix considerably affects the coefficient estimates of the spatial models and, in turn, spillover effect calculations. However, it is not possible to estimate or determine the weight matrix that best defines the spatial connectedness between geographic entities in advance and then estimate a spatial model. Common practice in the literature is a quest for the 'correct' matrix: this entails repeating the estimation with various types of spatial weight matrices, such as contiguity, k-nearest neighbour and inverse distance matrices (Seldadyo et al. 2010; Ertur and Koch (2007). Following that the estimation that produces the highest likelihood function value is chosen as the best specification and the other estimations serve to test the robustness of the accepted estimation as the best specification.

We use a three nearest neighbour matrix (W1) and power distance matrix (W2), whose diagonal elements are set to zero, as a spatial unit cannot be a neighbour of itself. Non-diagonal elements (w_{ij}) of W1 take a value of one if country j is one of the three nearest neighbours of country i and zero otherwise, while non-diagonal elements of W2 take the values of $1/d^2$ where d represents the distance in kilometres between the given countries, calculated using latitudes and longitudes. Both W1 and W2 are row-normalised so that each row-normalised weight (w_{ij}) reflects a fraction of all spatial influence on spatial unit i coming from spatial unit j. Because the three nearest neighbour matrix limits spatial interaction to only nearest neighbours, only 'local' spatial effects are analysed in this setting. The power distance matrix specifications, on the other hand, take global effects into consideration by assigning non-zero weights to all spatial units and also allowing for local clusters by attaching larger weights to nearer neighbours than those located farther (Kopczewska et al, 2017).

5. Empirical analysis

5.1. Variable measurement, data sources and descriptive statistics

The 24 African countries included in our study are listed in Appendix A. Annual data covering the 2006–2017 period has been collected. Although data availability did constrain the number of countries employed in our sample, the FDI stock in this group of African nations nevertheless accounts for around 70% of China's total FDI stock in the African region from 2006 to 2017 (based on the Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance). Our study is thus soundly representative of Chinese investment in Africa. 2006 is the earliest year for which Chinese investment data is available for a sufficient number of African countries.

For the estimation (described in Section 5.2) of the two components of TFP, namely pure technological progress and structural change, we employ data from the Penn World Table (PWT) 9.1. This database provides measures of real GDP that correct for changing prices over time by employing interpolated price indexes. Furthermore, as it adopts International Comparison Programme benchmarks from multiple years, all series calculated are in real terms, making it less sensitive to the choice of the base year and minimising the problem associated with using real GDP estimates in non-benchmark years noted by Johnson et al. (2013). It is worth mentioning that for the structural change variable, the PWT 9.1 does not provide sectoral employment series, and hence we obtained this data from the World Development Indicators compiled by the World Bank. Following You and Saranstis (2013), this variable is defined as the ratio of persons employed in non-agricultural sectors (including the industrial and service sectors) to the total number of people employed. A higher value of this variable implies deeper structural change, where a substantial portion of the labour force is moving from the less productive agriculture sector to the more productive industrial and service sectors, raising an economy's overall TFP.

For the spatial analysis in Section 5.3, we adopt the FDI stock in Africa as our independent variable. Specifically, we employ: 1) total FDI stock in each African country; 2) FDI stock in each African country that is originated from China; and 3) non-Chinese FDI stock in each African country, i.e. the difference between the values of 1 and 2. This will enable us to examine specifically the technological impact of Chinese investment in Africa and, at the same time, to provide a comparison between the Chinese and non-Chinese FDI. We adopt FDI stock rather than flow for two reasons. First, the former is much less volatile than the latter. More importantly, given that we are interested in measuring technological impact, FDI stock should capture local firms' technological benefits from multinationals that are already established in the host country. See for example Baltabaev (2014), Cipollina et al. (2012) and Elu and Price (2010) who use FDI stock to analyse whether it raises host economies' productivity at the country, industry and firm level, respectively.

In addition to the FDI stock in Africa as the key variable of interest, we include a number of control variables to reflect the host country environment. These variables include human capital (following Roy (2016), Woo (2008), Baltabaev (2014), Li and Tanna (2018)), financial development (following Senbeta (2008), Malikane and Chitambara, 2018, Li and Tanna (2018), Asongu (2019)), institutional quality (following Li and Tanna (2018)), trade openness (as in Senbeta (2008), Baltabaev (2014), Malikane and Chitambara (2017), Lukongo and Rezek, (2016), Asongu et al (2020)) and infrastructure (as in Fedderke and Bogetic (2009), Issahaku et al (2018) and Asongu and Acha-Anyi (2020)).

Human capital could help countries develop technologies and increase their ability to absorb technologies developed elsewhere (Keller, 2005). Trade openness could grant a country better access to technologies developed abroad as well as enhance their effective adaptation of advanced foreign technologies (Keller, 2004). Sound institutions attract individuals as well as the market system to invest in factors of production, raising productivity through improvements in allocative efficiency (Lasagni et al., 2015; Li and Tanna, 2018). Financial development can assist technological advancement by lowering agent costs and by diversifying innovation risks (King and Levine, 1993; Han and Shen, 2015). Infrastructure can raise productivity by reducing transaction and other costs as well as by facilitating a more efficient use of conventional productive inputs (Fedderke and Bogetic, 2009).

The measurement of all variables used in our study and their data sources are summarised in Appendix B. Table 5 reports a summary of the descriptive statistics. There are clear variations of the values of variables across the sample set. FDI stock (as a percentage of GDP) in the African countries analysed that originated from China (*FDIC*) averaged around 1.6% and ranged from 0.01% for Tunisia at the beginning of our sample period (2006, when China started to engage in more overseas investment in Africa) to 12.82% for Zambia in 2016. Similar variation is observed for FDI stock in Africa that did not originate from China (*FDINC*), as well as for the total stock (*FDI*). It is also interesting to note that some countries in Africa have experienced much deeper structural change (e.g. over 90% in South Africa) than others (e.g. below 10% in

Table 5
Descriptive statistics.

Variables used in the production function					
Variable	Obs	Mean	Std. Dev.	Min	Max
y	288	15823.96	14444.08	1591.75	51295.39
k	288	55570.77	60117.70	2279.32	224713.10
SC	288	51.55	24.30	8.00	95.40
Variables used in spatial analysis					
Variable	Obs	Mean	Std. Dev.	Min	Max
PTP	288	374.16	224.20	68.98	868.11
FDI	288	35.61	34.56	0.60	327.75
FDIC	288	1.61	2.28	0.01	12.82
FDINC	288	33.99	33.90	0.22	320.57
FD	288	32.69	33.28	1.06	160.13
HC	288	1.95	0.44	1.16	2.89
OPEN	288	72.64	28.17	20.72	161.89
INSQ	288	3.73	0.57	2.59	5.19
MOBILE	288	71.38	38.85	2.63	163.88

Note: See Appendix B for variable measurement and data source.

Burundi). Judging from the descriptive statistics on pure technological progress, some countries possess much more advanced technology than others: Egypt holds the highest value at 868.11, while Zimbabwe holds the lowest at 68.98.

5.2. Productivity: pure technological progress and structural change

We estimate the productivity function, Eq. (3), where TFP is decomposed into pure technological progress (PTP) and structural change (SC). We also estimate the standard Cobb-Douglas production function (Eq. (1)) where TFP is not broken down, so as to provide a comparison. All variables are in natural logarithm (except the time trend) and the results for both are presented in Table 6. We employ a panel regression with fixed effects, as indicated by the Hausman test. For the standard Cobb-Douglas production function in the second column, all factors are significant and correctly signed. The coefficient for the capital shares (k) is 0.234. This is slightly lower than the value of 0.3 that has been widely used (e.g. in Gollin, 2002; Bekaert et al., 2011; Kose et al., 2009; Li and Tanna, 2018; Baltabeav, 2014), implying that the African economy is, overall, less capital-intensive than would normally be assumed for an economy. TFP is captured by the coefficient of the time trend, which is positive and highly significant (0.0073), confirming positive TFP growth in the region.

For the modified production function where TFP is split into its PTP and SC components, information in the last column again shows that all variables are significant and correctly signed. The coefficient of SC is positive and highly significant, implying that structural change does indeed play an important role in raising productivity and output. This confirms evidence found in previous studies that SC has a positive impact on productivity (e.g. McMillan et al, 2014; Mensah et al., 2018; Diao et al., 2019). The time trend now reflects the PTP and its coefficient is positive and significant (0.0046), indicating positive PTP growth. It is lower than the coefficient of TFP in the second column, which is as expected given that we have stripped out the SC component. The significant difference between the TFP and PTP coefficients substantiates our assertion that structural change should in fact be filtered out of TFP in order to measure technological progress more accurately. The capital share drops to 0.2085 in our modified function, which suggests that the importance of capital to output might have been overstated if structural change had not been accounted for.

5.3. Spatial analysis

The PTP estimates generated in the previous section become the dependent variable in the spatial analysis described in this section. All variables are in natural logarithm except those already in percentage form, namely FDI stock variables, financial development and trade openness. We estimate the results of Eq. (4) with a three nearest neighbour matrix (W1). Starting with preliminary panel OLS analysis,

Table 6
Production function: pure technological progress and structural change.

Dependent variable: Real output per labour (ly)			
lk	0.2342*** (0.0277)	lk	0.2085*** (0.0278)
TFP	0.0073*** (0.0021)	PTP	0.0046** (0.0022)
		lSC	0.3466*** (0.0869)
c	6.7434*** (0.2723)	c	5.7082*** (0.3715)

Note: Panel regression fixed effect results. ***, ** and * denote statistical significance at 1, 5 and 10 % level, respectively. Standard errors are in parentheses; y, k and SC denote real output pre labour, real capital stock per labour and structural change, respectively, and all are in natural logarithm; t is the time trend and c denotes the constant.

we move on to the SDM model and then check the robustness of our results by examining alternative spatial models (e.g. SAR, SAC, SEM, 2SLS) (Table 7) as well as using the alternative power distance matrix (W2) (Table 8). We also present information on the direct, indirect and marginal effects (Table 11). Finally, we re-estimate the above using a sub-sample focusing on SSA nations only (Tables 9, 10 and 12).

5.3.1. SDM and alternative spatial models

Table 7 presents the estimation results of Eq. (4) with a three nearest neighbour matrix (W1). We omit the coefficients of time-specific effects to conserve space. At the bottom of the table, we report the diagnostic tests results along with AIC scores where appropriate.

The first four columns in Table 7 show non-spatial model results, where we assume away all the spatial interaction effects by setting three spatial coefficients ρ, θ and λ to zero. Significant Hausman test indicates that fixed effects model is more appropriate than random effects model. In Column 1 we employ the total FDI stocks (*FDI*), then we break down the total *FDI* into Chinese FDI (*FDIC*) (Column 2) and non-Chinese FDI (*FDINC*) (Column 3), and finally we include both Chinese and non-Chinese FDI in Column 4. Only *FDIC* turns out to be significant in Columns 2 and 4. Hence it provides some preliminary evidence that FDI from China has had a positive technological impact in Africa, whilst FDI from other investors (mainly developed economies, shown in Column 3) has not. Possibly due to the latter, the overall FDI stock does not enhance the technological progress in Africa (Column 1). As far as the control variables are concerned, only the infrastructure variable represented by mobile phone usage (*lmobile)* appears to be significant in Columns 1 to 4.

In the rest of Table 7, we present results using SDM and a range of alternative spatial models to account for the spatial dependence of technological progress among African countries in our sample. Columns 5–8 show the results of the SDM model with the spatial and time fixed effects where the spatially lagged independent variables are included along with the spatially lagged dependent variable. Identical to the non-spatial models in Columns 1 to 4, only the hypothesis that Chinese investment is positively and significantly associated with technological progress is accepted (*FDIC* in Columns 6 and 8). The effect of total FDI stocks (*FDI* in Column 5) and non-Chinese FDI (*FDINC* in Columns 7 and 8) remains insignificant. This result is consistent with our preliminary analysis in the first four columns, where only FDI from China has a technology-enhancing impact in Africa. Given this, in the rest of our estimations, we base our analysis on the specification under Column 6 where only *FDIC* is included.

In the SDM model in Column 6, in addition to the outcome of a highly significant and positive coefficient for *FDIC*, the spatially lagged dependent variable (ρ) is highly significant at the 1% significance level but negative (−0.343), suggesting that technological progress in a given country in Africa tends to move in the opposite direction to that of its surrounding countries. As for the control variables in the SDM model in Column 6, human capital (*lhc*) is significant at the 5% level and its spatially lagged counterpart under Wx (*Wlhc*) is positively associated with technological progress at the 1% level. The SDM model informs us not only about endogenous interaction effects, but also about exogenous interaction effects shown by the spatially lagged independent variables. Therefore, the positive and significant *Wlhc* indicates that the impact of an increase in technological progress in location i instigated by an increase in human capital in location i is augmented by a simultaneous increase in human capital in surrounding countries. The only other statistically significant control variable is the infrastructure proxy captured by mobile usage (*lmobile*), albeit at the 10% level.

The statistically significant spatially lagged dependent and independent variables in the SDM clearly shows that the exclusion of the relevant variable causes bias in the fixed effects estimations in Column 1 to 4. In comparison with the correct specification in Column 6, the bias concerning *FDIC* in OLS in Column 2 is slightly downward.

We then test whether the SDM model can be simplified into a SAR model via two indicators, the likelihood ratio test (LR) and Wald test.

Table 7
Estimations using the three nearest neighbour matrix (W1): full sample.

	OLS				SDM-FE				Other Models-FE			
	OLS-FE	OLS-RE	OLS-FE	OLS-RE					FDICsar	FDICsac	FDICsem	FDICtwols
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI	0.001				0.001							
	(1.175)				(1.300)							
FDIC		0.014**		0.012**		0.018***		0.018***	0.015***	0.015***	0.014***	0.014***
		(2.351)		(2.099)		(3.441)		(3.779)	(2.857)	(2.884)	(2.665)	(2.599)
FDINC			0.000	0.000			0.000	0.000				
			(1.009)	(0.629)			(1.076)	(0.413)				
fd	0.002	0.002	0.002	0.002	0.001	0.000	0.001	0.000	0.002	0.001	0.002	0.002
	(0.907)	(1.325)	(0.918)	(1.244)	(0.480)	(0.169)	(0.496)	(0.141)	(0.773)	(0.739)	(0.930)	(0.851)
lhc	0.734*	0.736***	0.727*	0.785***	0.741**	0.614**	0.720**	0.652**	0.501*	0.476	0.646**	0.282
	(1.827)	(2.951)	(1.795)	(2.768)	(2.538)	(2.331)	(2.471)	(2.426)	(1.734)	(1.557)	(2.184)	(1.045)
open	−0.002	−0.002*	−0.002	−0.002*	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002	−0.002*	−0.001
	(−1.576)	(−1.900)	(−1.538)	(−1.755)	(−1.164)	(−1.524)	(−1.093)	(−1.418)	(−1.530)	(−1.452)	(−1.708)	(−1.248)
linsti	0.122	0.105	0.119	0.124	0.201	0.168	0.190	0.181	0.065	0.072	0.025	0.042
	(0.868)	(0.865)	(0.847)	(1.016)	(1.625)	(1.441)	(1.554)	(1.596)	(0.508)	(0.548)	(0.201)	(0.372)
lmobile	0.111**	0.112***	0.112**	0.113***	0.113**	0.093*	0.114**	0.094**	0.101**	0.103**	0.088**	0.115**
	(2.169)	(2.857)	(2.159)	(2.878)	(2.032)	(1.949)	(2.042)	(1.962)	(2.376)	(2.285)	(2.109)	(2.543)
cons	4.911***	4.898***	4.913***	4.860***								
	(10.618)	(15.029)	(10.573)	(14.484)								
Wx												
WFDI					0.000							
					(0.447)							
WFDIC						0.007		0.008				
						(0.951)		(0.945)				
WFDINC							0.000	−0.000				
							(0.269)	(−0.079)				
Wfd					0.000	−0.001	0.000	-0.000				
					(0.044)	(−0.181)	(0.048)	(−0.146)				
Wlhc					1.229**	1.392***	1.190**	1.351**				
					(2.034)	(2.620)	(1.990)	(2.353)				
Wopen					0.000	−0.001	0.001	−0.001				
					(0.263)	(−0.731)	(0.379)	(−0.572)				
Wlinsti					−0.193	−.202	−0.211	−0.207				
					(−0.850)	(−0.974)	(−0.943)	(−0.905)				
Wlmobile					−0.055	−0.080	-−0.051	−0.084				
					(−0.982)	(−1.489)	(−0.932)	(−1.466)				
ρ (rho)					-0.290***	-0.304***	-0.289***	-0.299***	-0.325**	−0.373		-0.482**
					(−2.817)	(−2.587)	(−2.827)	(−2.591)	(−2.559)	(−1.462)		(−1.980)
λ (lambda)										0.056	−0.341**	
										(0.236)	(−2.395)	
N	288	288	288	288	264	264	264	264	264	264	264	264
Log likelihood	342.5		342.1		325.7	336.4	325.1	336.7	315.7	315.7	314.4	350.2
AIC	-651.0	.	−650.2	.	−605.5	−626.8	−604.2	−627.3	−593.4	−591.5	−590.9	−666.5
R2	0.227		0.225		0.405	0.258	0.412	0.267	0.415	0.408	0.452	0.337
R2 adjusted	0.178		0.176									0.215
R2 within	0.227	0.253	0.225	0.256	0.327	0.374	0.325	0.377	0.269	0.272	0.253	
R2 overall	0.510	0.488	0.513	0.484								
Hausman test	16.55***	7.25	16.43***	3.48	64.31***	69.73***	75.06***	61.17***	55.84***		35.71***	
Waldtest θ=0					10.37	11.83*	10.27	12.30*				
Waldtest θ+βρ=0					10.59	13.13**	10.43	13.73*				
Lrtest θ=0					31.27***	41.37***	30.65***	41.38***				
Underidentification test												13.17***
Hansen J over-identification test												0.276
instruments												L.WPT and Wfd

Note: All variables are in natural logarithm except FDI stock (FDI, FDIC, FDINC), trade openness and financial development which are all ratios to the GDP. The same applies to Tables 9-12. Spatial models are estimated using xsmle command of Stata. The bias correction procedure proposed by Lee and Yu (2010) is applied to all the spatial models. All the models include time dummies. Robust and clustered standard errors are in parentheses. Wx stands for spatially lagged independent variables; t-values are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 8
Estimations using the power distance matrix (W2): full sample.

	(1) SDM	(2) SAR	(3) SAC	(4) SEM	(5) 2SLS
FDIC	0.019***	0.017***	0.016***	0.016***	0.017***
	(3.175)	(3.163)	(3.028)	(3.148)	(3.149)
fd	0.001	0.001	0.002	0.002	0.001
	(0.354)	(0.707)	(0.804)	(0.810)	(0.720)
lhc	0.717**	0.586**	0.638**	0.661**	0.405
	(2.510)	(1.961)	(2.224)	(2.338)	(1.382)
open	−0.002**	−0.002*	−0.002**	−0.002**	−0.002*
	(−2.150)	(−1.935)	(−2.010)	(−1.966)	(−1.868)
linsti	0.113	0.070	0.053	0.045	0.055
	(0.937)	(0.569)	(0.430)	(0.385)	(0.512)
lmobile	0.089**	0.098**	0.096**	0.094**	0.108**
	(2.002)	(2.349)	(2.238)	(2.337)	(2.436)
Wx					
WFDIC	0.016				
	(1.029)				
Wfd	0.003				
	(0.784)				
Wlhc	1.056				
	(1.404)				
Wopen	−0.001				
	(−0.385)				
Wlinsti	−0.168				
	(−0.455)				
Wlmobile	−0.027				
	(−0.292)				
ρ (rho)	−0.358***	−0.309***	−0.116		−0.481*
	(−3.164)	(−2.848)	(−0.435)		(−1.954)
λ (lambda)			−0.235	−0.348***	
			(−0.915)	(−3.342)	
N	264	264	264	264	264
Log likelihood	318.7	311.8	312.2	312.1	342.6
AIC	−591.3	−585.5	−584.4	−586.1	−651.3
R2	0.385	0.404	0.427	0.438	0.297
R2 adjusted					0.168
R2 within	0.289	0.256	0.256	0.256	
Hausman test	33.27***				
Waldtest θ=0	6.42				
Waldtest θ+βρ=0	6.52				
Lrtest θ=0	13.83**				
Underidentification test					10.92
Hansen J over-identification test					0.554
instruments					*L.WPT and Wfd*

Note: The bias correction procedure proposed by Lee and Yu (2010) is applied to all the spatial models. All the models include time dummies. Robust and clustered standard errors are in parentheses. Wx stands for spatially lagged independent variables; t-values are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

The null hypothesis that the spatially lagged independent variables are jointly insignificant (H_0: θ=0) is rejected by the LR test at the 1% level. In addition, the hypothesis that SAR is nested in SDM is also rejected by a Wald test at the 5% level. Furthermore, we estimate a SAR model in Column 9 to compare it with the SDM (Column 6) based on the AIC scores. A lower AIC score reported in Column 6 than that in Column 9 further suggests that the SDM is more appropriate than the SAR model.

Having established that the SDM is superior to the SAR model on the basis of the AIC score, we now wish to compare the results of SDM to those of alternative models such as SAC (Column 10) and SEM (Column 11). Compared with the SDM, the SAC model in Column 10 produces estimates that are similar to those of SDM concerning *lmobile* and *FDIC* in terms of coefficient estimates. When it comes to the spatially lagged variable (ρ), SAC model estimates show that it is not statistically significant. Unlike SDM, SAC model does not estimate spatially lagged independent variables but only a spatial error parameter (*lambda*), which is also insignificant. With regard to the SEM model, although the Wald test for $\theta+\beta\rho$=0 in Column 6 rejects the hypothesis that the SDM model can be simplified to SEM model at the 5% level, we provide here SEM model in Column 11 for comparison. Concerning our variable of interest, *FDIC*, in Column 11, the SEM produces a slightly smaller coefficient estimate than the SDM does. The spatial error parameter, *lambda*, is significant with a negative sign. Looking at the AIC information provided in the second panel of Table 7, again the SDM model (Column 6) outperforms both SAC (Column 10) and SEM (Column 11) models. It is worth noting that *FDIC* turns out to be positive and significant regardless of the choice of spatial models.

Lastly, we estimated Eq. (4) with a two-stage least square (2SLS) estimator instrumenting the spatially lagged dependent variable by its temporally lagged variable and spatially lagged financial development variable (*Wfd*) (Column 12)[6]. Although the 2SLS results in Column 12 are comparable to the SAR model only as the two models incorporate the same parameters, the coefficient on our main variable of interest, i.e., *FDIC*, is positive and highly significant at 1% with similar values across SAR, SDM, SAC, SEM and 2SLS, showing that it remains robust across different models. Results that are consistent across models also include *lmobile*, the spatial lagged dependent variable (except in the SAC case) and *lhc* (except in the SAC and 2SLS cases).

[6] Dunne and Masiyandima (2017) focus on FDI between South Africa and other developing countries in the region but they analyse the relationship between FDI and income convergence. Ssozi and Asongu (2016b) find that international remittance, an alternative source of external finance flows to FDI inflows, raised TFP for 31 SSA countries in 1980-2010.

Table 9
Estimations using the three nearest neighbour matrix (W1): sub-sample.

	OLS				SDM-FE				Other Models-FE			
	OLS-RE	OLS-FE	OLS-RE	OLS-RE					SAR	SAC	SEM	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI	0.000				0.000							
	(0.955)				(0.919)							
FDIC		0.021***		0.017***		0.016***		0.016***	0.020***	0.020***	0.018***	0.018***
		(3.396)		(3.127)		(4.372)		(4.510)	(3.877)	(3.749)	(3.319)	(3.267)
FDINC			0.000	0.000			0.000	−0.000				
			(0.778)	(0.355)			(0.653)	(−0.001)				
fd	0.006***	0.003**	0.006***	0.004***	0.003**	0.001	0.004**	0.001	0.003**	0.003*	0.002	0.002*
	(3.378)	(2.108)	(3.398)	(3.493)	(2.091)	(1.070)	(2.180)	(1.014)	(2.231)	(1.863)	(1.354)	(1.821)
lhc	0.697***	0.418	0.691***	0.553**	0.436	0.291	0.417	0.291	0.319	0.322	0.362	0.112
	(2.763)	(1.322)	(2.720)	(2.452)	(1.644)	(1.292)	(1.580)	(1.242)	(1.239)	(1.259)	(1.429)	(0.448)
open	−0.001	−0.001	−0.001	−0.001	−0.000	−0.001	−0.000	−0.001	−0.001	−0.001	−0.001	−0.000
	(−1.058)	(−1.506)	(−1.019)	(−1.221)	(−0.398)	(−0.775)	(−0.314)	(−0.628)	(−0.819)	(−0.818)	(−0.892)	(−0.389)
linsti	0.243**	0.212	0.238*	0.245*	0.257**	0.213*	0.243**	0.212*	0.248**	0.247**	0.203*	0.217**
	(1.969)	(1.654)	(1.935)	(1.923)	(2.198)	(1.875)	(2.121)	(1.914)	(2.096)	(2.058)	(1.809)	(2.035)
lmobile	0.135***	0.122**	0.135***	0.131***	0.146***	0.141***	0.146***	0.141***	0.130***	0.131***	0.132***	0.140***
	(2.899)	(2.768)	(2.881)	(3.133)	(2.950)	(3.289)	(2.955)	(3.301)	(3.160)	(3.080)	(3.317)	(3.232)
cons	4.471***	4.766***	4.477***	4.595***								
	(12.422)	(12.641)	(12.420)	(14.147)								
Wx												
WFDI					0.000							
					(0.512)							
WFDIC						0.017*		0.017*				
						(1.886)		(1.839)				
WFDINC							0.000	−0.000				
							(0.255)	(−0.073)				
Wfd					−0.008*	−0.012***	−0.008*	−0.012***				
					(−1.752)	(−2.998)	(−1.755)	(−2.986)				
Wlhc					−0.173	−0.305	−0.217	−0.320				
					(−0.385)	(−0.809)	(−0.492)	(−0.849)				
Wopen					0.003	0.002	0.003	0.002				
					(1.395)	(1.441)	(1.489)	(1.218)				
Wlinsti					−0.110	−0.098	−0.135	−0.105				
					(−0.452)	(−0.443)	(−0.562)	(−0.431)				
Wlmobile					0.072	0.090*	0.072	0.090*				
					(1.263)	(1.759)	(1.288)	(1.682)				
ρ (rho)					−0.380***	−0.449***	−0.376***	−0.447***	−0.392***	−0.358*		−0.587**
					(−3.561)	(−3.588)	(−3.546)	(−3.804)	(−2.812)	(−1.821)		(−2.315)
λ (lambda)										−0.046	−0.411**	
										(−0.229)	(−2.487)	
N	240	240	240	240	220	220	220	220	220	220	220	220
Log likelihood					278.2	291.3	277.7	291.3	280.4	280.4	278.0	307.8
AIC	.		.	.	−518.4	−544.6	−517.5	−544.6	−522.7	−522.8	−517.9	−581.5
R2		0.362			0.362	0.135	0.361	0.133	0.523	0.530	0.573	0.445
R2 adjusted		0.313										0.333
R2 within	0.304	0.362	0.302	0.359	0.367	0.419	0.366	0.419	0.373	0.372	0.353	
R2 overall	0.582	0.547	0.584	0.563								
Hausman test	6.72	64.38***	4.97	23.11	121.42***	136.57	125.61	99.05	20.10		22.69	
Waldtest θ=0					12.12*	16.71***	12*	17.6***				
Waldtest θ+βρ=0					9.85	13.80**	9.75	14.38**				
Lrtest θ=0					15.95	21.87***	15.73	21.74***				
Underidentification test												10.72
Hansen J over-identification test												2.176
instruments												L.WPT and Wfd

Note: 'Sub-sample' refers to the 20 sub-Saharan countries in our set (all countries listed in Appendix A except Algeria, Egypt, Morocco and Tunisia). The same is true for Tables 10 and 12. Spatial models are estimated using xsmle command of Stata. The bias correction procedure proposed by Lee and Yu (2010) is applied to all the spatial models. All the models include time dummies. Robust and clustered standard errors are in parentheses. Wx stands for spatially lagged independent variables; t-values are in parentheses; ***, ** and * indicate statistical significance at the 1, 5 and 10% level, respectively.

Table 10
Estimations using the power distance matrix (W2): sub-sample.

	(1) SDM	(2) SAR	(3) SAC	(4) SEM	(5) 2SLS
FDIC	0.019***	0.022***	0.021***	0.021***	0.021***
	(4.259)	(4.273)	(3.982)	(3.923)	(3.900)
fd	0.002*	0.003**	0.003**	0.003**	0.003**
	(1.670)	(2.269)	(2.091)	(2.067)	(2.049)
lhc	0.431*	0.438	0.440*	0.441*	0.291
	(1.949)	(1.594)	(1.698)	(1.743)	(1.041)
open	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.611)	(−1.489)	(−1.543)	(−1.509)	(−1.359)
linsti	0.230*	0.218*	0.210*	0.201*	0.183*
	(1.890)	(1.911)	(1.902)	(1.903)	(1.827)
lmobile	0.127***	0.125***	0.128***	0.128***	0.129***
	(2.920)	(3.064)	(3.170)	(3.204)	(3.069)
Wx					
WFDIC	0.012				
	(0.982)				
Wfd	−0.007				
	(−1.556)				
Wlhc	−0.073				
	(−0.117)				
Wopen	0.001				
	(0.540)				
Wlinsti	−0.075				
	(−0.254)				
Wlmobile	0.138				
	(1.430)				
ρ (rho)	−0.410***	−0.335***	−0.136		−0.523***
	(−4.042)	(−3.543)	(−0.586)		(−2.764)
λ (lambda)			−0.249	−0.375***	
			(−1.050)	(−3.895)	
N	220	220	220	220	220
Log likelihood	279.2	275.2	275.9	275.6	299.8
AIC	-520.4	−512.5	−513.8	−513.3	−565.6
R2	0.335	0.499	0.529	0.544	0.403
R2 adjusted					0.283
R2 within	0.371	0.356	0.360	0.360	
Hausman test	45.74***	79.29***		85.13***	
Waldtest θ=0	8.12				
Waldtest θ+βρ=0	7.34				
lrtestsdm	7.94				
Underidentification test					11.00
Hansen J over-identification test					0.462
instruments					*L.WPT and Wfd*

Note: The bias correction procedure proposed by Lee and Yu (2010) is applied to all the spatial models. All the models include time dummies. Robust and clustered standard errors are in parentheses. Wx stands for spatially lagged independent variables; t-values are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

5.3.2. *An alternative weight matrix*

Coefficient estimates may be sensitive to the selection of weight matrix and employing an alternative weight matrix. Elhorst (2010) points out that the weak spatial dependence is a sign of the wrong choice of spatial weight matrix, which in turn may distort coefficient estimates considerably. Judging by the significance level, the spatial dependence in the SDM model in Column 6 is strong, which minimises the chance of choosing the wrong spatial weight matrix. Although this finding increases the credibility of our results, we want to check their consistency by re-estimating Eq. (4) using power distance matrix (W2), whose spatial weights are constructed such that the non-diagonal entries equal $1/d_{ij}^2$. Here, *d* represents the distance between locations *i* and *j*, and values decrease as the distance between two locations increases.

Table 8 shows the results of the estimation of the SDM, SAR, SAC, SEM and 2SLS with the W2 matrix. Again, we focus on the specification of using *FDIC* only. Regardless of the model choice, the coefficients on the *FDIC* variable carry positive signs and are statistically significant at the 1% level. We observe a slight increase in the magnitude of the coefficient on *FDIC* but it does not show any erratic behaviour as a reaction to the change of spatial weight matrix, indicating that our results are robust to the specification of W2. Variables *lhc* and *lmobile* remain positively signed and significant (except *lhc* in the 2SLS case), trade openness (*open*) turned significant and is negatively signed, and the spatial lagged dependent variable remains negative and significant across all models except the SAC. The SDM model again yields the lowest AIC values, suggesting that it is the best specification.

Comparing Column 1 in Table 8 with Column 6 in Table 7 where the SDM model is estimated using two different spatial weight matrices, none of the spatially lagged independent variables turn out to be significant in the former whilst the *Wlhc* variable is significant in the latter. We employ log-likelihood function values reported in Table 7 and Table 8 to decide the true specification between the two. The SDM model using the three nearest neighbour weight matrix (W1) (Column 6 in Table 7) shows higher log-likelihood function values than those obtained using the power distance matrix (W2) (Column 1 in Table 8). Therefore, we conclude that the SDM model in Table 7 best describes the data and we base our interpretation of direct and indirect effects of the independent variables (Table 11) on this specification.

5.3.3. *Direct, indirect and total effects*

As mentioned in the previous section, we adopt the SDM model in Column 6 in Table 7 as our specification to calculate these effects and the results are presented in Table 11. Direct effects of *FDIC* refer to the impact of a change in Chinese FDI stock to GDP ratio in a given African

Table 11
Direct, indirect and total marginal effects: full sample.

	Based on the SDM model Table 7 Column 6		
	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
FDIC	0.019***	0.002	0.020***
	(3.281)	(0.314)	(2.862)
fd	0.000	−0.000	−0.000
	(0.141)	(−0.162)	(−0.065)
lhc	0.563**	0.991**	1.554***
	(2.225)	(2.057)	(3.088)
open	−0.001	−0.000	−0.002*
	(−1.585)	(−0.434)	(−1.681)
linsti	0.198	−0.221	−0.023
	(1.599)	(−1.213)	(−0.142)
lmobile	0.104**	−0.096*	0.008
	(2.048)	(−1.807)	(0.164)

Note: t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

country on the technological progress in that country, whereas indirect effects of the same variable refer to the impact of this change on the technological progress in the rest of the African countries in the sample. Table 11 shows that these direct effects of *FDIC* (in Column 1) are highly significant at the 1% level. As a result, one unit of change in *FDIC* in a given country results in a 1.9 percentage increase in the technological progress in that country. The sum of these two effects amounts to the total effects and is presented in Table 11, Column 3.

As for other variables, both direct and indirect effects of human capital, *lhc*, are statistically significant at the 5% level, implying that an increase in human capital in country *i* not only positively affects technological progress there but spills over and has a positive impact on technological progress in neighbouring countries. Overall, its total effects, statistically significant at the 1% level, amount to a 1.55 percentage change in technological progress. As far as infrastructure is concerned, positive and significant direct effects of *lmobile* are exceeded by its negative and significant indirect effects, leading to negative but insignificant total effect. For trade openness (*open*), although its direct and indirect effects are both insignificant, its total effects show a very small significant negative impact on technological progress.

5.3.4. Discussion of our findings so far

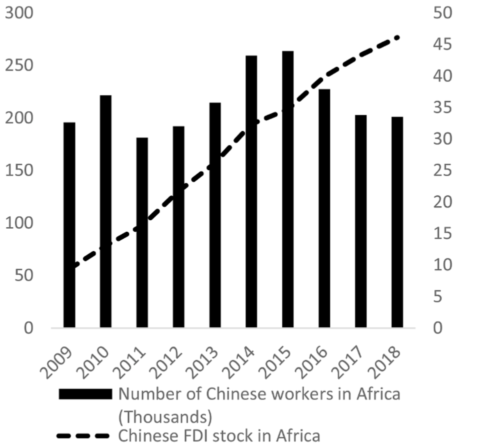
Overall, the results show that our main variable of interest, *FDIC*, is a successful predictor of technological progress and the positive and significant coefficient estimate of *FDIC* is consistent throughout different specifications and two weight matrices. This important finding implies that Chinese investment in Africa has been making positive contributions to technological progress in the African region. In contrast, non-Chinese FDI – mainly from developed countries – does not seem to have a technological impact on African nations. This provides evidence in support of the claim that developing-to-developing FDI presents a more valuable chance for Africa to raise its technological capability. It substantiates our proposition that the particular characteristics of Chinese FDI (i.e., narrower China-Africa technological gap, less concern about institutional quality, more long-term financing flexibility and willingness to take on risky projects, as detailed in Sections 3.2 and 3.4) facilitate stronger beneficial technological externality to the African region.

Although consistent with our expectation, our finding is at odds with the widespread perception that Chinese investment in Africa often employs Chinese instead of local labour (French, 2014). If this perception were true, then the technology-enhancing effect of Chinese FDI ought to be very limited or at least weaker (rather than stronger) than non-Chinese FDI which consists mainly of investment from Africa's longstanding developed investors. To fully evaluate this perception, though, we will start with a brief background discussion on China's national policy of "Go Global" launched in 1999 and the Chinese business model in Africa.

The "Go Global" policy reflected China's ambition to extend its influence and power in the world economy and in international politics (Luo et al., 2010), as well as to support China's own economic growth by securing overseas natural resources and markets (Ding et al., 2009; Donou-Adonsou and Lim, 2018). In the fast-expanding realm of Chinese investment to Africa (Figs. 2 and 3), over half has been directed to the mining and construction sectors (see Table 3). For construction projects, China often offered loans to fund Africa's infrastructural development but under the condition that Chinese firms were involved in the construction (Bräutigam and Gallagher, 2014; Bräutigam et al., 2017). Many Chinese companies indeed brought Chinese workers to Africa, at least at the beginning of their operations, as Chinese workers were familiar with the companies' organisation and processes. Chinese technicians were required to install and test the machinery, and experienced Chinese workers can tutor local workers on-site to demonstrate and transfer their skills to local employees. Although it leads to a sudden influx of Chinese workers when the projects start, it in fact represents the Chinese business model of employing large numbers of Chinese and African workers at the same time in the beginning of the projects, using Chinese to train local labours on the job and later replacing the Chinese staff with a local workforce (Tang, 2016). Many media critics may have protested the sudden influx of Chinese workers without understanding the Chinese business model and have hence missed the broader picture and the long-term trend.

Although literature on the labour market effects of FDI is still in its infancy, with more comprehensive data becoming available only in recent years, an increasing number of recent analyses have indeed found evidence opposing the view that Chinese firms in Africa tend to rely on Chinese labour (Oya and Schaefer, 2019). Based on their database on workforce localisation of over 400 Chinese firms across 40-plus African countries, Sautman and Yan (2015) conclude that, on average, locals make up four-fifths of the employees. In a more recent and comprehensive study on workforce localisation, McKinsey (2017) surveyed 1000 Chinese firms in eight African countries. The report shows that the average rate of localisation of African workers by Chinese firms is 89%. Furthermore, Rounds and Huang (2017) compare firms of different foreign nationalities in Kenya and find similar rates of workforce localisation between Chinese and US firms (78% and 83%, respectively). High rates of workforce localisation of Chinese firms are also found by Sinkala and Zhou (2014) for Ethiopia and by Cheru and Oqubay (2019) for Zambia. Several studies (e.g. Tang (2016), Lam (2014), Corkin (2012)) have also discover that the longer Chinese companies operate in Africa, the more they rely on local workers. Using a formal robust regression estimation, Boakye-Gyasi and Li (2015) suggest that there is a positive and significant impact of inward Chinese FDI flows on employment in Ghana via a direct effect on Ghana's building and construction sector. Oya and Schaefer (2019), based on interviews of 1500 Angolan and Ethiopian workers, further demonstrate that Chinese firms pay local workers comparable wages and train them to similar standards as non-Chinese foreign firms in Africa, although usually less formally.

Fig. 4(a) further illustrates numbers of Chinese workers in Africa juxtaposed with the amount of Chinese FDI stock in Africa between 2009 and 2018. The number of Chinese workers has been relatively stable around 200,000 except going slightly above 250,000 in 2014 and 2015, followed by a significant reduction after 2015. During the same period, Chinese FDI stock in Africa has been growing steadily, from just 9 billion USD in 2009 to over 46 billion USD in 2018. Focusing on the 24 African countries in our sample, Fig. 4(b) shows a similar picture: a rising Chinse FDI stock to local GDP ratio and declining Chinese workers in proportion to the local labour force between 2009 and 2017. The contrast between the stable or even gradually weakening presence of Chinese workers in Africa and the fast-growing Chinese FDI stock in the continent (the majority of which has flowed into the construction and mining sectors, as indicated in Table 3) enables us to safely deduce that most of the expansion in employment created by new Chinese projects during this



(a) Number of Chinese workers (left scale) and Chinese FDI stock in Africa (billion USD) (right scale)

(b) Average Chinese workers to domestic labour ratio (left scale) and average Chinese FDI stock to local GDP ratio (right scale) in the 24 African countries in our sample

Fig. 4. Chinese workers and FDI stock in Africa. (a) Number of Chinese workers (left scale) and Chinese FDI stock in Africa (billion USD) (right scale). (b) Average Chinese workers to domestic labour ratio (left scale) and average Chinese FDI stock to local GDP ratio (right scale) in the 24 African countries in our sample. *Data source*: Chinese FDI stock in Africa is from Statistical Bulletin of China's Outward Foreign Direct Investment, Chinese Ministry of Finance. For Chinese workers in Africa, figures include both contracted projects and labour services; the data was collected from the SAIC-CARI database (provided by the Johns Hopkins University SAIS China-Africa Research Initiative) via http://www.sais-cari.org/. Data for number of domestic labour in Africa is collected from the ILOSTAT database of the International Labour Organization.

period must have gone to African workers (see Oya and Schaefer (2019) for a similar argument)[7].

Therefore, contrary to the popular negative perception about Chinese companies not recruiting local workers in Africa, Fig. 4(a) and 4(b) and recent studies based on more comprehensive surveys and databases seem to demonstrate that Chinese investment actually has a significant job-creation effect for local African workers. Such workforce localisation may have constituted an important conduit for technological transfer from Chinese firms to local economies in Africa.

Our next significant finding is that spatial dependence has a persistently negative sign. The spatial lag being negative can be puzzling at first glance, but it should be interpreted as a sign of competition between the countries in terms of technological advancement. To sustain the pace of technological progress, countries in Africa need a large pool of skilled labour along with other resources. Consequently, an African country with faster technological progress than its neighbours and insufficient human capital to maintain such progress would attract skilled labour from neighbouring countries, which would in turn reduce the prospects of technological progress in neighbouring countries. Recent migration trends in Africa lend support to our findings. Flahaux and De Haas (2017) report that labour migration in Africa is largely intra-regional (80%). The migration of young and educated workers takes a large toll on some African countries where human capital is already scarce. To make matters worse, the concentration of migrants among those who are educated is higher in Africa than in other developing economies (IMF, 2016). Taking South Africa, one of the region's most developed economies, as an example, most of the skills the country has gained have been through the migration of individuals from neighbouring countries (World Bank, 2017b).

Human capital (*lhc*) has been a consistently positive contributor to technological progress throughout our experiment. This result is consistent with previous studies that suggest more human capital indicates stronger absorptive capacity for advanced technology and thus helps enhance technological progress in African countries. Equally important, human capital seems to benefit the technological progress in its own country (positive direct effects) as well as in neighbouring countries (positive indirect effects) as shown in Table 11. Thus, it reinforces our explanation for the negative spatial dependence as the positive indirect effect of human capital probably captures the fact that skilled labour has been attracted away from less developed countries with lower levels of technological capability towards more developed ones with more advanced technology.

Furthermore, we find better infrastructure (captured by mobile phone usage, *lmobile*) is conducive to technological progress in African countries (Table 7). However, we also find that stronger infrastructure, which promotes technological progress in a country (i.e. positive direct effect – see Table 11), has a negative impact on the neighbouring countries (i.e. negative indirect effects). This again supports our conclusion that countries compete for resources underlying the technological progress as indicated by a negative sign of the spatial dependence.

Whilst trade openness (*open*) has not turned out to be significant in the SDM model in Table 7, it has a negative sign and is significant in some specifications in Tables 7 and 8. In Table 11, it has a significant (only at the 10% level) but negative total impact on technological progress, despite its direct and indirect effects both being insignificant. This unexpected relationship between technological progress and openness could occur if fast-growing natural resource-exporting sectors, in the presence of imperfect institutions that are unable to stop the depletion of natural resources, prevent these resources of economies from supporting the achievement or continuation of technological progress (Mullings and Muhabir, 2018). Such an adverse effect of international trade on an economy is also well-documented in trade-growth literature (see Nsiah and Fayissa (2019) for a review of this strand of literature).

5.3.5. Sub-Saharan Africa subset: tests and comparison with the full sample

We now restrict our data to a more homogeneous sample of the 20 sub-Saharan African (SSA) countries only (i.e., excluding Algeria, Egypt, Morocco and Tunisia), in order to test the robustness of our main variable of interest, *FDIC*, against a sub-sample. We follow the same strategy as we used for the full sample: we first use the three nearest neighbour weight matrix (W1) and then switch to power distance matrix (W2).

Table 9 presents the results using the sub-sample data under W1. With very few exceptions, we detect similar patterns in Table 9 to the full-sample ones in Table 7. The Chinese FDI stocks in Africa variable (*FDIC*) remains significantly positive at the 1% level. The SDM model continues to be the best spatial specification. However, the human capital variable (both *lhc* and *Wlhc*) is no longer significant in any spatial models, while the institutional quality factor (*linsti*) is. Also, spatially

[7] Also focusing on manufacturing firms in Africa, Cheruiyot (2017) and Kreuser and Newman (2018) examine, respectively, the determinants of technical efficiency in the Kenyan manufacturing sector and TFP in various manufacturing subsectors in South Africa.

lagged Chinese FDI, financial development and infrastructure (*WFDIC, Wfd* and *Wlmobile*) become significant in the sub-sample case. The removal of the four north African countries from the sample reduces the average distance between the countries, leading to greater connectedness (through stronger competition in this case) between countries and results in a spatial autoregressive parameter (ρ) that is greater in magnitude.

Table 10 presents additional results using W2. *FDIC* and ρ continue to be positively and negatively signed, respectively, and highly significant (except ρ in the SAC model). Financial development and institutional quality (*fd* and *linsti*) have now become significant and positive in the sub-sample, implying they have a positive impact on technological progress in SSA. Although in Table 10, SEM seems to be the more appropriate model as the hypothesis that the SDM can be simplified to the SEM is not rejected by the Wald tests ($\theta+\beta\rho=0$), the results using W1 in Table 9 show higher log-likelihood function values than those using W2 in Table 10. Hence, we adopt the SDM model (as was the case in the full sample data) in Column 6 of Table 9 to calculate direct, indirect and total effects.

These direct, indirect and total effects based on the SDM model are presented in Table 12, in Columns 1 to 3. As in the estimations using the full sample in Table 11, direct effects of *FDIC* are statistically significant, while indirect effects are not. By the same token, total effects are still significant at the 1% level. As for financial development variable, *fd*, it has the same sign as in Table 11, positive direct effects, negative direct effects and total effects, but now all these effects are statistically significant. Hence financial development directly promotes technological progress in a country. The negative indirect effects imply that deeper financial development in a country negatively influences its neighbouring countries' technological advancement. It again emphasises the competing relationship between African nations, suggesting that a country with more developed financial markets can lower agency costs and diversify innovation risks and thus can attract financial resources from its neighbouring countries, leaving the latter less capable of developing new technology. While the direct effects of *lmobile* remain statistically significant and positive as in Table 11, the indirect effects have now turned positive but insignificant, leading to positive total effects. The institutional index, *linsti*, has positive significant direct effects but negative insignificant indirect effects, leading to positive but insignificant total effects.

Both the subset and the full-sample results (Tables 7-11) clearly point to a technology-enhancing effect of Chinese FDI in Africa. They both show negative spatial dependence, suggesting competing rather than corporative relationship in achieving technological progress among African nations, with the main areas for competition being human capital and infrastructure in the full-sample case and financial resources in the sub-sample case.

Table 12
Direct, indirect and total marginal effects: sub-sample.

	Based on the SDM model Table 9 Column 6		
	(1) Direct effects	(2) Indirect effects	(3) Total effects
FDIC	0.015***	0.008	0.023***
	(3.782)	(1.249)	(3.432)
fd	0.002*	−0.010***	−0.008***
	(1.949)	(−3.538)	(−2.678)
lhc	0.355	−0.377	−0.023
	(1.528)	(−1.129)	(−0.070)
open	−0.001	0.002	0.001
	(−0.990)	(1.541)	(0.844)
linsti	0.245*	−0.177	0.068
	(1.827)	(−0.891)	(0.496)
lmobile	0.141***	0.020	0.161***
	(3.127)	(0.459)	(3.211)

Note: t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

6. Conclusions and implications

This study investigates the impact of FDI between developing markets on the host country's technological progress. When both the host and origin of FDI are developing economies, there are relatively narrower technological gaps between the two, investors are less discouraged by poor institutional environments in the host market, and the investment often has fewer financially constraints and thus a longer time horizon. These distinctive characteristics of FDI from developing nations may lead to a stronger technology-enhancing effect on the host economies than that of FDI from developed economies, yet the existing literature offers limited insight in this respect, despite the global phenomenon of rising FDI between developing countries. Adopting the context of FDI from China to a group of 24 African countries from 2006 to 2017, which represents a noteworthy portion of this recent phenomenon, our study provides a first country-level analysis on this important issue. We first examined the separate role of structural change and pure technological progress in sustaining TFP growth. The latter provides a more accurate estimate of technological progress than the commonly employed total factor productivity – both generally and in Africa in particular, where structural change is a significant factor. In the second part of our analysis, we investigated the technological impact of Chinese investment in Africa using the technological progress measurement obtained in the first step. While existing studies on the FDI-productivity relationship in Africa often assume that country-specific productivity growth is independent of that of its neighbours, our study accounted for spatial technological dependence among African nations by employing a range of spatial models (i.e., SDM, SAR, SAC, SEM, IV-2SLS). We also explored the robustness of results using alternative weight matrix and by testing a more homogenous sub-sample that excludes non-SSA countries (i.e., Algeria, Egypt, Tunisa and Morocco).

In the first part of analysis, we find that structural change makes a positive and significant contribution to TFP growth in Africa, confirming findings of previous studies (e.g. McMillan et al, 2014; Mensah et al., 2018; Diao et al., 2019). Pure technological progress also brings positive and significant contribution to productivity growth. Having filtered structural change out of TFP to obtain the pure technological progress series, our estimates provide a more accurate account of technological advancement in Africa.

In the second step of our investigation, we find several interesting results. First, the coefficient for Chinese investment in Africa has been consistently positive and significant, regardless of specifications, weight matrices and number of countries used. It provides strong evidence that FDI from China to Africa has a positive impact of the technological progress in the host region. In contrast, no such positive impact is seen from FDI from countries other than China. Since the main investors in Africa beside China are developed countries such as France and the US, this contrast implies that China's FDI generates more profound technological benefits in Africa than advanced economies' FDI do. This confirms our expectation that *developing*-to-developing FDI has a stronger technology-enhancing effect than *developed*-to-developing FDI. It also lends support to recent studies that have found high rates of labour localisation among Chinese firms in Africa. Second, there is negative spatial dependence in Africa, suggesting that technological progress in a given country is negatively affected by changes of those in neighbouring countries. This implies that overall, competition for resources is stronger than cooperation between more developed and less developed countries in the region. These resources include human capital and infrastructure for the full sample and financial resources in the sub-sample of SSA nations. Finally, among the control variables that capture host country conditions, human capital and infrastructure are shown to be important contributing factors to a country's technological progress for the full sample, while financial development, institutional quality and infrastructure are the major factors in the case of the SSA sub-sample.

6.1. Implications for theory and practice

Building upon various theoretical channels and rationale, our paper contends that the technology-enhancing effect on the host developing country would be stronger when FDI originates from other developing nations than when it originates from developed economies. Our empirical analysis demonstrates firm evidence supporting the theoretical underpinnings set out in Sections 3.1 and 3.2. Against the background of rising investment among developing nations as an important form of South-South cooperation (World Bank, 2017a), our study thus enriches the technology spillover and international business literature by providing sound rationale supported by empirical evidence that certain unique characteristics of FDI from developing nations generate more profound technological effects on host developing nations. Our consistent empirical findings substantiate the claim that FDI among developing countries constitutes a great opportunity for more effective implementation of the global partnership goal under the 2030 Agenda for Sustainable Development.

It is also clear that, given its positive and significant contribution to TFP, structural change presents a huge growth opportunity for Africa. However, structural change in Africa has not been taking place at a quick pace (Diao et al., 2019). Enache et al (2016) find that in general, African countries have seen a significant increase in the share of labour force employment in the service sector instead of in the manufacturing industry. As such, unlike East Asia, Africa will not experience a rapid expansion of labour-intensive manufacturing that would bring about the export accelerated structural change–led growth (Diao et al., 2019). Therefore, to accelerate structural change in Africa, one way is to develop service exports as an alternative to manufacturing exports. Indeed, between 1998 and 2015, service exports grew more than six times faster than merchandise exports in Africa (Page, 2018). To deepen structural change towards more service exports, more directional policy is needed to shift resources more rapidly towards the most dynamic service sectors (e.g. ICT-based services, tourism and horticulture) (Martins, 2015; Page, 2018; Asongu and Odhiambo, 2019; Tchamyou, Erreygers and Cassimon, 2019).

More importantly, this study finds robust evidence supporting our expectation that FDI flows from China to Africa positively influence technological progress in the host countries. Attracting more Chinese investment through fully utilising opportunities such as the One Belt One Road Initiative presents vast potential for economic growth in Africa, especially given that a large proportion of Chinese outward FDI currently still goes to non-African countries. Also, as suggested by Megbowon et al (2019), SSA governments could consider prioritising Chinese investment in sectors where the potential for technology gains is larger (e.g. sectors with close ties to manufacturing). At the same time, it is important to bear in mind that China's new relationship with Africa has somewhat altered the pre-existing relationship between Africa and its traditional partners. Donou-Adonsou and Lim (2018) find that Chinese investment has been crowding out US investment in Africa, whereas France seems to be competing with China. Thus, a strategic plan needs to be put in place to effectively manage the total amount of inward FDI in Africa.

In addition, the negative spatial variable suggests that a higher technological level in one African country attracts skilled labour and capital from its neighbouring countries, posing a negative effect on its neighbours' technological advancement. Such a competitive rather than cooperative relationship highlights the importance of retaining labour and other resources within a country's own borders. Given that most movement by African migrants has been intra-regional, keeping countries stable and creating facilities able to match the aspirations of ambitious professionals must be made a priority for African governments, especially those of countries lagging furthest behind technologically.

Finally, our results point to the importance of infrastructure (represented by mobile usage), human capital, financial development and institutional quality to technological progress in Africa. This prompts calls – echoing suggestions by, for instance, Amankwah-Amoah (2016), Kodongo and Ojah (2016) and Epaphra and Kombe (2017) – for favourable national policy towards more development in these areas to create a better environment for technological progress (as evidenced in our study), which will in turn foster sustainable economic growth in the region.

6.2. Limitations and new research agenda

Our paper investigates the impact of FDI on the host country's technological progress when both the destination and origin of FDI are developing economies. Our analysis focuses on country-level evidence. Examining this phenomenon at a more disaggregated industrial level is beyond the scope of this paper, but would be an important area for future research. Different sectors have characteristics that vary from each other and hence they may react differently to foreign technology. A number of previous studies have found that technology spillover is greater in sectors that have technology that is more comparable to the relevant foreign sectors (e.g., Wakelin, 2001), a narrower gap in labour productivity relative to foreign sectors (Takii, 2005), a higher level of competition (Blalock and Gertler, 2004), and stronger absorptive capacity (Todo and Miyamoto, 2002). Therefore, adding a sectoral dimension onto developing-to-developing FDI can inform national policymakers with findings at a more granular level. For instance, while on the one hand developing-to-developing FDI may introduce technology that is more compatible with existing local sectors, on the other hand developing countries are also more prone to invest in less competitive sectors in order to avoid competition with investors from advanced economies (He and Zhu, 2018). As such, studying the sector-level technological effects of developing-to-developing FDI presents a promising extension of this research paper.

An additional future research direction is linked to the rising importance of institutional factors shown in the FDI literature. Some recent studies find that for developed countries, their institutional quality plays a vital role in attracting foreign investment, but that for developing markets, the institutional quality impact is quite minor in determining FDI inflows (e.g., Peres et al., 2018; Sabir et al., 2019). However, comprehensive explanations for this contrast are missing from these analyses. One possible explanation is that (as noted earlier in this study), in contrast to investors from advanced countries, investors from developing markets are often less concerned with relatively poor institutional quality in the host economy (Dixit, 2012; Darby et al., 2013). This divergence in attitude may have resulted in institutional environment being a less important determinant of FDI inflows to developing economies. Thus, further research that compares FDI from developed and developing economies within an examination of institutional quality factors could provide valuable rationale for why these factors tend to have weaker impact in developing nations.

Author Statement

Dengfeng Hu: Conceptualisation, Formal analysis, Writing-Original draft preparation, Writing-Reviewing and Editing.

Kefei You: Data curation, Methodology, Formal analysis, Writing-Original draft preparation, Writing- Reviewing and Editing.

Bulent Esiyok: Data curation, Methodology, Formal analysis, Writing-Original draft preparation, Writing-Reviewing and Editing.

Appendix A. List of African countries analysed

The set of 24 African countries analysed in this study is comprised of: Algeria, Benin, Botswana, Burundi, Cameroon, Egypt, Gambia, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Nigeria, South Africa, Tanzania, Tunisia, Uganda, Zambia and Zimbabwe.

Appendix B. Variable measurement and data sources

1 Variables used in the production function (Eq. (3)): *y*: Real GDP per labour. Real GDP is the Output-side real GDP at chained PPPs (in million 2011 USD). The series is collected from PWT 9.1 under code RGDPO. Labour is the number of persons engaged (in millions) from PWT 9.1 under EMP.
2 *k*: Real capital stock per labour. The real capital stock is measured using the capital stock at chained PPPs (in million 2011 USD). To obtain this variable, we follow You et al. (2019) and first calculate the ratio of capital stock and the output-side real GDP, both expressed at current PPPs (in million 2011 USD). These two series are collected from PWT 9.1 under CGDPO and CN, respectively. We then multiplied this ratio by the output-side real GDP at chained PPPs to obtain capital stock data, expressed in chained PPPs.
3 *SC*: Structural change. Following You and Sarantis (2013), it is measured as the ratio of persons employed in non-agricultural sectors (including the industrial and service sectors) to the total number of employed persons. A higher value implies proportionally fewer workers in the agriculture sector and hence a deeper stage of structural development. Employment in agriculture, services and industry (% of total employment) are collected from the World Bank.

Variables used in spatial analysis:

1 *FDI*: Total FDI stock to local GDP ratio in each African country. Data is collected from World Investment Report by UNCTAD.
2 *FDIC*: FDI stock in each African country that is originated from China divided by local GDP. Data is collected from the Statistical Bulletin of China's Outward Foreign Direct Investment (various years), Chinese Ministry of Finance.
3 *FDINC*: FDI stock in each African country that is not originated from China divided by local GDP. It is the gap between 1 and 2.
4 *OPEN*: This is the trade openness and it is measured as the sum of exports and imports divided by GDP. Exports and imports (% to GDP) are collected from the World Development Indicators (WDIs).
5 *MOBILE*: mobile phone per 100 persons. Data is collected from WDIs. It is used an indicator of infrastructure.
6 *HC*: It denotes the human capital index based on the average years of schooling and returns to education. The series is collected from PWT 9.1 under code HC.
7 *FD*: financial development is measured as the domestic credit to GDP ratio. Data is collected from the WDIs.
8 *INSQ*: the data series for institutional quality is collected from the Global Competitiveness Index by the World Economic Forum under the first pillar, Institutions.

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