The Quarterly Review of Economics and Finance xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

US foreign investments: Technology transfer, relative backwardness, and the productivity growth of host countries

Samia Benzaim[a], Zied Ftiti[b,*], Anis Khedhaouria[c], Rebai Djermane[d]

[a] University of Khenchela (Univ Khenchela), Department of Economics, BILD-Lab, Khenchela, Algeria
[b] EDC Paris Business School, OCRE-Lab, Paris, France
[c] Montpellier Business School and Montpellier Research in Management, Montpellier, France
[d] University of Khenchela (Univ Khenchela), Department of Economics, BILD-Lab, Khenchela, Algeria

ARTICLE INFO

Article history:
Received 25 November 2020
Received in revised form 15 March 2021
Accepted 18 March 2021
Available online xxx

JEL classification:
E22
E23
F14
F23
O11

Keywords:
Foreign direct investment
R&D expenditures
Multinational enterprises
Technology gap
Total factor productivity

ABSTRACT

Our study investigates the impact of US foreign investments on total factor productivity (TFP) growth, controlling for the innovation capability of host countries, for a large dataset of 61countries from 1988 to 2017. Using the panel system GMM approach, our study presents some interesting findings. First, we reveal that foreign direct investment (FDI) has a negative effect on the productivity growth of all host countries. This finding suggests that FDI does not necessarily enhance the productivity growth of host countries. We also use R&D expenditures of multinational companies (MNEs) as an alternative for FDI to filter out any supplementary effects in technology transfer. The results indicate a negative R&D effect on the productivity growth of OECD countries and a positive effect on developing countries. We also find that the technology gap, when measured as labor productivity, only enhances the TFP growth of OECD countries, but when it is measured as innovation capability, the technology gap is found to decrease TFP growth in developing countries. These findings contrast against the theoretical assumption that a large technology gap (relative backwardness) increases the TFP growth of host countries.

1. Introduction

The relationship between international technology transfer and domestic productivity growth has become a subject of many studies (Adetutu & Ajayi, 2020; Baltabaev, 2014; Carbonell & Werner, 2018; Ferreira, Fernandes, & Ferreira, 2020; Lee, 2019). Based on endogenous growth theory, studies consider technology spillovers from advanced economies to host economies to be particularly strong (Aghion & Howitt, 1998, 2009). Endogenous growth theory stipulates that foreign technology can increase local technology productivity due to the positive externalities and spillover effects of a knowledge-based economy (Romer, 1994). From this perspective, influential studies argue that international trade and foreign direct investment (FDI) are valuable channels for promoting knowledge flows and technology transfer between trading partners (Baltabaev, 2014; Borensztein, De Gregorio, & Lee, 1998; Iwasaki & Tokunaga, 2016). International trade is an important mechanism through which foreign technological knowledge can be transmitted across countries due to the positive spillover effect of foreign research and development (R&D) activities. Indeed, host countries may gain from foreign R&D spillovers by importing intermediate goods embodying technological know-how, and therefore may increase domestic total factor productivity (TFP) growth (Xu & Chiang, 2005). Moreover, host countries may benefit from FDI that often not only introduces new technological knowledge but also increases managerial skills, incentives for innovation, and encourages competition (Adetutu & Ajayi, 2020; Almodóvar, Saiz-Briones, & Silverman, 2014; Fu & Gong, 2011; Fu, Pietrobelli, & Soete, 2011; Xu, 2000).

Theoretically, the impact of trade and FDI on TFP in relation to technological progress has been assumed to depend on the country's distance to the technological frontier, that is, the extent to which the technology gap between advanced and host countries is

* Corresponding author at: EDC PBS, 70 Galeries des damiers, La défense 1, Courbevoie 92415, Paris, France.
E-mail addresses: samia4016b@gmail.com (S. Benzaim), Zied.Ftiti@edcparis.edu (Z. Ftiti), a.khedhaouria@Montpellier-BS.com (A. Khedhaouria), djerobert20@yahoo.com (R. Djermane).

https://doi.org/10.1016/j.qref.2021.03.012
1062-9769/

Please cite this article as: Benzaim, S., et al, US foreign investments: Technology transfer, relative backwardness, and the productivity growth of host countries, *The Quarterly Review of Economics and Finance*, https://doi.org/10.1016/j.qref.2021.03.012

large or small (Findlay, 1978; Wang & Blomstrom, 1992). Indeed, technology transfer is assumed to be higher when the host country is relatively backward, which may lead domestic firms to adopt, adapt, and absorb foreign R&D activities to drive growth (Aghion & Howitt, 2009). However, this assumption has generated somewhat contradictory results in the literature. Some studies have reported that the effect of trade and FDI on TFP implies a large technology gap (Blalock & Gertler, 2008; Simona & Axèle, 2012), some have found that a large technology gap presents an impediment to FDI technology absorption (Li & Liu, 2005; Malikane & Chitambara, 2017; Owoeye & Oloniluyi, 2019), and other studies suggest that a large technology gap is beneficial for increasing the effect of technology transfer on TFP, but too large a technology gap may reduce such an effect because host countries may not have the absorptive capacity to use and assimilate the new technological knowledge (Pachamuthu, 2011). These contradictory findings render the effect of technology transfer on TFP related to the technology gap inconclusive, and this should be addressed. From another perspective, some studies (Danquah, 2018; Fu & Gong, 2011; Fu et al., 2011; Wang, 2010) have investigated the transmission, based on FDI and trade, of foreign R&D activities and have assessed its effect on domestic R&D activities in relation to the technology gap.

Another stream of literature has highlighted the role of innovation capability in increasing productivity growth and helping host countries catch up with the highest-performing countries and assimilate new technological knowledge (Furman, Porter, & Stern, 2002). More specifically, this literature stipulates that improving innovation capability may help a country manage resources and skills to transform existing foreign R&D activities into new knowledge, which will create benefits for domestic firms and the economy (Furman & Hayes, 2004).

Our study aims to marry both the strands of literature, as we aim to assess whether the innovation channel, based on the innovation capability gap, might have a role in investigating the relationship between foreign direct investments and productivity growth. More specifically, we extant the literature through testing whether considering the innovation capability gap as a new technology gap estimator explains the divergence of previous studies on investigating this relationship. Interestingly, we assess the impact of United States (US) foreign investments on productivity growth by considering the innovation capability channel to absorb technology transfer, which might be benefitting from foreign R&D activities. Examining the relationship between the US and host countries is appropriate for our study because the US is currently the largest investor in the world. The US confirmed its position with FDI outflows reaching USD 342 billion according to the United Nations Conference on Trade and Development (UNCTAD) World Investment Report 2019[1] .

From an empirical perspective, we investigate this issue for a panel of 61 countries with different levels of economic development over the period 1988–2017. Our study diverges from previous studies on several interesting issues. First, we use the FDI stock as a share in the gross domestic product (GDP) of a host country to define the penetration of US multinational corporations (MNEs) in the host economy. The use of the FDI stock minimizes the dynamicity that causes strong biases in estimation and helps to capture US MNE activities already established in a host country (Waker, 2013). Second, we use the intensity of R&D expenditures by affiliates as a share in the GDP of host countries to define the technology diffusion by MNEs. The use of R&D expenditures may help to exclude other productivity-enhancing effects that cause strong endogeneity and heterogeneity problems in the estimation of the relationship between FDI and productivity growth. The use of R&D expenditures may help with examining the real effect of technology transfer of US MNEs to host countries. Based on a panel system generalized method of moments (GMM) model, our study reveals two main findings. First, our results support that R&D activities have a negative effect on the TFP growth of Organization for Economic Cooperation and Development (OECD) countries and a positive effect on the TFP growth of developing countries. The negative effect may be explained by the mature markets of developed countries (Bende-Nabende, Ford, Santoso, & Sen, 2003; Johnson, 2006). Second, we show that labour productivity gap enhances only TFP growth of OECD countries, while the technology gap through innovation capability is found to decrease TFP growth in developing countries.

This study makes several useful contributions to the literature. First, our study contributes a robust analysis of the real effect of technology transfer by controlling for US MNEs' R&D expenditures as an alternative variable of FDI stock. The impact of MNE R&D expenditures on TFP growth of host countries has received little attention at the macro level in previous studies. To our knowledge, Xu (2000) is the only study that has addressed this, but differently. To treat the bias of FDI in terms of technology transfer, Xu (2000) used technology transfer costs (affiliates' spending on royalties and license fees). We think that technology transfer costs do not include R&D activities abroad because they only reflect the transfer of technology developed in the home country. Hence, our study uses affiliates' expenditures on R&D activities. This would help detect the technological progress effect generated by MNEs in host countries. Second, to evaluate whether host countries can catch up with US MNE R&D activities, we introduce the innovation capability gap, which complements previous studies. We also use innovation capability as a new technology gap estimator to overcome the issue related to conflicting findings in previous studies. Indeed, introducing innovation capacity as a new technology gap estimator aids in comparing the size of the innovation capacity effect in explaining technology transfer, and the size of the technology gap effect often used in previous studies. This is a particularly important contribution that may enrich the existing literature and overcome conflicting findings. Third, although the literature has examined the role of technology transfer on TFP growth for host countries, to our knowledge, little is known about the impact of technology transfer from US MNEs to host countries. In particular, a large body of growth model studies argue for the importance of considering which industries MNEs come from (Azeroual, 2016; Helpman, Melitz, & Yeaple, 2004). Our research provides insightful knowledge that can enrich the existing literature and help policy makers of host countries increase their productivity growth.

We structure our study as follows. Section 2 discusses the theoretical background and related literature. The empirical framework and data are presented in Section 3. Section 4 discusses the results. Section 5 concludes the paper.

2. Theoretical background and Literature review[2]

2.1. Technology transfer, relative backwardness, and productivity growth

Technology transfer has been suggested to benefit from the positive spillover effect of foreign R&D activities that can be transmitted through international trade and FDI (Ferreira et al., 2020; Lumenga-Neso, Olarreaga, & Schiff, 2005; Wang, 2010). MNEs have been considered to be catalysts of technology transfer that

[1] https://unctad.org/en/PublicationsLibrary/wir2019_en.pdf

[2] For more readability of the literature review, we have present a relevant summary in the Table A1 (Appendix A).

affect domestic R&D investment decisions. Interestingly, MNEs may increase competition among firms and stimulate domestic technological skills through FDI spillovers (Adetutu & Ajayi, 2020; Blomstrom & Kokko, 1998; Fu & Gong, 2011; Fu et al., 2011). Indeed, domestic firms may benefit from FDI that often not only introduces new technological knowledge, but also increases managerial skills, incentives for innovation, and encourages competition (Crespo & Fontoura, 2007; Ferreira et al., 2020; Iwasaki & Tokunaga, 2016; Simona & Axèle, 2012; Sinani & Meyer, 2004; Xu, 2000). FDI spillovers may affect the technological productivity of host countries depending on whether the externalities are positive or negative (Caves, 1974; Haddad & Harrison, 1993; Sinani & Meyer, 2004; Yudaeva, Kozlov, Melentieva, & Ponomareva, 2003). Positive externalities may occur when MNEs demonstrate up-to-date technologies to domestic firms and improve their productivity through FDI, while negative externalities may impose the negative effects of FDI on the productivity of local firms (Das, 1987). Among factors that may influence externalities, the literature identifies the technology gap (relative backwardness) between advanced and recipient countries (Aghion & Howitt, 2009; Blalock & Gertler, 2008; Blomstrom & Kokko, 1998; Cohen & Levinthal, 1989; Findlay, 1978; Glass & Saggi, 1998; Wang & Blomstrom, 1992). The literature reports somewhat conflicting results about the effect of externalities related to the technology gap. Some studies assert that a large technological gap may involve positive externalities, that is, the positive effects of FDI on the productivity of local firms (Blalock & Gertler, 2008; Findlay, 1978; Wang & Blomstrom, 1992), while other studies suggest that a large technology gap may result in negative externalities (Cohen & Levinthal, 1989; Glass & Saggi, 1998; Wang & Blomstrom, 1992) because the inflow of foreign technology may act as a substitute for domestic R&D activities (Okabe, 2003, p. 106). A large technological gap may also involve increased international trade through imports, which may reduce R&D efforts of purely domestic firms (Funk, 2003). While other studies report that technology gap does not matter to the effect of FDI externalities if it is very close to the technological frontier (Haskel, Pereira, & Slaughter, 2007), because the results demonstrate that technology spillovers from FDI accrue away from the best practice frontier.

Previous studies have mostly examined how technology transfer can benefit from the positive spillover effect of foreign R&D activities and affect domestic R&D activities in relation to the technology gap, but have neglected the role of the innovation capability of host countries (UNCTAD, 2014; Wang, 2010). Specifically, some studies investigate the relationship between FDI and innovation and support that FDI inflows have a positive impact on innovations of host country firms (Ghazel & Zulkhibri, 2015; Khachoo & Sharma, 2016). However, some other studies support the negative effect of FDI inflows (García, Jin, & Salomon, 2013).

From another perspective, the distance to the technology frontier explains the potential mixed relationship between technological gap and FDI. This theory stipulates that the larger the technological gap between the host FDI and home FDI, the more pronounced the positive innovation impact of FDI. More interestingly, the FDI's impact on innovation depends on the absorptive capacity of host firms. For instance, the FDI will be a benefit, through a positive spillover effect, for a country with higher absorptive capacity innovation. However, FDI will have a negative impact on innovation of a domestic country, when it is characterized by a low level of absorptive capacity. Based on this theoretical background, we stipulate that innovation capability plays a crucial role in increasing productivity growth and helps host countries assimilate foreign technological knowledge and catch up with the highest-performing countries (Furman et al., 2002). Theoretically, innovation capability can be linked to three main factors that have been suggested to be crucial for the capability of a host country to absorb foreign knowledge and to innovate (Khedhaouria & Thurik, 2017; Furman & Hayes, 2004; UNCTAD, 2014). These are innovative inputs, that is, the investment efforts made by host countries to develop R&D activities; scientific outputs, that is, the scientific publications produced by the public sector; and technological outputs, that is, innovations such as patents generated by private firms. Indeed, a strong innovation capability, through these factors, is key to addressing many issues related to technology transfer and the productivity growth of host countries. Hence, our theoretical hypotheses are defined as follows:

H1. *There is a positive technology transfer and innovation activities spillovers from FDI to host country's TFP growth.*

H2. *FDI correlation takes advantage (disadvantage) from relative backwardness with TFP for developed (developing) economic, as they have high labour and innovation capabilities (as they have low level of labour and innovation capabilities).*

2.2. FDI, trade openness, and productivity growth

From a theoretical perspective, the more the country's production structure contains varied products, the more the country's innovation capability is high. This is supported empirically by Borensztein et al. (1998) who constructed a model based on endogenous growth theory of innovation of Romer (1990)[3]. The model reports that countries producing low varieties have a higher chance of benefiting from goods and capital introduced by FDI than countries close to the technological frontier. Here, Borensztein et al. (1998) indirectly associate technological gap to production diversification and thus to innovation capability. Their assumption considers technical progress as the result of 'capital deepening' in the form of number of varieties of capital goods.

The effect of FDI on the productivity growth of host countries has been extensively studied in the literature (Baltabaev, 2014; Crispolti & Marconi, 2005; Herzer, 2010; Hong, Sun, & Huang, 2016; Malikane & Chitambara, 2017; Mencinger, 2003; Ray, 2005; Türkcan, Duman, & Yetkiner, 2008; Wang, 2010). However, studies have yielded conflicting results. Some studies found a positive effect of FDI on TFP (Bitzer & Gorg, 2009; Crispolti & Marconi, 2005; Li & Liu, 2005; Malikane & Chitambara, 2017). For instance, Li and Liu (2005) carried out a study on 84 countries over the period 1970–1999 and found that the positive effect of FDI on TFP involves a high human capital quality. Likewise, Borensztein et al. (1998) found that the positive effect of FDI on TFP is high and significant when the quality of human capital is high. High levels of human capital may help domestic firms to attract and absorb large amounts of foreign technological knowledge and generate long run growth (Xu, 2000).

Furthermore, studies suggest that the positive effect of FDI on TFP is also conditional on the openness of host countries to international trade (Abdul Karim, Winters, Coelli, & Fleming, 2003; Agyapong & Bedjabeng, 2019; Asiamah, Ofori, & Afful, 2019; Balasubramanyam, Salisu, & Sapsford, 1996; Cecchini & Lai-Tong, 2008). Indeed, the more a host country is open to foreign capital goods and investments, the more positive R&D spillovers.

In contrast, other studies reported a negative effect of FDI on the TFP of host countries (Azman-saini, Farhan, Tee, & Tun, 2018; Herzer, 2010; Hong et al., 2016; Ray, 2005) and even an insignificant effect (Makki & Somwaru, 2004). Negative results are often

[3] Theoretically, Romer's product range expansion model is the most appropriate model for empirical research that attempts to explore the relationship between foreign direct investment and a country's economic growth. Romer (1990) based growth on product innovation, (i.e. the expansion of the product range, in the way of Horizontal differentiation by increasing the number of products without changing their quality)

reported to be related to the poor quality of human capital in developing countries. For instance, Azman-saini et al. (2018) carried out a study on 48 developing countries between 1996 and 2013. They found a negative effect of FDI on local R&D activities and on TFP, suggesting that firms in developing countries are more inclined to imitate and consume foreign imported products rather developing new products.

Other studies report a negative effect of FDI on economic growth even in developed countries (Carbonell & Werner, 2018; Mencinger, 2003; Türkcan et al., 2008). For instance, Bende-Nabende et al. (2003) carried out a study on East Asian countries and found that the effect of FDI on TFP is negative for countries with more developed economies, such as Taiwan, Hong Kong, and Japan, and positive for less developed economies such as Thailand and Philippines. According to Bende-Nabende et al. (2003), the results can be explained by the dynamic change of productivity of baby tiger economies, which may explain the positive effect of FDI on GDP in Thailand and Philippines. Likewise, Johnson (2006) carried out a study on 90 developed and developing countries from 1980 to 2002, and found that FDI only improves the economic growth of developing countries. Johnson (2006; p.44) concluded that the negative effect may be reflected by the fact that '*in a mature market economy there is no difference between domestic and transborder investment*'.

Furthermore, the negative effect of FDI on TFP may reveal how foreign competitors may impede domestic productivity. Openness to international trade may decrease the domestic productivity relative to foreign investors in the long run. In a study carried out on 28 OECD countries between 1996 and 2006, Wang (2010) found a negative effect of foreign technology on R&D activities (through FDI and trade). The author explained this result by the fact that foreign R&D activities may substitute domestic R&D activities due to the increased FDI and openness to trade. Indeed, FDI may generate a negative competition effect that may hamper R&D activities of purely domestic firms (Krammer, 2008). Moreover, foreign investors may attract high qualified domestic skills through higher wages, which may result in a decrease in qualified skills and the productivity of domestic firms. Aitken and Harrison (1999) found that FDI has lowered the productivity of domestic firms in Venezuela since foreign firms hired highly qualified workers from domestic firms.

Conflicting results on the effects of FDI and trade on TFP may be related to the lack of consistent estimation of FDI. Most previous studies have used FDI flows rather than FDI stocks (Waker, 2013). According to Lensink and Morissey (2006), FDI flows can reduce R&D costs and their volatility can lead to the contraction of GDP. The volatility in FDI flows can create uncertainty in R&D costs. studies suggest using FDI stock as an appropriate estimator to capture established foreign firms rather than new entrants (Baltabaev, 2014; Bitzer & Gorg, 2009). In our study, we use the FDI stock as a share of the GDP of a host country to define the penetration of US MNEs in the host economy. Moreover, Xu (2000) describes FDI flows as a biased proxy for technology transfer because FDI flows do not distinguish between the real effect of technological transfer by MNEs and other influences such as employment and competition, which may generate endogeneity issues. To address this, Xu (2000) used MNEs' affiliates' spending on royalties and license fees as an alternative measure of FDI to investigate the impact of technology diffusion on the TFP of host countries. Hence our third theoretical hypothesis is defined:

H3. *In term of technology diffusion, FDI is a biased proxy for MNE. Therefore, substituting FDI by R&D activities in our study will yield to different results.*

Conflicting results on the effect of FDI on productivity growth may also be related to the fact that previous studies have examined growth in relation to income rather than TFP (Baltabaev, 2014). Studies suggest using TFP rather than income when studying the impact of technology change on growth because technology is an important determinant of TFP, and most of the cross-country per capita income difference is due to differences in TFP (Comin, 2006; Seker & Federica, 2018).

There have been extensive investigations on the indirect effect of FDI on growth through interaction with the technology gap (Baltabaev, 2014; Li & Liu, 2005; Malikane & Chitambara, 2017; Owoeye & Oloniluyi, 2019). However, the studies have yielded mixed results. For example, Li and Liu (2005), Malikane and Chitambara (2017), and Owoeye and Oloniluyi (2019) used income per capita as measure for the technology gap. They find that the technology gap inhibits the positive effect of FDI. Against this result, they contrasted the hypothesis of the advantage of relative backwardness. Baltabaev (2014) uses labour productivity to measure the technology gap. He finds a positive significant effect of the indirect role of FDI. His result supports that a large technology gap helps countries to catch up faster to technology introduced by FDI. However, Baltabaev (2014) used an aggregated sample composed of countries at different stages of development, which may create biased results due to the issue of heterogeneity.

3. Empirical framework and data sources

3.1. Methodology

As has been specified in earlier paragraphs, technological change has been suggested to be an important determinant of TFP growth (Comin, 2006; Seker & Federica, 2018). Therefore, we choose TFP to be the dependent variable in our econometric model. We assume that FDI may increase TFP growth. By taking the role of the relative backwardness into consideration, the TFP growth (GTFP) of host countries becomes a function of FDI stock (SFDI), the technology gap (DTF), and the control variables (CT).

$$GTFP_{it} = f(SFDI_{it}, DTF_{it}, CT_{it})$$

where *GTFP* is the total factor productivity growth; *SFDI* is the intensity of the FDI stock as a share of the real GDP of the host country under consideration; *DTF* is the technology gap (relative backwardness); *CT* represents the vector of control variables (taken from endogenous growth theory) that accounts for the R&D embodied in imports from the US weighted American R&D expenditures stock to host countries (IMP), domestic patent applications (DK), human capital (H), population growth (GPOP), and trade openness (OP). The following equation summarizes the analysis of the study:

$$GTFP_{it} = a_i + a_1 SFDI_{it} + a_2 DTF_{it} + a_3 SFDI_{it} * DTF_{it} + a_4 IMP_{it} + a_5 DK_{it} + a_6 OP_{it} + a_7 GPOP_{it} + T_t + \mu_i + \varepsilon_{it} \quad (1)$$

Where a_i is a constant; *T* represents time dummies; μ_i is the unobserved time-invariant country effect; ε_{it} is the idiosyncratic disturbance term at time (t) and for country (i).

Our model (Eq.1) might be rewritten as follows for simplicity

$$Q_{it} = a_{it} + X_{it}B + T_{it} + \vartheta_{it} \quad (2)$$

Where Q_{it} denotes the $GTFP_{it}$; $X_{it} = (SFDI_{it} + DTF_{it} + SFDI_{it} * DTF_{it} + IMP_{it} + DK_{it} + OP_{it} + GPOP_{it})$,

$B=\begin{pmatrix} a_1 \; a_7 \\ . \\ . \\ . \end{pmatrix}$ is coefficient matrix of the explanatory variable (X),

and the error term (ϑ_{it}) is defined as follows: $\vartheta_{it} = \mu_{it} + \varepsilon_{it}$.

Our model as presented above might suffer from an endogeneity bias, referred to the condition of correlation among explanatory variables (input) and the error term that causes inconsistent estimation (Ullah, Zaefarian, & Ullah, 2020). The bias can be generated in the production equation, especially when endogenous variables such as investments and R&D expenditures are introduced (Ullah, Akhtar, & Zaefarian, 2018; Ziesemer, 2019). The problem of endogeneity is not taken into consideration by Ordinary Least Square as it does not account for the error component of disturbance and the time invariant country effect (μ_{it})(Baltabaev, 2014; Bond, Hoeffler, & Temple, 2001; Roodman, 2009; Ullah et al., 2020). Although that the fixed effect technique is able to consider the time invariant country effect, it does not solve completely the issue of correlation of explanatory variable with the error term (Ullah et al., 2020). To deal with the endogeneity, Arellano and Bond (1991) developed a differential equation obtained from moment conditions as follows:

$$\Delta Q_{it} = \Delta X_{it} B + \Delta T_{it} + \Delta\vartheta_{it} \tag{3}$$

$$E\left(B_{i,\,t-\tau}\Delta\vartheta_{it}\right) = 0,\ \tau = 2, \ldots, T; t \geq 3 \tag{4}$$

Where Δ denotes the first order of differentiation. Based on Arellano and Bond (1991), the second and further lags of X_{it} are used as instruments for the differenced transformation in (Eq 3). Arellano and Bover (1995) have shown that difference GMM estimation suffers from bias that leads to weakness in the instruments. First, when the explanatory variables are persistent or the variance of specific effects is large, the lagged levels become weakly correlated with lagged differences. Second, in unbalanced panel, first differencing creates gaps for missing data (Baltabaev, 2014; Ullah et al., 2018). To overcome simultaneity bias, Blundell and Bond (1998, 2000) recommend the system GMM method that jointly estimates the production function in first differences and levels. Lagged inputs are used as instruments of the first difference equation and lagged differences as instruments of the level equation:

$$E\left[\Delta X_{i,\,t-\tau}\left(\mu_{it} + \varepsilon_{it}\right)\right] = 0,\ with\ \tau = 1 \tag{5}$$

Therefore, moment conditions (4) and (5) are used for system GMM. Hence, we estimate our econometric model using the system GMM method to deal with endogeneity and also the nonlinearity of the regressors in the production equation (Hansen, 1982). In addition, we opt for system GMM as it has been suggested to be the most appropriate estimator technique for empirical growth models because of its superior ability to exploit stationarity restrictions (Bond et al., 2001).

We used the two-step system GMM estimator as it is asymptotically more efficient and robust. Additionally, we applied fixed effects based on the Hausman test to check for the robustness of our findings.

Our model (Eq.1) is estimated based on data that are averaged or differenced over five- year periods, in line with Baltabaev (2014), Basu, John, and Miles (2006), and Madsen, Islam, and Ang (2010). This estimation strategy aims to filter out the effects of random and cyclical fluctuations on TFP growth, and to better check for the technology catch-up relations (Xu & Chiang, 2005)[4] . In business cycle literature, we have different types of business cycles with different horizons; Kitchin cycle is for medium term (3–5 years), Juglar is for 8–10 years, and so on. Madsen et al. (2010) checked the robustness of their results by estimating their models based on data that were averaged or differenced over 10-year periods. In our study, we checked the robustness over six years, explained through the limited number of observations, avoiding re-estimation of the model for 10-year periods. Therefore, TFP growth is calculated as follows:

$$\Delta TFP_{it} = TFP_{it} - TFP_{i,t-5} \tag{6}$$

Splitting the series into five-year differences yields six observations for each country: 1988–1992, 1993–1997, 1998–2002, 2003–2007, 2008–2012, and 2013–2017. Thus, we consider the analysis without dynamics, since we use TFP growth. In other words, the lagged dependent variable enters insignificantly in our model, which means that GTFP in the previous five-year period does not impact GTFP at level. All explanatory variables are averaged over the five-year intervals.

3.2. *Data and selected variables*

We collect TFP data from the Penn World Table (PWT) 9.1. In this version, TFP is calculated using a general production function that uses capital services instead of capital stock. The variable is calculated in real values at the 2011 constant dollar, which means that all explanatory variables will be driven to the 2011 constant dollar. The data spans from 1988 to 2017.

3.2.1. *Foreign direct investment (FDI)*

We use FDI stock as it is less volatile than FDI flows. Data on total FDI has been collected by the Bureau of Economic Analysis (BEA)[5] . FDI stock values are provided in nominal amounts. Real FDI was calculated by deflating the nominal amounts with the investment deflator calculated from the PWT 9.1. We choose the host countries deflator because we study the impact of FDI on domestic economic growth. The deflator was computed by dividing FDI by the price level of capital formation (price level of US GDP in 2011 = 1) and multiplying this by the exchange rate in national currency/USD (market + estimation).

To obtain the relative measure of penetration of US FDI in the host country, we divide the corresponding stock of real FDI by real GDP. The formula for this variable is measured over five-year averages.

3.2.2. *Technology gap*

To measure the technology gap (DTF1) between the leader and the host country, we followed the methodology used by Baltabaev (2014) and Madsen et al. (2010). The authors used the labour productivity of the leader country (A^{max}) (i.e. the US) and the labour productivity of the host country under consideration (A_i)to avoid the correlation between the gap computed from TFP and the error term. Since annual data on hours worked were only available for OECD countries, we computed labour productivity by extracting the number of persons engaged from the PWT 9.1. We also use the innovation capability term (DTF2). Using the 'innovation capability gap' helps to measure the host country's capability to catch-up

[4] We choose a five-year interval as it expresses the minimal threshold of the long run dynamics. It also yields good results in our econometric model.

[5] https://www.bea.gov/international/di1usdbal

with the innovation activities of established US MNEs. Innovation capability is calculated as follow:

$$DTF = \left(A^{max}/A_i\right)_t, \tag{7}$$

Where A^{max} represents the domestic labour innovation productivity of the leader country (i.e. the US) and A_i represents the domestic labour innovation productivity of the host country. We divide the patent applications (using residents count) by the number of persons engaged to measure the labour innovation productivity of each country. We collected data on patent applications from the World Intellectual Property Organization (WIPO) using residents count[6] . For labour, we use the number of persons engaged from the PWT 9.1.

3.2.3. Control variables

We add international trade in our analysis. International trade is an international technology spillover channel that is considered to be a complement of MNE activities (Krammer, 2008). Many studies demonstrate that openness to trade tends to improve long-run economic growth (Edwards, 1998; Xu & Wang, 1999; Zhu & Jeon, 2007). Studies have computed the technology spillover using Coe and Helpman (1993) formula. Coe and Helpman (1993) posited that as developing countries increase imports from developed countries, technology spillovers increase, where imports are defined as the share of total average imports of the domestic R&D capital stock of the leader country. Lichtenberg and de la Potterie (1996) report that the total imports weight suffers from aggregation bias that randomly affects the productivity of the recipient country. The formula does not reflect trade intensity. Therefore, Lichtenberg and de la Potterie (1996) developed a new formula with a new weight that allows the elasticity of imports to vary across countries:

$$\mathrm{IMP}_{\mathrm{it}} = \sum_{j \neq i} \frac{\mathrm{m}_{\mathrm{ijt}}}{\mathrm{Q}_{\mathrm{it}}} \mathrm{S}^{\mathrm{d}}_{\mathrm{jt}}, \tag{8}$$

Where $\mathrm{IMP}_{\mathrm{it}}$ denotes imports weighted by R&D; Q_{it} is the output of developing county in year t (i.e. GDP); and S^d_{jt} is the domestic R&D stock of country *j* (i.e. the US).

The imports of the countries under consideration were collected from the US Census Bureau database[7] . We deflate the nominal amount of imports using price level of imports and multiplying this by the exchange rate in national currency/USD (market + estimation) from PWT 9.1. The imports are limited to the trade in capital goods by the country. We choose capital goods because they have a higher content of technology than non-capital goods (Xu & Wang, 1999). Thus, we use the perpetual inventory method to calculate the stock of R&D expenditures of the US embodied in imports. Firstly, we determine the initial stock according to the following formula:

$$\mathrm{S}_0 = \frac{\mathrm{I}_0}{\left(\mathrm{g} + \delta\right)} \tag{9}$$

Where S_0 denotes the initial stock relating to the data availability[8], I_0 is the initial amount of R&D expenditures, g is the average growth rate of US R&D expenditures over the first ten years, and δ is the depreciation rate, assumed to be 15 % following Griliches (2000). The inventory method is then applied as:

$$\mathrm{S}_\mathrm{t} = \mathrm{I}_\mathrm{t} + \left(1 - \delta\right) \mathrm{S}_{\mathrm{t}-1} \tag{10}$$

Where S_t is the stock at time *t* (i.e. 1988), S_{t-1} is the stock in year *t-1*, I_t is the amount of US R&D expenditures in year *t*. US R&D expenditures in 2010 USD were collected from OECD data[9], and were converted to 2011 USD using the investment deflator from the PWT 9.1.

Domestic knowledge through aggregate output is decisive for improving productivity and employing local and foreign technology (Aghion & Howitt, 1998; Howitt, 1999). The data related to R&D expenditures are in most cases only available for developed countries in the sample, which justifies the use of patent applications as output of R&D. The use of patents was econometrically validated by Crosby (2000), Türedi (2016), Voutsinas, Tsamadias, Carayannis, and Staikouras (2018), and Xu and Chiang (2005), who find a high correlation between R&D expenditures and patents. We use the ratio of patent to product as defined in Schumpeterian endogenous models. This ratio could be expressed as a share of GDP or labour. In this study we use labour. We incorporate the term only when the DTF1 is used as the technology gap in the analysis because of the strong multicollinearity between the patent ratio (DK) and DTF2 calculated from patents.

We incorporate a human capital variable in the model. The quality of human capital is important for MNEs' technology transfer and for the exploitation of imported goods. As noted by Blomstrom and Kokko (2003), host economies with high levels of human capital attract and absorb large amounts of technology that generates long-run growth. For the human capital variable, we used the H index based on years of schooling and returns to education, collected from the PWT 9.1.

We also incorporate population growth in our analysis. Theoretically, population growth is expected to impact productivity growth positively. The population growth (GPOP) index was collected from the World Bank's 2020 World Development Indicators (WDI).

In addition to population growth, we add trade openness in the analysis. This is because foreign affiliates can export their finished products to the market in their home country and can import machinery or products from parent companies (Abdul Karim et al., 2003). Data on trade openness was collected from the 2020 WDIs.

The study contains 61 countries for which data are available. We are limited to this sample due to the observations of FDI, patent applications, and R&D expenditures of MNEs. A few missing data points for variables in the sample are interpolated using the middle-point method. Endogenous growth theory indicates that at different stages of development, different patterns of technology absorption are exhibited. Therefore, we divide the sample into 2 sub-groups. The first group contains developed countries (OECD), and the second group contains developing countries (LDC). Table A2 in Appendix A shows the countries included in the sample.

4. Empirical findings and discussion

Table 1presents summary statistics for the variables. The average of US FDI in the total sample is about 25.4 % with a standard deviation of 2.113. The technology gap (DTF1) is about 0.84, meaning that on average the total labour productivity in host countries is 0.84 times lower than that of the US. The average distance to the technological frontier (DTF2) is about 2.76, for the total sample, meaning that the innovation capability of host countries is 2.75 times less than that of the US, on average.

The average of US FDI penetration is higher in OECD countries (34 %) than in developing countries (16 %). The technology gap (DTF1) is about 0.41 in OECD countries and 1.29 in developing countries, which means that the technology gap is larger in developing countries. Likewise, the average of the innovation capability gap

6 https://www3.wipo.int/ipstats/index.htm?tab=patent
7 https://www.census.gov/foreign-trade/balance/index.html
8 The initial stock for US R&D expenditures is in 1981.
9 https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm

Table 1
Descriptive statistics of variables.

Variables	GTFP	SFDI	MNE	LnDTF1	LnDTF2	lnIMP	LnDK	LnH	LnOP	GPOP
Total sample (61 countries)										
OBS	361	357	307	366	362	365	362	366	364	366
Mean	0.015	0.2539	0.0006	0.839	2.757	22.536	4.363	0.989	4.189	0.912
S.D	0.074	2.113	0.001	0.685	1.958	3.022	1.967	0.218	0.547	0.902
Min	−0.459	−0.001	0	−0.624	−1.964	9.956	−0.631	0.284	2.750	−1.568
Max	0.343	26.27	0.016	2.916	7.915	33.84	8.754	1.319	5.992	3.586
OECD countries (31 countries)										
OBS	183	182	167	186	184	185	184	186	184	186
Mean	0.013	0.340	0.001	0.406	1.523	23.401	5.597	1.115	4.244	0.600
S.D	0.070	2.300	0.002	0.343	1.314	2.326	1.282	0.144	0.479	0.751
Min	−0.459	0.00001	4.36e-08	−0.482	−1.964	17.631	2.301	0.585	2.856	−1.568
Max	0.343	26.278	0.016	1.354	4.740	28.922	8.754	1.319	5.960	3.184
Developing countries (30 countries)										
OBS	178	175	140	180	178	180	178	180	180	180
Mean	0.017	0.164	0.0001	1.286	4.032	21.647	3.088	0.859	4.132	1.234
S.D	0.079	1.901	0.0005	0.664	1.680	3.382	1.725	0.205	0.606	0.933
Min	−0.368	−0.0018	0	−0.624	−1.102	9.956	−0.631	0.284	2.750	−1.392
Max	0.292	25.118	0.005	2.916	7.915	33.842	8.392	1.215	5.992	3.586

NOTE: GTFP is differenced five years. SFDI, MNE, DTF, IMP, DK, H, OP and GPOP are averaged five years. All variables are in log form apart from SFDI, MNE and GPOP. OBS, S.D, Min, and Max denote the observations, the standard deviation, the minimum and maximum values, respectively.

(DTF2) is larger than technology gap DTF1, and is also larger in developing countries (4.03) compared to OECD countries (1.52).

The correlation matrix among the variables is shown in Table A3 in the Appendix A. We find a preliminary negative relationship between TFP growth and SFDI in all samples. For the technology gap (DTF1), we can see that there is positive relationship with GTFP in both the full sample and OECD countries, and a negative relationship with GTFP for developing countries. For DTF2, we observe a negative coefficient. All control variables appear to have a positive association except for population growth (GPOP). To better analyse the relationships between the variables and TFP growth, we conduct a more detailed analysis.

4.1. Analysis of empirical results

Table 2provides the estimation outputs of the three samples using system GMM (fixed effect results are in Table A4 in the Appendix A). We examine two different models taken from the main econometric model given in Eq. (1). Model (1) takes the coefficient of DTF1 as the technology gap term into consideration. In Model (2), we incorporate DTF2 as another measure for the technology gap. Regression (1.1) from model (1) shows the direct roles of FDI and the technology gap. We also report the indirect role of FDI through the technology gap (DTF1) in regression (1.2). For this, we multiply FDI by DTF $\left(\sum_{J\neq I}\left(\frac{FDI_{ij}}{Q_i}\right)*DTF_d^i\right)$ to get the indirect role of FDI. We report the indirect role of FDI separately to avoid multicollinearity that can occur when the two variables SFDI and the technology gap are interacted. This process is the same for model (2), which reports the direct role in regression (2.1) and the indirect role through the interaction term between FDI and the innovation capability gap in regression (2.2). All regressions have been run with constant and time dummies, which are not reported to save space. In almost all cases, the first to second and second to third lagged right-hand-side level variables are used as instruments for the first difference equation, and the first lagged differences are used as instruments for the level equation. All *p*-values and *t*-tests are reported based on robust standard errors that solve the issues of heteroscedasticity and autocorrelation.

The coefficient of SFDI is negative and significant at the 1 % level in all samples (except for OECD sample at 5 and 10% levels), as previously shown in the correlation matrix. Our robust finding contrasts against the first hypothesis constracted based on previous studies (Baltabaev, 2014; Li & Liu, 2005; Malikane & Chitambara, 2017) and confirms that FDI has a negative relationship with productivity growth (Herzer, 2010; Hong et al., 2016; Mencinger, 2003; Ray, 2005; Türkcan et al., 2008). Indeed, an increase of 1 % in US FDI may lead to a 0.22 % decrease in the TFP growth of host countries, a 0.13 % decrease in OECD countries, and a 0.09 % decrease in developing countries.[10]

Another important result is the relationship of technological gap with TFP growth. DTF1 has a positive significant correlation in the full and OECD samples. We note that a large technology gap (DTF1) in developing countries has no relationship with TFP, which justifies the insignificant coefficient it has on TFP growth. This is consistent with the finding of Xu (2000) who reports that the technology gap has a positive correlation with the TFP of developed countries and negative correlation with the TFP of developing countries. Our result supports the theoretical assumption of (Pachamuthu, 2011) who posits that a large technology gap is good for increasing the effect of technology transfer on TFP, but too large a gap may reduce such an effect. This means that only OECD countries have the capacity to use and catch-up with foreign technology. The interaction term between DTF1 and SFDI shows a negative coefficient in all samples except for OECD but with insignificant p-value, which means that FDI does not benefit from relative backwardness. This contrast the second hypothesis about the advantage of technology gap on FDI in advanced countries (Haskel et al., 2007), which means that technology gap does not matter to the effect of FDI. Such result might support the strong negative relationship of FDI with GTFP due to the negative selection effect from increased openness (Aitken & Harrison, 1999; Co, 2000; Krammer, 2008; Wang, 2010). The innovation capability gap (DTF2) in regression (2.1) is negative and significant in both the full sample and the developing country sample. For OECD countries, the coefficient of DTF2 is positive but statistically insignificant. This indicates that the more the technology gap is large, the more it harms TFP growth of economies. Hence, we note that developing countries in the sample do not have the innovation capacity to catch up with leader countries, which may be an impediment to the technology innovation activities of FDI in

[10] We multiply the average mean of FDI for each sample from Table 1 with the coefficients of FDI in regressions (1.1) from Table 2 to get the average impact percentage.

Table 2
GTFP regressions.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
SFDI	−0.009*** (0.00)	–	−0.005*** (0.01)	–	−0.004* (0.10)	–	−0.001** (0.05)	–	−0.006 *** (0.00)	–	−0.006*** (0.00)	–
lnDTF1	0.02** (0.03)	–	–	–	0.03* (0.06)	–	–	–	0.006 (0.57)	–	–	–
lnDTF2	–	–	−0.005* (0.10)	–	–	–	0.007 (0.73)	–	–	–	−0.009* (0.08)	–
lnDTF1 * SFDI	–	−0.003*** (0.00)	–	–	–	0.007 (0.22)	–	–	–	−0.004* (0.08)	–	–
lnDTF2* SFDI	–	–	–	−0.003*** (0.00)	–	–	–	0.001 (0.32)	–	–	–	−9.61e-07 (0.19)
lnIMP	−0.003** (0.03)	−0.004*** (0.00)	−0.004*** (0.00)	−0.04*** (0.00)	0.02*** (0.00)	−0.02** (0.02)	−0.002 (0.30)	−0.04*** (0.01)	−0.003** (0.02)	−0.001 (0.36)	−0.004** (0.02)	−0.004** (0.02)
lnDK	0.01** (0.02)	0.02 (0.50)	–	0.002 (0.50)	0.02** (0.05)	−0.01 (0.48)	–	−0.02 (0.27)	0.01* (0.10)	0.008* (0.09)	–	0.008* (0.07)
lnH	0.02 (0.33)	0.01 (0.48)	0.006 (0.80)	0.01 (0.48)	0.02 (0.44)	0.04 (0.27)	0.12*** (0.01)	0.07 (0.27)	0.03 (0.31)	0.04 (0.11)	0.02 (0.39)	0.03 (0.29)
lnOP	0.03*** (0.00)	0.02*** (0.00)	0.03*** (0.00)	0.02*** (0.00)	0.01 (0.37)	−0.05 (0.86)	0.02 (0.13)	0.01 (0.54)	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)
GPOP	0.006 (0.47)	−0.002 (0.76)	0.002 (0.71)	−0.002 (0.76)	−0.004 (0.83)	−0.005 (0.65)	−0.004 (0.58)	0.01 (0.35)	0.01 (0.31)	0.007 (0.38)	0.01 (0.30)	0.01 (0.28)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.598	0.304	0.626	0.304	0.070	0.188	0.147	0.197	0.277	0.682	0.277	0.302
Difference in hansen test (p-value)	0.178	0.336	0.169	0.336	0.600	0.395	0.558	0.532	0.833	0.386	0.844	0.99
AR2(p-value)	0.102	0.129	0.104	0.129	0.310	0.377	0.360	0.405	0.389	0.687	0.395	0.451
Observations	352	352	352	352	150	150	150	150	172	172	172	172

NOTE: all models are static apart from OECD samples, which lagged TFP growth results are not reported to save space. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from SFDI and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

their territory. Therefore, we conclude that the greater the technology gap, the less countries have the capacity to catch up with leader countries. This supports the theoretical assumption of Cohen and Levinthal (1989), Glass and Saggi (1998), Pachamuthu (2011), and Wang and Blomstrom (1992), who report that the large technological gap between recipient and leader countries harms technology transfer, and contrast Blalock and Gertler (2008), Findlay (1978), and Wang and Blomstrom (1992), who assert that the greater the technology gap, the more it stimulates technology diffusion and absorption.

We also report the effect of control variables. In relation to the effect of international trade (through imports) on TFP growth, all regressions reveal a negative spillover of R&D embodied in capital goods. Our finding contrasts to previous studies, suggesting that R&D flows embodied in products can positively improve the technical progress of host countries (Coe & Helpman, 1993, 1995; Lichtenberg & de la Potterie, 1996). Our finding confirms that foreign R&D knowledge embodied in capital goods may be a substitute for domestic R&D activities due to the increased openness to trade (Abdel Fattah, 2015; Acharya & Keller, 2008). The results show that there is a positive relationship between patents (DK) and GTFP in the full sample and the developing countries sample. This finding suggests that patent applications may play an active role in increasing the domestic productivity growth of developing countries. Human capital (H) has a positive relationship with the TFP growth of OECD countries, and we also find that openness to trade (OP) has positive coefficients in all samples.

We also analyse the fixed effects results in Table A4 to check the sensitivity of our results. Fixed effects have been used after applying the Hausman test. The advantage of fixed effects compared to random effects is that the former takes into account unobserved heterogeneity bias. The FDI coefficients seem to have the same size and negative relations as in the system GMM model. When examining the role of DTF1, we find that both the size and significance of the coefficients decrease. In OECD countries, DTF2 is positive and insignificant. This is consistent with the system GMM finding. However, fixed effects do not take the issue of endogeneity into consideration, which may explain the divergence in our findings.

The results of the fixed effects and system GMM models indicate a negative association between FDI and the TFP growth of host countries. This does not necessarily imply a negative association of technology diffusion with TFP. FDI is a variable that contains different aspects, in addition to the technology flows that may negatively affect the economic growth of host countries (Ferragina & Mazzotta, 2014; Xu, 2000). The endogenous relationship between FDI and TFP may result in the results not being robust. In addition, the heterogenous relationship between SFDI and GTFP supported by the standard deviation results (see Table 1) presents evidence for using an alternative proxy of US foreign investments in the analysis. These doubts motivate the use of R&D expenditures of MNEs as an alternative variable (see the pairwise correlation between SFDI and MNE in Table A3 in the appendix) to check the sensitivity of the results of SFDI. We can use MNEs' R&D expenditures as alternative to US FDI in terms of technology diffusion, since MNEs are the major producers and drivers of R&D globalization. For example, US MNEs alone accounted for more than three quarters of the national R&D performed by all US enterprises. US parents accounted for R&D expenditures of $298.3 billion and major owned affiliates for $56.6 billion according to the BEA's last release for 2017. Thus, incorporating MNEs in the analysis seems very important for determining the relationship of technology transfer by US Foreign investments with domestic TFP growth of host countries.

Xu (2000) uses three different forms for technology transfer by MNEs: value added of MNE affiliates to host country GDP; the affili-

Table 3
GTFP regressions, MNE as alternative variable.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.03	–	−0.01	–	−0.07**	–	−0.11 ***	–	0.17***	–	0.12*	–
	(0.48)		(0.68)		(0.04)		(0.00)		(0.00)		(0.07)	
lnDTF1	0.03***	–	–	–	0.15*	–	–	–	0.008	–	–	–
	(0.00)				(0.06)				(0.60)			
lnDTF2	–	–	−0.005	–	–	–	−0.01	–	–	–	−0.02**	–
			(0.21)				(0.68)				(0.05)	
*lnDTF1 * MNE*	–	0.18**	–	–	–	−0.16	–	–	–	0.16***	–	–
		(0.02)				(0.15)				(0.01)		
lnDTF2 MNE*	–	–	–	0.006	–	–	–	−0.04 ***	–	–	–	0.06**
				(0.65)				(0.01)				(0.03)
lnIMP	−0.003**	−0.007***	−0.005***	−0.006***	0.01	0.003	0.02*	0.01	−0.007***	−0.007***	−0.008**	−0.007***
	(0.03)	(0.00)	(0.00)	(0.00)	(0.22)	(0.72)	(0.10)	(0.46)	(0.00)	(0.00)	(0.02)	(0.00)
lnDK	0.01**	0.005	–	0.005	0.01	0.002	–	0.002	0.007	0.007	–	0.005
	(0.02)	(0.22)		(0.28)	(0.42)	(0.74)		(0.74)	(0.28)	(0.33)		(0.30)
lnH	0.04	−0.001	0.004	0.005	0.04*	0.001	−0.004	0.006	0.005	−0.003	−0.03	−0.006
	(0.77)	(0.96)	(0.88)	(0.86)	(0.09)	(0.79)	(0.92)	(0.70)	(0.89)	(0.94)	(0.55)	(0.88)
lnOP	0.03***	0.02***	0.02***	0.02***	0.01	0.01	0.01	−0.004	0.03***	0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.18)	(0.47)	(0.63)	(0.00)	(0.00)	(0.00)	(0.00)
GPOP	0.0006	−0.003	−0.003	−0.003	−0.005	−0.006	−0.01	0.02*	−0.003	−0.004	−0.007	−0.0009
	(0.93)	(0.67)	(0.68)	(0.68)	(0.79)	(0.49)	(0.29)	(0.10)	(0.82)	(0.82)	(0.51)	(0.45)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.947	0.566	0.858	0.225	0.630	0.070	0.089	0.177	0.261	0.260	0.823	0.230
Difference in hansen test (p-value)	0.193	0.261	0.204	0.204	0.600	0.926	0.284	0.109	0.190	0.113	0.394	0.179
AR2(p-value)	0.165	0.230	0.174	0.185	0.292	0.302	0.316	0.312	0.572	0.563	0.511	0.554
Observations	304	304	304	304	142	142	142	142	138	138	138	138

NOTE: all models are static apart from OECD samples, which lagged TFP growth results do not appear to save space. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from MNE and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

ates' spending on royalties and license fees of affiliates to their value added; and the interaction term between these two forms. Using the two-stage least squares (2SLS) technique, he finds that the interaction term, which reflects the intensity of affiliates' spending on royalties and license fees as a share of the host country's GDP, is the better proxy for technology transfer by affiliates. The intensity allows access to relative R&D penetration. We use the same Xu (2000) formula, where in our study MNE denotes the intensity of R&D expenditures by all foreign affiliates of US MNEs as a share of the real GDP of the host countries under consideration. The sample of this study is composed of affiliates of all US parents exceeding 50 percent. Based on the US Department Reports, we assume that majority owned affiliates (MOFAs) are the most relevant sample that motivates us to examine the international technology transfer; US 2018–2019–2020 Investment Climate Statements declare that '*several U.S. companies have reported they have internal policies that preclude them from investing overseas without maintaining a majority share, out of concerns for both IPR and financial control of the local venture*'[11]

Data on R&D expenditures of MOFAs have been collected by the BEA[12] . According to the BEA, MOFAs' R&D expenditures include all US MNEs expenditures for R&D activities without regard for whom it was performed or the source of funding. MOFAs R&D activities were deflated similarly to FDI stocks. The summary statistics in Table 1 indicate that the penetration of US MNE's technology was on average 0.06 % for the full sample, 0.1 % for OECD countries, and 0.01 % for developing countries.

Table 3presents the results of the system GMM analysis. In model (1), the coefficient of MNEs in regression (1.1) is negative and statistically significant at the 5 % level for OECD countries, which confirms the results of FDI in Table 2.This suggests that an increase of 1 % in R&D expenditures in OECD countries would decrease local TFP growth by 0.0007 %. In developing countries, we observe that MNEs have a strong positive correlation at the 1 % level, contrary to FDI. This means that an increase of 1 % in R&D activities in developing countries would increase TFP growth by 0.001 %[13] . We conclude that R&D spending of MNEs in developing countries plays an important role in enhancing technological progress. Hence, our results support the third hypothesis posulating that R&D expenditures of affilaites gives different results from FDI. These results contrast against the finding of Xu (2000) who finds that technology transfer by MNEs plays a significant positive role in developed countries and an insignificant role in developing countries. This may support the views of Bende-Nabende et al. (2003) and Johnson (2006) who postulate the hypothesis of dynamic change of productivity growth of developing countries and the mature market of developed countries to explain such results on the GTFP of host countries. The technology gap (DTF1) is positive and statistically significant in both the full sample and the OECD countries sample, and is statistically insignificant in the developing countries sample. This confirms that the OECD countries drive the results of the full sample. Additionally, this supports the assumption of Pachamuthu (2011). The interaction term between DTF1 and MNE in regressions (1.2) shows a negative relationship in OECD countries, which means that the technological progress of OECD countries does not benefit from MNEs. The interaction term in the developing countries regression shows a positive significant correlation, which means that DTF1

[11] https://www.state.gov/reports/2019-investment-climate-statements/algeria/
[12] https://www.bea.gov/international/di1usdop

[13] We multiply the average mean of MNE of each sample from Table 1 with the coefficients of MNE in regressions (1.1) from Table 3 to get the percentage average impact.

Table 4
GGDP regressions.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
FDI	−0.008***	–	−0.009***	–	−0.003***	–	−0.002***	–	−0.01***	–	−0.01***	–
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
lnDTF1	0.03***	–	–	–	0.04*	–	–	–	0.03***	–	–	–
	(0.01)				(0.09)				(0.01)			
lnDTF2	–	–	0.005	–	–	–	0.005	–	–	–	−0.02***	–
			(0.14)				(0.15)				(0.00)	
*lnDTF1 * FDI*	–	−0.006***	–	–	–	−0.008***	–	–	–	−0.0001	–	–
		(0.00)				(0.01)				(0.31)		
lnDTF2 FDI*	–	–	–	−0.002***	–	–	–	−0.001***	–	–	–	−2.59e-07
				(0.00)				(0.00)				(0.61)
lnIMP	−0.005***	−0.007***	−0.008***	−0.009***	−0.007***	−0.007***	−0.009***	−0.008***	−0.007***	−0.006**	−0.009***	−0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
lnDK	0.006*	0.006***	–	0.01**	0.001	−0.003	–	−0.003	0.009*	0.003	–	0.002
	(0.08)	(0.01)		(0.04)	(0.77)	(0.56)		(0.48)	(0.08)	(0.50)		(0.57)
lnOP	0.03***	0.01*	0.03***	0.01**	0.04***	−0.03***	0.02***	−0.03***	0.03***	0.01**	0.003**	0.03***
	(0.00)	(0.06)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.08)	(0.00)
GPOP	−0.001	−0.03**	−0.004	−0.007	−0.004	−0.01	−0.009	−0.007	−0.09	0.02	−0.004	0.02
	(0.94)	(0.04)	(0.70)	(0.45)	(0.66)	(0.33)	(0.37)	(0.53)	(0.69)	(0.46)	(0.34)	(0.43)
$(\Delta lnL)^*h$	0.93	1.50***	0.78***	0.79***	0.76***	0.73***	0.78***	0.77***	1.04**	0.19	2.24**	0.26
	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.79)	(0.04)	(0.70)
ΔCAS	0.56***	0.51***	0.41***	0.46***	0.37**	0.43***	0.38***	0.40***	0.54***	0.70***	0.51***	0.68***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.270	0.329	0.237	0.212	0.660	0.391	0.445	0.620	0.164	0.908	0.685	0.703
Difference in hansen test (p-value)	0.341	0.888	0.338	0.444	0.178	0.189	0.275	0.188	0.682	0.679	0.741	0.807
AR2(p-value)	0.264	0.578	0.175	0.180	0.349	0.434	0.369	0.362	0.328	0.585	0.729	0.538
Observations	352	352	352	352	180	180	180	180	172	172	172	172

NOTE: all models are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from SFDI, CAS and GPOP, since CAS is already taken as price index from PWT9.1. GDP, CAS and L are calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

does not represents an impediment to technology absorption. In regressions (2.1), DTF2 is negative in OECD countries but statistically insignificant. In developing countries, DTF2 is negative and significant at the 5 % level. These results are similar to those from regression (2.1) of Table 2. The interaction term in regression (2.2) still shows a negative relationship in OECD countries. For developing countries, we find a positive correlation but the size of the effect has decreased from 0.12 to 0.06. This means that the innovation capability of developing countries does not represent an impediment to the absorption of R&D activities of US MNEs, but rather reduces it. This supports our second hypothesis suggesting that large technology gap harms to foreign technology absoption. This means that developing countries suffer from a large innovation capability distance.

4.2. Robustness checks

Several robustness checks are conducted in our study to understand the sensitivity of the results. First, we check for the sensitivity of the dependent variable used in the study. So far, we have chosen TFP as the dependent variable in the analysis. TFP is calculated using the PWT 9.1 general production function:

$$Q = Af(C, L) = AC^{a}(Lh)^{1-a} \tag{11}$$

In the first part of the general production function used by PWT 9.1, the capital input (C), the labour input (L), and the level of productivity (A) are combined to produce output (Q). The second part of the equality defines the labour input as the product of the number of workers (L) in the economy and their average human capital (h), and assumes constant returns to scale for capital services and labour. Some scholars argue that this production equation is not the best way to measure TFP. Ghosh and Kraay (2000) note that measuring TFP growth from a production function does not yield to an accurate result. TFP growth is very sensitive to several assumptions such as the simultaneity of the labour input and the degree of scale economies. To address this, we use the same production function. After differencing the log production function, we replace TFP with GDP in the equation. We obtain real income (GDP) as a function of the rate of capital services and labour multiplied by the average human capital (h). Therefore, the extra variables (capital services (CAS) and labour multiplied by average human capital (Lh)) and the dependent variable (GDP) are calculated in five-year differences. All of these variables are taken from the PWT 9.1 in real value. We report the results in Table 4.

We observe that the coefficient effect of SFDI is negative and statistically significant in all regressions. These results are similar to those in Table 2 where TFP growth is the dependent variable. This contrasts once again our first hypothesis that posits that FDI has positive spillovers on TFP growth. In contrast to the results in Table 1, DFT1 is significant and positive for developing countries. We conclude that the labour productivity gap is not positively associated with the GTFP but positively associated with the income growth (GDP) of developing countries. The interaction term with DTF1 does not change FDI correlations, which contrasts the second hypothesis that FDI take advantage from technology gap. Perhaps FDI creates strong negative competition in the host economies (Aitken & Harrison, 1999; Krammer, 2008; Wang, 2010). The innovation capability gap (DTF2) term is positive but statistically insignificant for the full sample and OECD countries. In the developing countries sample, DTF2 is negative and statistically sig-

Table 5
GGDP regressions, MNE as alternative variable.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.03	–	−0.03	–	−0.07***	–	−0.05***	–	0.17*	–	0.96	–
	(0.31)		(0.51)		(0.00)		(0.00)		(0.09)		(0.34)	
lnDTF1	0.04***	–	–	–	0.04*	–	–	–	0.04*	–	–	–
	(0.00)				(0.06)				(0.07)			
lnDTF2	–	–	0.002	–	–	–	0.0002	–	–	–	−0.03*	–
			(0.47)				(0.59)				(0.06)	
*lnDTF1 * MNE*	–	0.11	–	–	–	−0.10	–	–	–	0.18**	–	–
		(0.27)				(0.19)				(0.02)		
*lnDTF2*MNE*	–	–	–	−0.009	–	–	–	−0.02***	–	–	–	0.02
				(0.53)				(0.00)				(0.53)
lnIMP	−0.007***	−0.01***	−0.01***	−0.01***	−0.003	−0.009***	−0.007***	−0.008***	−0.01***	−0.01***	−0.02***	−0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
lnDK	0.006	0.007	–	−0.004	0.007	−0.002	–	−0.001	0.01*	0.004	–	−0.001
	(0.12)	(0.36)		(0.16)	(0.20)	(0.96)		(0.85)	(0.06)	(0.35)		(.79)
lnOP	0.04***	0.01	0.03***	0.02**	0.04***	0.03***	0.04***	0.03***	0.05***	0.04***	0.04***	0.03***
	(0.00)	(0.48)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
GPOP	0.002	0.01	−0.002	−0.02	0.01	0.03	0.01	0.001	−0.07***	−0.07**	−0.03	−0.01
	(0.92)	(0.21)	(0.92)	(0.32)	(0.38)	(0.82)	(0.35)	(0.89)	(0.00)	(0.03)	(0.28)	(0.77)
$(\Delta lnL)^{*}h$	0.70	1.48***	0.76	1.15***	0.46***	0.61**	0.43***	0.47***	1.92***	1.79***	2..25***	0.70
	(0.13)	(0.00)	(0.13)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.53)
ΔCAS	0.42***	0.49***	0.42***	0.48***	0.35**	0.31**	0.39***	0.37***	0.57	0.57**	0.58***	0.64***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.05)	(0.00)	(0.00)	(0.11)	(0.02)	(0.01)	(0.00)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.407	0.947	0.488	0.486	0.737	0.543	0.912	0.353	0.675	0.220	0.982	0.796
Difference in hansen test (p-value)	0.742	0.713	0.694	0.903	0.154	0.410	0.279	0.737	0.137	0.416	0.406	0.105
AR2(p-value)	0.455	0.878	0.498	0.695	0.468	0.838	0.457	0.953	0.532	0.550	0.483	0.575
Observations	304	304	304	304	166	166	166	166	138	138	138	138

NOTE: all models are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from MNE, CAS and GPOP, since CAS is already taken as price index from PWT9.1. GDP, CAS and L are calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

nificant at the 1 % level. This is consistent with the results of Table 1. This confirms that developing countries do not have the capability to catch up with US innovations. This supports the assumption of Cohen and Levinthal (1989), Glass and Saggi (1998), Pachamuthu (2011), and Wang and Blomstrom (1992). This contrasts against the theory of the advantage of large relative backwardness. Overall, the results of the GDP growth regressions do not contradict those of Table 2, except for the result for DTF1, which plays an active role in the GDP growth of developing countries, contrary to the results of the GTFP regressions.

We do the same GDP regressions when MNEs are taken as being the channel of investment technology diffusion. Table 5shows the results when using system GMM. We observe that the coefficient of MNEs is negative and statistically significant for the GTFP of OECD countries. In developing countries, we find a positive significant coefficient. These results fit those of the GTFP regressions. The statistical correlation of DTF1 with GTFP is significant and positive in all regressions. This confirms that DTF1 plays an active role in the GDP growth of developing countries but does not play an active role in GTFP. DTF2 is positive but statistically insignificant in both the full sample and the OECD country sample. In the developing countries sample, DTF2 still has a negative significant correlation. Again, this result supports the assumption of Cohen and Levinthal (1989), Glass and Saggi (1998), Pachamuthu (2011), and Wang and Blomstrom (1992), who report that the larger the technology gap, the less the country benefits from foreign technology. This contrasts against the theoretical assumption of Blalock and Gertler (2008), Findlay (1978), and Wang and Blomstrom (1992), who assert that a large technology gap is good for the technological progress of host countries.

Second, we conduct a robustness study regarding the time intervals. We report the results with six-year intervals to check the business cycle dynamics not filtered out in five-year averages.

$$\Delta TFP_{it} = TFP_{it} - TFP_{i,t-6} \tag{12}$$

Splitting the series into six-year differences yields five observations for each country: 1988–1993, 1994–1999, 2000–2005, 2006–2011, and 2012–2017. The results appear in Tables 5 and 6. The economic significance level of the coefficients for SFDI and its interaction with DTF decrease: the direct correlation of SFDI drops from 1 to 5 %, but the direct coefficient sizes for DTF increase significantly. For MNE, we report an insignificant negative correlation with TFP growth in OECD countries and a positive significant correlation in developing countries. This is consistent with the results of five-year intervals. Other variables are mostly insignificant in the two tables. Perhaps, the six-year lags become very weak instruments for them and thus lose the statistical significance correlations. However, the results of those models are consistent with Tables 2 and 3 and do not contrast the results of the main variables.

Third, we conduct a robustness study regarding the division criteria. This would lead to more rigorous check of the credibility of our results and of the hypothesis of the advantage of the large technological gap. We report in Tables 8 and 9 the results of the econometric model by dividing our sample basing on quantile income criteria. Thus, we divide our sample into high and middle-to-low income groups. The criteria of division follow the World Bank method using GNI per capita calculation (2021)[14]. High

[14] https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

Table 6
GTFP regressions, six year averaged data.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
SFDI	−0.006*	–	−0.006*	–	−0.01**	–	−0.0006	–	−0.008	–	−0.009**	–
	(0.10)		(0.08)		(0.04)		(0.80)		*** (0.00)		(0.05)	
lnDTF1	0.02**	–	–	–	0.56**	–	–	–	0.06	–	–	–
	(0.03)				(0.04)				(0.34)			
lnDTF2	–	–	−0.009	–	–	–	0.003	–	–	–	−0.01**	–
			(0.12)				(0.80)				(0.05)	
*lnDTF1 * SFDI*	–	−0.004***	–	–	–	−0.005	–	–	–	−0.005***	–	–
		(0.00)				(0.22)				(0.00)		
lnDTF2 SFDI*	–	–	–	−0.001***	–	–	–	−0.001	–	–	–	−0.001***
				(0.00)				(0.21)				(0.00)
lnIMP	0.01	0.003	0.001	0.003	0.04**	0.01**	0.007*	0.001**	−0.002	0.003	0.002	0.0007
	(0.16)	(0.35)	(0.68)	(0.31)	(0.02)	(0.02)	(0.10)	(0.02)	(0.394)	(0.93)	(0.62)	(0.86)
lnDK	0.05**	0.007*	–	0.008*	0.08**	0.01	–	0.01*	0.02*	0.01*	–	0.01*
	(0.03)	(0.07)		(0.06)	(0.02)	(0.17)		(0.08)	(0.10)	(0.10)		(0.10)
lnH	0.13	−0.01	−0.02	−0.01	0.009	0.03	0.07	0.40	0.05	0.04	0.02	0.05
	(0.28)	(0.76)	(0.59)	(0.74)	(0.54)	(0.74)	(0.69)	(0.61)	(0.48)	(0.54)	(0.59)	(0.49)
lnOP	0.0002	−0.001	0.0007	−0.0001	0.0004	−0.001**	−0.0001	−0.0004	0.0001	−0.0002	−0.002	−0.0002
	(0.16)	(0.30)	(0.96)	(0.34)	(0.32)	(0.04)	(0.24)	(0.77)	(0.76)	(0.43)	(0.49)	(0.35)
GPOP	0.01	−0.005	−0.004	−0.005	0.01	−0.0001**	−0.02***	0.01*	0.02	0.01	0.01	0.01
	(0.52)	(0.57)	(0.72)	(0.62)	(0.57)	(0.04)	(0.01)	(0.06)	(0.32)	(0.60)	(0.52)	(0.56)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.100	0.131	0.100	0.110	0.379	0.309	0.154	0.334	0.189	0.353	0.117	0.367
Difference in hansen test (p-value)	0.694	0.550	0.592	0.569	0.448	0.606	0.800	0.829	0.406	0.434	0.835	0.517
AR2(p-value)	0.645	0.750	0.748	0.748	0.267	0.255	0.234	0.247	0.371	0.416	0.417	0.428
Observations	296	296	296	296	151	151	151	151	145	145	145	145

NOTE: All models are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from SFDI and GPOP. GTFP is calculated in 6 years differences. Other variables are calculated in 6 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

Table 7
GTFP regressions, MNE as alternative variable, six year averaged data.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.04	–	−0.03	–	−0.19	–	−0.09	–	1.04***	–	1.03**	–
	(0.12)		(0.55)		(0.34)		(0.61)		(0.01)		(0.02)	
lnDTF1	0.21*	–	–	–	0.29**	–	–	–	0.06***	–	–	–
	(0.09)				(0.05)				(0.01)			
lnDTF2	–	–	−0.01**	–	–	–	0.001	–	–	–	−0.006	–
			(0.03)				(0.97)				(0.23)	
*lnDTF1 * MNE*	–	0.42	–	–	–	−0.67	–	–	–	1.45***	–	–
		(0.46)				(0.19)				(0.00)		
lnDTF2 MNE*	–	–	–	0.003	–	–	–	−0.01***	–	–	–	0.33
				(0.87)				(0.00)				(0.14)
lnIMP	0.02	0.0004	0.001	0.006	0.02*	0.01*	0.002	0.002**	−0.004	−0.008**	−0.007**	−0.007**
	(0.13)	(0.90)	(0.85)	(0.23)	(0.08)	(0.10)	(0.40)	(0.02)	(0.25)	(0.03)	(0.05)	(0.05)
lnDK	0.04*	0.006	–	0.02**	0.04**	0.01*	–	0.008*	0.01**	0.007	–	0.006
	(0.08)	(0.15)		(0.05)	(0.05)	(0.06)		(0.16)	(0.02)	(0.29)		(0.27)
lnH	0.23*	−0.005	−0.02	−0.07	0.07	0.02	0.07	0.12***	0.12	0.03	−0.04	−0.03
	(0.09)	(0.89)	(0.56)	(0.41)	(0.48)	(0.77)	(0.79)	(0.01)	(0.12)	(0.57)	(0.50)	(0.58)
lnOP	0.0006	−0.0001	0.0001	0.0001	0.0005	0.0003	0.0006	0.007	0.0001	0.0002	−0.0001	−2.19e-06
	(0.15)	(0.71)	(0.46)	(0.85)	(0.31)	(0.39)	(0.90)	(0.54)	(0.63)	(0.86)	(0.50)	(0.99)
GPOP	0.02	−0.008	−0.001	−0.01	−0.001	0.001	−0.005	0.0003	0.01	−0.002	0.001	−0.001
	(0.45)	(0.40)	(0.91)	(0.22)	(0.95)	(0.94)	(0.77)	(0.94)	(0.42)	(0.90)	(0.93)	(0.91)
F test p-value	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.368	0.248	0.113	0.108	0.218	0.592	0.136	0.614	0.442	0.374	0.234	0.405
Difference in hansen test (p-value)	0.570	0.315	0.916	0.568	0.513	0.827	0.430	0.557	0.946	0.756	0.906	0.751
AR2(p-value)	0.519	0.918	0.659	0.104	0.098	0.171	0.156	0.317	0.413	0.662	0.449	0.410
Observations	260	260	260	260	141	141	141	141	119	119	119	119

NOTE: all mdels are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from MNE and GPOP. GTFP is calculated in 6 years differences. Other variables are calculated in 6 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

Table 8
GTFP regressions, quantile income division criteria.

Sample	All countries (61)				High income countries (34)				Middle to low income countries (27)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
SFDI	−0.009*** (0.00)	–	−0.005*** (0.01)	–	−0.007*** (0.00)	–	−0.002** (0.03)	–	−0.001 *** (0.00)	–	−0.009*** (0.00)	–
lnDTF1	0.02** (0.03)	–	–	–	0.22*** (0.00)	–	–	–	0.02 (0.55)	–	–	–
lnDTF2	–	–	−0.005* (0.10)	–	–	–	−0.01 (0.94)	–	–	–	−0.02** (0.02)	–
*lnDTF1 * SFDI*	–	−0.003*** (0.00)	–	–	–	−0.005 (0.11)	–	–	–	−0.007*** (0.00)	–	–
lnDTF2 SFDI*	–	–	–	−0.003*** (0.00)	–	–	–	−0.001*** (0.01)	–	–	–	0-002*** (0.00)
lnIMP	−0.003** (0.03)	−0.004*** (0.00)	−0.004*** (0.00)	−0.04*** (0.00)	0.005 (0.24)	−0.005 (0.11)	−0.005 (0.12)	−0.004 (0.18)	0.016 (0.18)	0.001 (0.31)	0.008 (0.23)	0.01 (0.32)
lnDK	0.01** (0.02)	0.02 (0.50)	–	0.002 (0.50)	0.009 (0.13)	−0.005 (0.43)	–	−0.003 (0.57)	0.02* (0.10)	0.008 (0.31)	–	0.01 (0.32)
lnH	0.02 (0.33)	0.01 (0.48)	0.006 (0.80)	0.01 (0.48)	0.05** (0.04)	0.03** (0.03)	0.04** (0.02)	0.04*** (0.00)	−0.01 (0.80)	−0.02 (0.74)	−0.01 (0.61)	−0.01 (0.76)
lnOP	0.03*** (0.00)	0.02*** (0.00)	0.03*** (0.00)	0.02*** (0.00)	0.0002*** (0.00)	0.0001** (0.03)	0.0001*** (0.01)	0.002*** (0.00)	0.0002 (0.31)	0.0001 (0.48)	0.0002 (0.38)	0.0002 (0.42)
GPOP	0.006 (0.47)	−0.002 (0.76)	0.002 (0.71)	−0.002 (0.76)	0.03* (0.06)	−0.01** (0.05)	−0.01 (0.05)	−0.01* (0.08)	0.01 (0.49)	0.003 (0.83)	0.01 (0.26)	0.004 (0.42)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.598	0.304	0.626	0.304	0.397	0.121	0.172	0.137	0.185	0.265	0.255	0.270
Difference in hansen test (p-value)	0.178	0.336	0.169	0.336	0.832	0.541	0.762	0.673	0.670	0.809	0.543	0.825
AR2(p-value)	0.102	0.129	0.104	0.129	0.627	0.355	0.362	0.345	0.325	0.402	0.314	0.398
Observations	352	352	352	352	195	195	195	195	157	157	157	157

NOTE: all models are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from SFDI and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively. High income countries group includes: Australia, Austria, Belgium, Canada, Chile, Greece, Czech Republic, Denmark, Finland, France, Germany, Hong Kong, Hungary, Iceland, Israel, Italy, Korea south, Latvia, Lithuania, Luxembourg, Malta, Japan, Netherland, New zealand, Norway, Poland, Portugal, Romania, Saudi Arabia, Spain, Sweden, Switzerland, Taiwan and UK. Middle to low income group includes: Argentina, Brazil, China, Colombia, Ecuador, Egypt, Guatemala, India, Indonesia, Jamaica, Kenya, Sri Lanka, South Africa, Morocco, Mexico, Malaysia, Peru, Philippines, Thailand, Tunisia, Turkey, Venezuela, Bulgaria, Iran, Kazakhstan, Russia and Uruguay.

income group reports a mean value of 0.38 with a standard deviation of 0.026 for DTF1 and 1.56 with standard deviation of 0.098 for DTF2. In the middle-to-low income group, the DTF1 is of 1.40 mean value with standard deviation of 0.558, and 4.22 mean value with standard deviation of 1.590 for DTF2.

We find that SFDI has a negative association with GTFP in all samples. Additionally, we find that DTF1 has a positive significant relationship with TFP growth in full and high income groups and an insignificant relationship in middle-to-low income group. The interaction term of SFDI with DTF1 yields negative correlation in all samples. This is consistent with the results of the previous criteria of the sample division, which indicates that high income countries do not take advantage from DTF1 in the relation with FDI. This indicates again that technology gap does not matter to the effect of FDI and perhaps the negative correlation is related to the strong negative effect of the trade openness selection as indicated earlier in the literature review (Aitken & Harrison, 1999; Krammer, 2008; Wang, 2010). The coefficients of DTF2 appear to be significantly negative in full and middle-to-low income groups. In addition, the interaction term of DTF2 with SFDI yields a negative significant relationship. This again supports our results that contrast the advantage of the large relative backwardness. MNE appears to be negative in full and high income groups and significantly positive in middle-to-low income group. This again validates the theoretical assumption of Bende-Nabende et al. (2003) and Johnson (2006). The interaction term of all DTF terms with MNE yields negative coefficients in the high income group and positive coefficients in middle-to-low income group. The positive correlation of the MNE is still positive but it reduced from 0.25 to 0.09 when it interacted with DTF2. This is consistent with the results of developing countries' sample. This means that the innovation capability of middle-to-low income countries does not represent an impediment to the absorption of R&D activities of US MNEs, but rather reduces it. Thus, we conclude that middle-to-low income countries suffer from a large innovation capability distance, which contrasts the assumption of the positive spillovers of a large technological gap.

Finally, we check the sensitivity of the approach used throughout the investigation. We choose the system GMM approach used by Blundell and Bond (1998, 2000) in the analysis. While the system GMM approach is robust against endogeneity problems, it is not robust against nonlinear moment conditions. Hence, in this section, we use a new efficient system GMM estimation for a linear panel with nonlinear moment conditions. This method, which includes both linear and nonlinear regressors, has sizeable efficiency gains and improves the finite-sample performance using the Windmeijer (2005) error correction. In addition, it presents more robust results to deviations from mean stationarity (Ahn & Schmidt, 1995) and at the same time allows for the inclusion of time dummies in the analysis. Table 6 and 7 show the results of estimation. Table 10reports the results of FDI and Table 11reports those of MNEs. We can observe that all results fit those of the system GMM approach of Tables 2 and 3.

5. Conclusion

This paper investigates the relationship of technology transfer with the TFP growth of host countries. Our assumption is that technology transfer through FDI (US investments) in relation to relative backwardness may affect the productivity growth of host countries. Our model is empirically tested with 61 countries over the

Table 9
GTFP, MNE as alternative variable, quantile income division criteria.

Sample	All countries (61)				High income countries (34)				Middle to low income countries (27)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.03	–	−0.01	–	−0.04***	–	−0.04***	–	0.43***	–	0.25**	–
	(0.48)		(0.68)		(0.00)		(0.01)		(0.00)		(0.04)	
lnDTF1	0.03***	–	–	–	0.04**	–	–	–	−0.17*	–	–	–
	(0.00)				(0.04)				(0.10)			
lnDTF2	–	–	−0.005	–	–	–	−0.001	–	–	–	−0.01	–
			(0.21)				(0.74)				(0.38)	
*lnDTF1 * MNE*	–	0.18**	–	–	–	−0.13**	–	–	–	0.32***	–	–
		(0.02)				(0.02)				(0.00)		
lnDTF2 MNE*	–	–	–	0.006	–	–	–	−0.01***	–	–	–	0.09**
				(0.65)				(0.01)				(0.04)
lnIMP	−0.003**	−0.007***	−0.005***	−0.006***	0.0003	−0.002*	−0.002	−0.003**	−0.04***	−0.01***	−0.01***	−0.02***
	(0.03)	(0.00)	(0.00)	(0.00)	(0.85)	(0.07)	(0.16)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
lnDK	0.01**	0.005	–	0.005	0.003	0.001	–	0.0005	−0.02	0.003	–	0.004
	(0.02)	(0.22)		(0.28)	(0.37)	(0.83)		(0.90)	(0.43)	(0.73)		(0.62)
lnH	0.04	−0.001	0.004	0.005	0.03***	0.02*	0.02**	0.03***	−0.07	−0.005	−0.01	−0.0002
	(0.77)	(0.96)	(0.88)	(0.86)	(0.00)	(0.09)	(0.03)	(0.01)	(0.12)	(0.81)	(0.60)	(0.99)
lnOP	0.03***	0.02***	0.02***	0.02***	0.0002***	0.0001***	0.0001***	0.001***	0.001***	0.0006***	0.0006***	0.0006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GPOP	0.0006	−0.003	−0.003	−0.003	−0.003	−0.009	−0.007	−0.01*	−0.004	−0.005	0.002	−0.0004
	(0.93)	(0.67)	(0.68)	(0.68)	(0.61)	(0.17)	(0.19)	(0.08)	(0.85)	(0.83)	(0.84)	(0.90)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen test (p-value)	0.947	0.566	0.858	0.225	0.131	0.121	0.156	0.285	0.619	0.116	0.150	0.149
Difference in hansen test (p-value)	0.193	0.261	0.204	0.204	0.986	0.970	0.990	0.720	0.634	0.850	0.379	0.826
AR2(p-value)	0.165	0.230	0.174	0.185	0.230	0.247	0.238	0.240	0.858	0.701	0.676	0.660
Observations	304	304	304	304	175	175	175	175	129	129	129	129

NOTE: all models are static. Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. F test checks for the joint significance of estimated coefficients. Hansen and difference in Hansen tests check for the validity and exogeneity of subset of instruments. Numbers in parentheses are p-values based on robust standard errors. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from MNE and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively. High income countries group includes: Australia, Austria, Belgium, Canada, Chile, Greece, Czech Republic, Denmark, Finland, France, Germany, Hong Kong, Hungary, Iceland, Israel, Italy, Korea south, Latvia, Lithuania, Luxembourg, Malta, Japan, Netherland, New zealand, Norway, Poland, Portugal, Romania, Saudi Arabia, Spain, Sweden, Switzerland, Taiwan and UK. Middle to low income group includes: Argentina, Brazil, China, Colombia, Ecuador, Egypt, Guatemala, India, Indonesia, Jamaica, Kenya, Sri Lanka, South Africa, Morocco, Mexico, Malaysia, Peru, Philippines, Thailand, Tunisia, Turkey, Venezuela, Bulgaria, Iran, Kazakhstan, Russia and Uruguay.

1988–2017 period. We applied system GMM technique to control for unobserved endogeneity biases.

Our results show that FDI may be negatively associated with TFP growth of host countries. Indeed, FDI may be negatively associated with the productivity growth of both developed and developing countries. To increase the robustness of our results, we used R&D activities of US MNEs as an estimation of FDI to exclude any other effect that could be produced and to better investigate the pure relationship of technology transfer with the TFP growth of host countries. We find that R&D activities have a negative correlation with the TFP growth of OECD countries and a positive correlation with the TFP growth of developing countries. The negative association may be explained by the mature markets of developed countries (Bende-Nabende et al., 2003; Johnson, 2006).

Relative backwardness is also examined in this paper. We used two new estimators of the technology gap. The first estimator expresses labour productivity capability and the second expresses innovation capability. Our results show that labour productivity only enhances the TFP growth of OECD countries, while the technology gap is found to decrease TFP growth in developing countries through innovation capability. Our findings contradict the theoretical assumption suggesting that a large technology gap is crucial for countries to benefit from foreign technology (Blalock & Gertler, 2008; Findlay, 1978; Wang & Blomstrom, 1992), and instead support some previous findings that report that too large a technology gap may not enhance the technology transfer (Pachamuthu, 2011). Indeed, our results support previous works suggesting that a large technology gap may prevent host countries from benefitting from foreign technology (Li & Liu, 2005; Malikane & Chitambara, 2017; Xu, 2000).

Our findings have useful practical implications. Policy makers in OECD countries should be aware of foreign competition that may be harmful for economic growth. For OECD countries, it is strongly recommended that their policy regarding openness to trade be revised. Openness to trade through US investments can be better exploited by protecting domestic firms through reinforcing employment compensation and market share. For developing countries, policy makers should be aware that foreign US investments may improve domestic technology progress but may also act as a substitute for domestic R&D activities (Okabe, 2003). Indeed, a large technological gap may involve increased international trade, which may reduce R&D efforts of purely domestic firms (Funk, 2003). Hence, it is recommended that developing countries reinforce their market share to protect domestic firms and safeguard domestic skills. Moreover, developing countries should reinforce their technology capability to increase their productivity. Strong domestic innovation and technology is a key factor for addressing many issues related to technology transfer and productivity growth (Furman & Hayes, 2004; UNCTAD, 2014).

It should be noted that the effect of FDI in relation to productivity is highly heterogeneous across countries. For this reason, many scholars suggest conducting investigations using single-country studies to better check for the FDI effect. It is also important to note that the FDI effect may differ from industry to industry (Amoroso & Müller, 2018; Azeroual, 2016). For instance, Azeroual (2016) found that the impact of FDI on the productivity of 22 manufacturing industries in Morocco differs according to its source, whether from France or Spain, and depending on the industry level. He reported a positive effect of Spanish FDI and a negative effect of FDI coming from France, especially, in medium- and high-level tech-

Table 10
GTFP regressions, nonlinear moment conditions.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.004***	–	−0.003***	–	−0.003**	–	−0.001*	–	−0.007	–	−0.006***	–
	(0.00)		(0.01)		(0.00)		(0.07)		*** (0.00)		(0.00)	
lnDTF1	0.02***	–	–	–	0.05**	–	–	–	0.01	–	–	–
	(0.00)				(0.03)				(0.34)			
lnDTF2	–	–	0.002	–	–	–	0.005	–	–	–	−0.006**	–
			(0.28)				(0.46)				(0.04)	
*lnDTF1 * MNE*	–	−0.003***	–	–	–	−0.006***	–	–	–	−0.004*	–	–
		(0.00)				(0.100)				(0.08)		
lnDTF2 MNE*	–	–	–	−0.001***	–	–	–	−0.001***	–	–	–	−0.001**
				(0.00)				(0.00)				(0.00)
lnIMP	−0.002	−0.004***	−0.004***	−0.04***	−0.002	−0.001	−0.002	−0.001	−0.003**	−0.003**	−0.004***	−0.003**
	(0.11)	(0.00)	(0.00)	(0.00)	(0.25)	(0.42)	(0.36)	(0.45)	((0.02)	(0.04)	(0.00)	(0.03)
lnDK	0.005*	0.001	–	0.002	0.005	−0.001	–	−0.0001	0.01**	0.006*	–	0.006*
	(0.07)	(0.45)		(0.44)	(0.22)	0.97)		(0.97)	(0.02)	(0.09)		(0.10)
lnH	0.02	0.004	0.003	0.002	0.07**	0.07*	0.09**	0.07*	0.04	0.009	0.02	0.009
	(0.18)	(0.84)	(0.87)	(0.90)	(0.04)	(0.07)	(0.03)	(0.06)	(0.24)	(0.73)	(0.37)	(0.73)
lnOP	0.02***	0.02***	0.02***	0.02***	0.02**	0.01***	0.02**	0.01*	0.02***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00	(0.00)	(0.00)
GPOP	−0.009	−0.01***	−0.01**	−0.01***	−0.004	−0.006	−0.008	−0.005	0.01	−0.001	0.007	−0.001
	(0.14)	(0.01)	(0.05)	(0.00)	(0.39)	(0.33)	(0.21)	(0.38)	(0.42)	(0.83)	(0.19)	(0.83)
Moment-conditions (nonlinear/total)	(4 on 23)	(4 on 20)	(4 on 16)	(4 on 20)	(4 on 28)	(4 on 27)	(4 on 27)	(4 on 30)	(4 on 31)	(4 on 24)	(4 on 37)	(4 on 28)
Sargan-hansen test 2-step (p-value)	0.110	0.445	0.370	0.347	0.750	0.842	0.693	0.830	0.691	0.378	0.821	0.402
Sargan-hansen test 3-step (p-value)	0.102	0.269	0.343	0.144	0.547	0.326	0.153	0.092	0.224	0.094	0..224	0.098
AR2(p-value)	0.155	0.146	0.152	0.148	0.160	0.162	0.128	0.159	0.399	0.442	0.433	0.443
Observations	352	352	352	352	180	180	180	180	172	172	172	172

NOTE: Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. Sargan-hansen 2-step and sargan-Hansen 3-step tests check for the validity and exogeneity of instruments. Numbers in parentheses are p-values based on the Windmeijer finite-sample error correction. ll regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from SFDI and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1%, 5%, and 10%, respectively.

Table 11
GTFP regressions, MNE as alternative variable, nonlinear moment conditions.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.02	–	−0.01	–	−0.02**	–	−0.02	–	0.74**	–	0.36*	–
	(0.18)		(0.59)		(0.04)		(0.18)		(0.02)		(0.10)	
lnDTF1	0.03***	–	–	–	0.05**	–	–	–	0.02	–	–	–
	(0.00)				(0.02)				(0.11)			
lnDTF2	–	–	0.002	–	–	–	0.03	–	–	–	−0.009**	–
			(0.40)				(0.55)				(0.04)	
*lnDTF1 * MNE*	–	−0.04*	–	–	–	−0.03	–	–	–	0.13***	–	–
		(0.07)				(0.62)				(0.00)		
lnDTF2 MNE*	–	–	–	−0.008	–	–	–	−0.001	–	–	–	0.05***
				(0.36)				(0.35)				(0.00)
lnIMP	−0.002 *	−0.006***	−0.006***	−0.006***	−0.007	−0.003**	−0.002*	−0.002**	−0.01***	−0.006***	−0.01**	−0.006***
	(0.06)	(0.00)	(0.00)	(0.00)	(0.60)	(0.05)	(0.10)	(0.04)	((0.00)	(0.00)	(0.03)	(0.00)
lnDK	0.007***	0.002	–	0.002	0.002	−0.001	–	−0.002	0.009**	0.006	–	0.006
	(0.01)	(0.39)		(0.43)	(0.53)	0..58)		(0.69)	(0.02)	(0.12)		(0.11)
lnH	0.05 *	0.005	0.01	0.004	0.08***	0.09***	0.10***	−0.10*	0.04	−0.002	−0.01	0.01
	(0.06)	(0.83)	(0.72)	(0.98)	(0.01)	(0.01)	(0.01)	(0.06)	(0.65)	(0.93)	(0.72)	(0.68)
lnOP	0.02***	0.02***	0.02***	0.007*	0.02***	0.01***	0.02	0.01	0.04***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.01)	(0.28)	(0.11)	(0.00)	(0.01)	(0.01)	(0.00)
GPOP	−0.006*	−0.007	−0.004	−0.02***	−0.008***	−0.006	−0.004	−0.006	0.007	−0.006	0.002	−0.003
	(0.09)	(0.12)	(0.26)	(0.00)	(0.01)	(0..28)	(0.35)	(0.24)	(0.58)	(0.39)	(0.79)	(0.66)
Moment-conditions (nonlinear/total)	(4 on 23)	(4 on 21)	(4 on 16)	(4 on 23)	(4 on 33)	(4 on 28)	(4 on 36)	(4 on 27)	(4 on 37)	(4 on 28)	(4 on 37)	(4 on 28)
Sargan-hansen test 2-step (p-value)	0.698	0..357	0.582	0.353	0.1912	0.537	0.701	0.430	0.905	0.694	0.738	0.476
Sargan-hansen test 3-step (p-value)	0.630	0..364	0.092	0.351	0.153	0.109	0.153	0.101	0.220	0.098	0..263	0.258
AR2(p-value)	0.184	0.1203	0.183	0.183	0.1210	0.203	0.197	0.185	0.936	0..588	0.738	0.574
Observations	304	304	304	304	166	166	166	166	138	138	138	138

NOTE:Second order AR (2) denotes the Arellano and Bond test for autocorrelation, indicating that the models do not suffer from autocorrelation. Sargan-hansen 2-step and sargan-Hansen 3-step tests check for the validity and exogeneity of instruments. Numbers in parentheses are p-values based on the Windmeijer finite-sample error correction. All regressions have been running with constant and time dummies, which are not reported to save space. All variable are in natural logs form apart from MNE and GPOP. GTFP is calculated in 5 years differences. Other variables are calculated in 5 years averages. ***, **, and * indicate the statistical significance level at 1 %, 5 %, and 10 %, respectively.

nology industries. Considering these limitations in our study, future research should focus on examining the impact of US FDI on domestic productivity growth. It will be worthy to consider the role of FDI on total factor of production as well as environment degradation in future research, in line with Nasir, Huynh, and Tram (2019) and Pham, Huynh, and Nasir (2020).

Author contributions

All authors contributed to the study conception and design. Material preparation and data collection were performed by [Samia Benzaim]. The preliminary first draft of the manuscript was written by [Samia Benzaim], [Zied Ftiti], and [Anis Khedhaouria] The final draft (actual) have been written by all authors. All authors commented on previous versions of the manuscript. The supervision was done by [Rebai Djermane]. All authors read and approved the final manuscript.

Appendix A

Table A1
Summary review of the literature.

AUTHORS	SAMPLES	VARIABLES OF THE MODEL	METHODS	MAIN RESULTS
Technology transfer and productivity growth				
Xu (2000)	40 countries: 26 developed countries (OECD) and 14 developing countries (1966–1994)	Dependent variable • TFP growth Main determinants • MNE (Technology transfer costs) • Human capital Control variables • Distance to the technology frontier DTF (TFP distance)	Static Panel data (5 year intervals) using two stage least square (2SLS)	MNEs directly contribute to the TFP growth in developed countries but not in Less developed countries. MNE positive correlation depends on quality of host country human capital.
Choe (2003)	80 countries: 26 developed countries and 54 developing countries (1971–1995)	Main determinant • GDP growth • FDI (inflows) Control variables determinants • Trade openness • Growth of labour force • Stability of the macro economy	Panel data (5 year period), using Granger causality tests	Rapid economic growth might lead to high FDI inflows and vice versa. But the bi-causality from growth to FDI is stronger.
Xu and Chiang (2005)	48 countries: 17 high income countries, 15 middle income countries, and16 low income countries. 22 developed countries and 26 developing countries. (1980–2000)	Dependent variables • TFP growth Main determinants • Foreign patent • Domestic patent • Domestic R&D spending • R&D embodied in imports • Intellectual property rights protection Control variables • Total trade • Distance to the technology frontier DTF (measured as TFP distance)	Static panel data (5 year intervals) using Ordinary Least Square (OLS)	The rich countries benefit from imported goods, middle income countries enjoy technology spillovers from both foreign patents and imported goods and poor countries benefit from foreign patents. The technology transfer depends on host country government policy conditions on intellectual property rights protection and trade openness
Sunde (2017)	South Africa (1990–2014)	Dependent variable • GDP Main determinants • FDI • Exports	Time series using ARDL and Causality analysis	FDI and exports led to positive effect on GDP.
Technology transfer, relative backwardness, and productivity growth				
Li and Liu (2005)	84 countries: 21 developed countries, 21 Latin American countries, 16 African countries, 5 fast growing countries and 21 other developing countries (1970–1999).	Dependent variable • GDP per capita growth • Main determinants • FDI (inflows) • Distance to the technology frontier DTF (measured as GDP per capita) • The interaction term between FDI and DTF • Human capital • The interaction term between FDI and human capital Control variable • Domestic investment ratio	Panel data, using Single equation and simultaneous equation system technique	FDI directly promote GDP growth. This is the same for human capital. The interaction term of FDI with human capital gives a positive significant effect on GDP growth. DTF is found to be negative, through which the indirect FDI role becomes negative. This contrasts the assumption under the hypothesis of the positive externalities of the large technological gap.

Table A1 (*Continued*)

AUTHORS	SAMPLES	VARIABLES OF THE MODEL	METHODS	MAIN RESULTS
Blalock and Gertler (2009)	Indonesian manufacturers (1988–1996).	Dependent variable • TFP Main determinants • FDI (foreign output) • Distance to the technology frontier DTF (measured as TFP distance) • The interaction term between FDI and DTF • Human capital • The interaction term between FDI and Human capital	Panel using fixed effect at level (FE)	FDI and DTF have a positive relationship with productivity growth. The interaction term has also a positive correlation, supporting the hypothesis of the advantage of the relative backwardness.
Baltabaev (2014)	45 developed and developing countries (1974–2008).	Dependent variable • TFP growth • Main determinants • FDI stock (Instrumented by investment promotion agency) • Distance to the technology frontier DTF (measured as labour productivity) • The interaction term between FDI and DTF (instrumented by the interaction between investment promotion agency and DTF). Control variables • Domestic knowledge (measured by domestic R&D expenditures as a share in GDP) • Human capital • Trade openness • Inflation rate • Population growth	Static panel with 5 year intervals, using Generalized Method of moment (one-step system GMM)	FDI and DTF have a positive relationship with productivity growth. The interaction term has also a positive correlation, supporting the convergence theory of the advantage of the relative backwardness.
Malikane and Chitambara (2017)	48 African countries (1980–2012).	Dependent variable • TFP growth Main determinants • FDI (inflows) • Distance to the technology frontier DTF (measured as labour productivity) • The interaction term between FDI and DTF Control variables • Human capital • Trade openness • Population growth • Investment promotion agency	Dynamic panel at level using Generalized Method of moment (two-step system GMM).	FDI has a positive but weak correlation with productivity growth. DTF has negative significant relationship. The interaction term has negative relationship with TFP growth and do not support the convergence theory of the advantage of the relative backwardness.
FDI, trade openness, and productivity growth				
Bende-Nbende et al.(2003)	5 East Asian countries: Hong Kong, Japan, Philippines, Taiwan and Thailand (1965–1999).	Dependent variable • GDP Main determinants • FDI (cash inflows) Control variables • International trade (exports) • Capital stock • Human capital • Employment • New technology transfer (imports value of goods)	Panel data using Johansen cointegration methodology and vector error correction (VECs)	The effect of FDI on TFP is negative for countries with more developed economies, such as Taiwan, Hong Kong and Japan, and positive for less developed economies such as Thailand and Philippines.
Johnson (2006)	90 countries: 22 developed countries and 68 developing countries (1980–2002).	Dependent variable • GDP average annual growth rate Main determinants • FDI (stock) • Gross capital formation Control variables • Human capital • Interaction FDI with human capital • War experience (dummy variable)	Cross section and panel data using Ordinary least square (OLS)	FDI only improves the economic growth of developing countries. The positive correlation of FDI with GDP growth depends on the dynamic growth of less developed countries.

Table A1 (*Continued*)

AUTHORS	SAMPLES	VARIABLES OF THE MODEL	METHODS	MAIN RESULTS
Wang (2010)	26 OECD countries (1996–2006)	Dependent variable • Domestic R&D expenditures intensity Main determinants • Patent protection index • Technology inflows from FDI • Technology inflows from imports Control variables • Human capital	Panel data using the Extreme-Bounds-Analysis (EBA)	FDI and imports negative affects domestic R&D activities. foreign R&D activities may substitute domestic R&D activities due to the increased FDI and openness to trade
Azman-saini et al. (2018)	48 developing countries (1996–2013)	Dependent variable • Domestic R&D expenditures intensity Main determinants • FDI (inflows) • Technology inflows from imports Control variables • Human capital	Dynamic panel at level using Generalized Method of moment (two-step system GMM).	FDI inflows discourage R&D activity in developing countries. This is consistent with the view that foreign R&D is substitute domestic R&D activities.
Carbonell and Werner (2018).	Spain (1984–2010)	Dependent variable • GDP growth Main determinants • FDI (inflows) • Productive credit creation • Bank lending from the rest of the world to Spain Control variables • Commodities index • Exchange rate • Human capital • Money supply M1 • Money supply M2 • Overnight interbank interest rates • Total G7 GDP	Time series data using Ordinary least square (OLS) and two stage least square (2SLS) following the analytically superior (GETS) methodology	There is no evidence of FDI relationship with economic growth. Theories assumptions on FDI require reflecting in economic models such as banks as creators of the money supply.

Table A2
List of countries

Total = 61			
Argentina (LCD)	Germany (OECD)	Latvia (OECD)	SaudiArabia (LCD)
Australia (OECD)	Greece (OECD)	Lithuania (LCD)	South Africa (LCD)
Austria (OECD)	Guatemala (LCD)	Luxembourg (OECD)	Spain (OECD)
Belgium (OECD)	Hong Kong (LCD)	Malta (LCD)	Sri Lanka (LCD)
Brazil (LCD)	Hungary (OECD)	Malaysia (LCD)	Sweden (OECD)
Bulgaria (LCD)	Iceland (OECD)	Mexico (OECD)	Switzerland (OECD)
Canada (OECD)	India (LCD)	Morocco (LCD)	Taiwan (LCD)
Chile (OECD)	Indonesia (LCD)	Netherland (OECD)	Thailand (LCD)
China (LCD)	Iran (OECD)	New Zealand (OECD)	Tunisia (LCD)
Colombia (LCD)	Israel (OECD)	Norway (OECD)	Turkey (OECD)
Czech Republic (OECD)	Italy (OECD)	Peru (LCD)	UK (OECD)
Denmark (OECD)	Jamaica (LCD)	Philippines (LCD)	Uruguay (LCD)
Ecuador (LCD)	Japan (OECD)	Poland (OECD)	Venezuela (LCD)
Egypt (LCD)	Kazakhstan (LCD)	Portugal (OECD)	
Finland (OECD)	Kenya (LCD)	Romania (LCD)	
France (OECD)	South Korea (OECD)	Russia (LCD)	

Table A3
Correlation matrix.

Variables	**GTFP**	**SFDI**	**MNEs**	**LnDTF1**	**LnDTF2**	**lnIMP**	**LnDK**	**LnH**	**LnOP**	**GPOP**
Total sample (61 countries)										
GTFP	1									
SFDI	−0.12***	1								
MNEs	−0.03	0.48***	1							
LnDTF1	0.01	−0.02	−0.26***	1						
LnDTF2	−0.13***	0.006	−0.19***	0.67***	1					
lnIMP	−0.14***	0.15***	0.41***	−0.34***	−0.14***	1				
LnDK	0.13***	−0.005	0.20***	−0.67***	−0.98***	0.13***	1			
LnH	0.11**	0.03	0.25***	−0.57***	−0.65***	0.25***	0.70***	1		
LnOP	0.13***	0.15***	0.29***	−0.23***	−0.035	0.20***	0.07	0.31***	1	
GPOP	−0.12**	0.12***	0.03	0.20***	0.45***	−0.03	−0.48***	−0.50***	−0.16***	1

Table A3 (*Continued*)

Variables	GTFP	SFDI	MNEs	LnDTF1	LnDTF2	lnIMP	LnDK	LnH	LnOP	GPOP
OECD countries (31 countries)										
GTFP	1									
SFDI	−0.06	1								
MNEs	−0.07	0.64***	1							
LnDTF1	0.09	−0.03	−0.17**	1						
LnDTF2	−0.04	0.05	0.05	0.44***	1					
lnIMP	−0.08	0.17***	0.47***	−0.31***	0.21***	1				
LnDK	0.01	−0.02	−0.01	−0.44***	−0.96***	0.19***	1			
LnH	0.06	0.05	0.16**	−0.35***	−0.54***	−0.02	0.66***	1		
LnOP	0.06	0.41	0.47***	−0.008	0.22***	0.16**	−0.13*	0.22***	1	
GPOP	−0.11	0.24***	0.25***	−0.23***	0.06	0.18***	−0.07	−0.04	−0.09	1
Developing countries (30 countries)										
GTFP	1									
SFDI	−0.20***	1								
MNEs	0.03	0.04	1							
LnDTF1	−0.07	0.03	−0.13	1						
LnDTF2	−0.15**	0.03	−0.16**	0.46***	1					
lnIMP	−0.19***	0.13*	0.27***	−0.17***	−0.02	1				
LnDK	0.17***	−0.06	0.11	−0.46***	−0.97***	0.006	1			
LnH	0.12*	−0.02	−0.003	−0.31***	−0.38***	0.16**	0.46***	1		
LnOP	0.15**	−0.11	−0.13	−0.31***	−0.07	0.19***	0.10	0.37***	1	
GPOP	−0.03	0.07	0.05	0.06	0.49***	0.01	−0.52***	−0.59***	−0.15**	1

Table A4
GTFP regressions, fixed effect.

Sample	All countries (61)				OECD countries (31)				Developing countries (30)			
Technology gap proxy	DTF1		DTF2		DTF1		DTF2		DTF1		DTF2	
Model	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2	1.1	1.2	2.1	2.2
MNE	−0.006*** (0.00)	–	−0.007*** (0.00)	–	−0.005** (0.04)	–	−0.005*** (0.01)	–	−0.009 *** (0.00)	–	−0.009*** (0.00)	–
lnDTF1	−0.4 (0.32)	–	–	–	0.007 (0.91)	–	–	–	−0.03 (0.54)	–	–	–
lnDTF2	–	–	−0.008 (0.40)	–	–	–	0.02 (0.13)	–	–	–	−0.01 (0.22)	–
*lnDTF1 * MNE*	–	−0.005*** (0.00)	–	–	–	−0.01** (0.02)	–	–	–	−1.22e-06 (0.50)	–	–
lnDTF2 MNE*	–	–	–	−0.001*** (0.00)	–	–	–	−0.003** (0.01)	–	–	–	−4.73e-07 (0.72)
lnIMP	−0.01 (0.36)	−0.01 (0.39)	−0.01 (0.38)	−0.009 (0.39)	−0.01 (0.35)	−0.01 (0.33)	−0.01 (0.31)	−0.01 (0.33)	0.003 (0.84)	−0.0044 (0.80)	0.002 (0.87)	−0.004 (0.80)
lnDK	0.01** (0.02)	0.008 (0.38)	–	0.008 (0.41)	−0.02 (0.15)	−0.02 (0.14)	0.30 (0.46)	−0.02 (0.11)	0.006 (0.29)	0.009 (0.28)	–	0.009 (0.28)
lnH	−0.04 (0.68)	−0.08 (0.48)	−0.06	−0.07 (0.50)	0.05 (0.18)	0.30 (0.47)	0.05 (0.24)	0.31 (0.45)	−0.16 (0.29)	0.21 (0.23)	−0.20 (0.24)	−0.21 (0.23)
lnOP	0.07*** (0.00)	0.07*** (0.01)	0.08*** (0.00)	0.07*** (0.01)	0.01** (0.03)	0.05 (0.24)	0.05 (0.24)	0.05 (0.23)	0.03 (0.34)	0.05 (0.12)	0.04 (0.24)	0.05 (0.12)
GPOP	0.03** (0.02)	0.03** (0.00)	0.04** (0.02)	0.002** (0.03)	−0.02 (0.11)	0.02 (0.11)	0.02 (0.11)	0.02 (0.11)	0.03* (0.06)	0.04* (0.06)	0.04** (0.05)	0.04* (0.06)
F test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-square	0.332	0.322	0.327	0.325	0.337	0.336	0.337	0.338	0.364	0.333	0.361	0.333
R-square adjusted	0.160	0.151	0.156	0.154	0.134	0.139	0.140	0.142	0.164	0.131	0.166	0.131

Declaration of Competing Interest

None.

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