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The Effects of Foreign R&D and Triadic Patent Propensity on Developing Economies Efficiency and Convergence

(Kesan P&P Asing dan Kecenderungan Paten Triadic ke atas Kecekapan dan Penumpuan Ekonomi Negara-negara Membangun)

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ABSTRACT

This research relies on the theory of endogenous growth, where the role of foreign imported capital and triadic patent propensity is assumed to endogenously determine the growth process of a group of 36 developing and emerging economies for the years 1990-2010. Our results confirm the monotonicity hypothesis from both foreign imported technology and triadic patent propensity toward technical efficiency improvement with no indication of pure TFP growth. The results indicate that initial foreign capital and initial triadic patent propensity only minimally improve the technical efficiency change for a small number of economies with nearly halve of the sample deviating from the convergence point.

Keywords: Foreign technology; triadic patent propensity; efficiency; convergence; stochastic frontier analysis

ABSTRAK

Kajian ini bergantung kepada teori pertumbuhan endogen, di mana peranan modal asing yang diimport dan kecenderungan paten triadic diandaikan secara endogennya menentukan proses pertumbuhan bagi sekumpulan 36 negara membangun dan ekonomi baru muncul pada tahun-tahun 1990-2010. Keputusan kami mengesahkan hipotesis keekanadaan dari kedua-dua teknologi asing yang diimport dan kecenderungan paten triadic ke arah penambahbaikan kecekapan teknik tanpa indikasi berkenaan pertumbuhan TFP tulen. Keputusan menunjukkan bahawa modal asing permulaan dan kecenderungan paten triadic permulaan hanya meningkatkan kecekapan teknikal secara minimal untuk sebilangan kecil ekonomi dengan hampir separuh daripada sampel menyimpang daripada titik penumpuan.

Kata kunci: Teknologi asing; kecenderungan paten triadic; kecekapan, penumpuan; analisa perbatasan stokastik

INTRODUCTION

A large volume of research in the past recognize the significant role of trade on foreign commercially oriented innovations as a source of research and development (R&D) spillovers to the domestic economy (Bayoumi et al. 1999; Bitzer & Geishecker 2006; Coe & Helpman 1995; Coe et al. 1997; Keller 1998) As explained by Eaton and Kortum (2001) most of the new technologies are produced by only a few R&D intensive countries and imported by almost all countries in the world. This reflects that imports of equipment, which embody new technology and innovation, dominate most of the growth in these countries. Furthermore, innovation of the three most advanced countries like the United States, Germany and Japan account for nearly half of the growth in 19 OECD countries (Eaton & Kortum 1996). The role of institutional quality in speeding up the growth process is emphasized by Coe et al. (2009). Despite a transparency on business environments and a high quality of tertiary educational systems, strong patent protections also tend to benefit domestic countries. A strong patent protection regime is believed to be strongly associated with higher TFP level, higher returns to domestic R&D, and larger international R&D spillover.

Alternatively, technology may also be generated and transferred endogenously through locally initiated innovations. Innovative capacity of a country has widely been regarded as the driving force behind economic growth and competitiveness among developed nations. As explained by Hu and Mathews (2005), most of the latecomers (i.e., developing economies) had taken a longer time to catch-up to the leading frontier due to different needs. While the leading frontier countries are interested in maintaining their position as a leader in the state-of-the-art technology race, the latecomer however focus their innovation efforts to more targeted sectors in order to maintain their status as leading producers of certain products for instance information and communication technology (ICT) and electronics being led by South Korea, China, Taiwan, Hong Kong and Singapore, whereas for pharmaceuticals, medical and biotechnology also being led by the aforementioned countries with the addition of India and Brazil.

In this research, our focus of innovation efforts among the developing countries is on the locally initiated innovation outputs referring to the number of successful patents applied/granted in three triad regions[1]. The triadic patent count is known to be at the forefront in the provision of world technology. The triadic patent family counts refer to a single identical invention with applications made and/or granted outside the territorial economic boundaries. Three economically important regions in the world in which the triadic patent count is measured are North America, i.e., the United States Patent and Trademark Office (USPTO); Europe, i.e., at the European Patent Office (EPO); and East Asia specifically the Japan Patent Office (JPO). All patent applications and/or granted in these three intellectual property (IP) offices are considered to be of high economic value since they are worthy of the costly application process on the world's most important regional markets of newly invented technology. As levels of domestic intellectual property rights (IPR) policy are hypothesized to react differently on the extent of imported foreign R&D, a different trajectory effect may be expected from the triadic patent family.

As patent-based statistics has been widely regarded as an indication of innovative performance of a country, it is also subject to various criticisms. The use of patent statistics as a measure of the level of innovation has long been considered a well-grounded proxy (Ang 2010; Eaton & Kortum 1996, 1997, 1999; Madsen et al. 2010; Park 2013) with earlier surveys of the literature by Basberg (1987) and Griliches (1990). Empirical studies using patent statistics may in some aspects produce a home-country bias[2]. Thus, the use of triadic patent family may avoid or reduce the problem. Another advantage is that, triadic patent is an outcome of a result of R&D initiatives undertaken. In fact, the usage of triadic patent statistics to proxy domestic innovation efforts used in this research managed to increase the total number of country observations compared to alternative available proxies such as the number of R&D personnel or R&D expenses at the cross-country level.

The motivation of this research is to examine the effect of both foreign technologies embodied in imported capital and triadic patent propensity in determining the efficiency and productivity among the developing economies. As research focusing on foreign R&D spillovers and its speed-up effect to improve efficiency had been widely discussed, the literatures discussing the role of domestic innovation efforts led by triadic patent to speed up the same process is however still unclear, thus, showing a gap in the literature. In fact, to the best of our knowledge, none of the existing empirical research address the speed-up effect in the context of triadic patent, the directions that we intend to explore in this research. Therefore, in this research, we intend to explore the effect of triadic patent intensity on speeding up of domestic innovations and this becomes our main contribution. In this respect, our research relies on the theory of endogenous growth, where both foreign technology embodied in imported capital and triadic patent propensity are endogenously assumed to determine the growth process.

The stochastic frontier analysis (SFA) is used to investigate the speed up effect when both foreign capital and triadic patent propensity is endogenously considered as additional inputs to determine the frontier. The SFA technique is used in this research due to its flexibility over the traditional accounting technique and ability in assessing and segregating technical efficiency from other total factor productivity (TFP) growth components. In fact, the SFA technique we employ in this research is able to estimate the individual speed-up effect both from foreign capital and the triadic patent. We address whether foreign technology and triadic patent propensity raises production efficiency by indirectly affecting the speed-up rate to reach the desired frontier. This argument relates to the issue of economic convergence or efficiency improvement triggered by foreign capital and triadic patent propensity in the process of achieving higher total factor productivity (TFP) growth. While past empirical studies indicate a monotonic direction of foreign capital towards domestic growth and productivity improvement, our results seem to confirm the hypothesis but some deviations are also observed. In fact, a similar finding is found for triadic patent propensity. In general, our results indicate that both foreign imported capital and triadic patent propensity only slightly improve technical efficiency with nearly halve of the sample either showing some divergence or at least reduction in the rate of divergence.

This article estimates the speed up effect of foreign imported capital and domestic innovation efforts for a panel of 36 developing and emerging economies for the period 1990 to 2010[3]. The construct of this article is as follows: Section 2 reviews some of the key literature; Section 3 outlines the proposed model, while Section 4 discusses the data coverage. Section 5 presents the results and Section 6 concludes the study.

LITERATURE REVIEW

This study relates to the literature on embodied technologies through capital imports from technological leaders. A number of key literatures highlight the significant role of imported capital as one of the major engines for technological progress either to developed or developing nations (Coe & Helpman 1995; Coe et al. 1997).

Coe and Helpman (1995) differentiate the role of domestic R&D and foreign R&D in determining the long-run relationship of TFP variation across a panel of 22 developed countries between 1971-1990. The authors underline that international trade of foreign capital imports to GDP ratio as a source for international R&D spillovers for both the seven largest economies (G7) and another 15 developed economies varying across individual countries and over time. This finding implicitly portray that the effectiveness of foreign R&D as a source of domestic total factor productivity (TFP) growth is partially determined by the domestic R&D stock. For countries with higher domestic R&D stock (i.e., the G7 group), the elasticity of TFP growth with respect to foreign capital import is found to be small; however, the elasticity is higher when domestic R&D stock is smaller (i.e., for another 15 economies). The authors also argue that, higher elasticity to TFP growth, an evidence of international spillover recorded among the smaller countries is due to the higher trade openness.

The substantial benefits derived from R&D initiative originating from industrial country trading partners as found in Coe and Helpman (1995) has led Coe et al. (1997) to examine the possible impact on a group of 77 less developing economies for the years 1970 to 1990. In contrast to the previous 1995 article, Coe et al. (1997) added that as developing countries trade-related experiences with industrialized countries increases over time, the benefit of such trade relationship to developing economies increases. In addition, the authors also add that, higher secondary school enrollment ratio may also trigger the benefits from marginalized foreign R&D into higher TFP growth.

As economic growth is a complex process, the effect from human capital and other institutional factors are also considered in many empirical studies. In a similar vein, the empirical evidence underlined in Coe and Helpman (1995) as revised in Coe et al. (2009)[4] also take these factors into consideration. The finding from Coe et al. (2009) stress that in addition to their earlier analysis, the evidence of significant human capital effect and differences in selected institutional factors in mediating growth processes to achieve higher TFP growth across developed economies further confirm the interdependence on foreign capital as a source of international R&D spillover indeed exist.

In the developing economies context, higher growth is achievable through various channels, but imported foreign technology[5] will always be a source of alternative technology preferred by developing economies. A majority of the developing nations rely on foreign technology to assist their growth, as the capacity of homegrown technology is constrained by a limited endowment of available quality resources. As global innovated technology and trade are dominated only by a few advanced countries (Eaton & Kortum, 2001) and with scarce access to homegrown technology, developing nations accessibility to new technology sourced through the importation of foreign technology embodied in capital imports is the best available alternative to assist growth and productivity. However, in some cases, this has not truly translated into pure technical efficiency especially for agricultural driven sectors for countries within the African region and other parts of the world.

A number of empirical studies (Henry et al. 2009; Mastromarco 2008; Mastromarco & Ghosh 2009) highlight higher efficiency rate resulting from utilizing foreign technology in assisting better growth and enhancing productivity for developing economies. These studies however employ comparably superior stochastic frontier analysis technique to previously proposed regression approaches appearing in Coe and Helpman (1995), Coe et al. (1997) and Coe et al. (2009). The advantages of SFA technique in simultaneously determining technical efficiency and other TFP growth components are discussed in the next section.

Among others, Henry et al. (2009), underline the importance of trade-related foreign R&D as a medium for transfer of technology by which a reduction in technical inefficiency among developing economies is significantly observed. The authors also emphasize that trend in productivity growth are regionally uneven due to differences in trade openness and non-negligible trade volume in imported capital activities and also in countries where activities are driven by agricultural sectors.

Mastromarco (2008) has highlighted the simultaneous importance of imported capital goods, FDI and human capital in the process of reaching the frontier. The author explicitly underline that the role of imported capital is insignificant compared to FDI and human capital. The important implication from Mastromarco (2008) points to the positive externality effect of FDI which suggest the explicit role of general knowledge as a key determinant in technology transfer rather than specific imported capital in determining higher efficiency.

Mastromarco and Ghosh (2009) re-emphasize the important role of four potential sources of efficiency, i.e., human capital, FDI, imports of machinery and equipment (ME) and imported foreign R&D when estimating a frontier for 57 developing economies between 1981-2000. The authors adopt a production function with two inputs and solve it using translog SFA production function. All four potential sources of technology are then included as determinants of inefficiency. The authors found a strong mediation effect of human capital either directly or indirectly through liberalization and global trade process.

The effects of R&D spillovers to the receiving countries have been largely documented in the past. Research on trade as a channel for knowledge diffusion as pioneered by Coe and Helpman (1995) have been a subject of discussion by many authors; see for examples, Coe et al. (1997), Keller (1998), Bayoumi et al. (1999), Bitzer and Geishecker (2006) and Coe et al. (2009). One thing in common is that trade in the commercialized foreign R&D by itself may induce growth and efficiency in different fashions either exogenously or endogenously. Earlier growth economists believe the former, and the latter as argued by Grossman and Helpman (1991) and a series of studies accepting his ideas, to be endogenously driven. However, due to the development on econometric tools and modeling strategy, the differences between the two may be justified according to specific objectives that a researcher wants to achieve (Mastromarco & Ghosh 2009).

There exist literature that accept the ideas of trade-related spillovers as a channel of diffusion for technology into the recipient countries as we mentioned earlier in this section. Why trade-related spillover becomes one of the important channels for technology diffusion? As argued by Eaton and Kortum (2001), trade on newly invented technologies is dominated by a few of the leading countries to the laggard countries, but it is always subject to various limitations than perfections (Coe et al. 2009).

Since newly invented technologies produced by the leading frontier countries are always as costly as its benefits, trade issues remain high on the agenda when standards of patent protection are not properly enforced in the first place. As an alternative source to foreign technology, domestic initiative of homegrown technology related to patenting activities is used to indicate innovation effort. The use of patent-based statistics as indicators of innovations has been widely recognized (Basberg, 1987; Griliches, 1990) and considered as a well-grounded proxy despite its criticisms. The patent-based statistics had been used in many empirical studies which can be found in Eaton and Kortum (1996, 1997, 1999), Ang (2010), Madsen et al. (2010) and Park (2013). It has also been used at various levels such as cross-country level (Hu & Mathews, 2005), industrial level (Fung & Chow 2002; Lach 1995), and firm level (Allred & Park 2007).

The application of patent citations to indicate level of innovation activities can be found in Hu and Jaffe (2003), MacGarvie (2005), Lee (2006), Gomes-Casseres et al. (2006), Sternitzke et al. (2008) and Hu & Jefferson (2009). Patents exist both to encourage inventive activity and to facilitate assimilation of new technologies into the broader economy. All patent systems require an invention to satisfy requirements for novelty, an inventive step ('non-obviousness') and industrial applicability in order to be patentable. The stringency of these standards sets the bar for earning exclusive rights, 20 years on average. Patent breadth defines the extent of the claim protected and permissible activities in using the patented information. Thus, having low novelty standards and recognizing only narrow claims encourages small and incremental inventions while limiting incentives for R&D into fundamental technologies. This is especially the case if the patent laws provide liberal treatment of reverse engineering of patented products, thereby promoting imitative forms of R&D.

Considering the significant use of patent-based statistic to indicate innovations in the past, empirical researches tend to selectively consider only patent of high quality to be used to indicate quality innovation activities. Since patent quality is a subjective matter, economists tend to indicate a quality patent according to specific geographical region of a patent application. In this instance, economists agree that, a high quality patent count referring to the destinations in which the patent is intended to seek for protection. In a large number of studies, the use of patent-based statistics applied and/or registered in the United States Patent & Trademark Office (USPTO), the Japanese Patent Office (JPO) and the European Patent Office (EPO) are preferred as the triadic patent families count destination. As the level of domestic IPR policy is hypothesized to react differently on the extent of imported foreign R&D, different trajectory effects may be expected from triadic patent family.

METHODOLOGY

We utilize the translog SFA model due to its flexibility in capturing non-neutral technical progress compared to the traditional Cobb-Douglas model. This method is found to be superior to the traditional Solow-residual or growth-accounting technique where the ability in measuring technical change[6] is widely doubted. Besides, measuring technical efficiency change as a result of foreign technology utilization is easily assessed; the decomposition of total factor productivity (TFP) growth using this technique is found to be robust.

Our method uses a modification of the time-varying inefficiency model. In general, there are various time-varying inefficiency models offered in the literature, but the method proposed by Kumbhakar and Wang (2005) and Cuesta (2000) fit our research objectives better. In this respect, one can estimate individual technological catch-up effect more easily by considering the SFA technique proposed by Cuesta (2000) capable of capturing the time-invariant or individual heterogeneity in the inefficiency function as in Kumbhakar and Wang (2005).

Precisely, the Kumbhakar and Wang (2005) approach has the advantage in controlling country heterogeneity either through country-specific fixed effects intercept in the production function or country-specific time-invariant feature within the inefficiency mean function. The Cuesta (2000) approach however has the advantage in estimating individual time temporal variation[7]. The combination of these techniques allows us to analyze both the technological catch-up effect and the convergence rate effect easily, which has not been attempted by existing empirical research.

Generally, the stochastic character of the frontier is described by the following common production set with X_{it} inputs and producing at the optimum output level Y^* as:

$$Y^*_{it} = f(x_{it}, t; \beta)\exp\{v_{it}\} \tag{1}$$

where β and t are coefficients and time trend respectively. The production frontier represented by Eq. (1) is the optimal set of output produced for a range of input vectors (X_{it}) with the stochastic features of the model captured by the v_{it} term. The term accommodates noise or random shock in the data and is assumed to be independent and identically distributed (i.i.d) for simplifying the inferences. See Kumbhakar and Lovell (2003) for details of the SFA model.

Some countries, however, may lack the ability to employ existing technologies efficiently and end up producing at the sub-optimal frontier. This difference refers to inefficiency i.e., denoted by the term $exp\{-u_{it}\}$. If $exp\{-u_{it}\} = \frac{Y_{it}}{Y^*} = 1$, then full efficiency is observed. The non-positive sign of u_{it} features the distribution skewness of the inefficiency term. The actual (Y_{it}) and the optimum output (Y^*) in each country i and time t can be expressed as a function of the stochastic frontier equivalent to;

$$Y_{it} = f(X_{it}, t; \beta) exp\{v_{it}\} exp\{-u_{it}\} \tag{2}$$

The stochastic production function in this research will utilize translog form in estimating the input coefficient (X_{it}) including the time trend (t). The Y_{it} or output is represented by per capita real gross domestic product (YL), with input vectors of X_{it} each represented by per capita Gross Capital Formation or capital stock (KL), per capita human capital (HL), per capita foreign research and development (FRDL) and triadic patent propensity (TPL). All output, capital stock and foreign R&D are measured in million US dollar at constant 2005 US price. All variables are transformed into logarithm form.

We modify the modeling approach of Cuesta (2000) by excluding the time dummy due to longer time series observations and also exclude the individual fixed effect intercept [as in Kumbhakar and Wang (2005)] from the production function setup. The exclusion of individual fixed effect intercept from the production function is substituted with individual time temporal variation (G_t) following the Cuesta (2000) approach. With both modifications, we manage to avoid complex modeling iteration process and also avoid losses in degrees of freedom when running the model specification using the log likelihood ratio (LR) test. The term $exp\{-u_{it}\}$ is composed of two inter-connected exponential functions; the individual time temporal variation (G_t) and inefficiency time-invariant mean function (u_t), which is assumed to follow;

$$u_{it} = G_t * u_i \tag{3}$$

$$u_{it} = exp\{\xi_t(t - \underline{t})\} * [\delta_0 + \delta_1(iniFRDL_{i\underline{t}})] \tag{4}$$

$$u_{it} = exp\{\xi_t(t - \underline{t})\} * [\eta_0 + \eta_1(iniTPL_{i\underline{t}})] \tag{5}$$

The u_i function is specified as the mean function of each country time-invariant initial endowment characteristics. In our case, we consider including the initial endowment of foreign R&D-to-labour ratio (*iniFRDL*) and initial triadic patent propensity ratio (*iniTPL*) as an initial specific capital specified at the earliest observation for each sample. Both *iniFRDL* and *iniTPL* are in logarithm form; with each δ_1 and η_1 coefficient in both Eq. (4) and Eq. (5) represent the percentage change. The underlined time trend (t) in the function in both Eq. (4) and Eq. (5) denotes the initial starting value of endowment variable[8]. The initial foreign R&D-to-labour ratio (*iniFRDL*) and initial triadic patent propensity ratio (*iniTPL*) estimated coefficient δ_1 and η_1 imply the initial inefficiency gap or distance from reaching the desired frontier. A negative δ_1 and η_1 coefficient signify the potential reduction in inefficiency and the individual "catch-up" rate estimated from the G_t function [$exp\{\xi_i(t - \underline{t})$] is the required momentum to reduce the inefficiency gap or to reach individual potential frontier gap. In our case, the "catch-up" rate varies across countries, with a negative sign indicating convergence and divergence if the sign is stated otherwise. The rate of convergences (ρ_{it}) is then simply derived by totally differentiating the function with respect to time (t) as described in Eq. (6) and prediction on the convergence rate is partially determined by the predicted value on conditional technical inefficiency $\hat{u}_i$[9].

$$\rho_{it} = -\xi_i exp\{\xi_i(t - \underline{t})\} * \hat{u}_i \tag{6}$$

This measure also represents technical efficiency change ($\dot{TE}$), a component of total factor productivity growth ($T\dot{F}P$) measure. The technological change (TC) measure is estimated by partially differentiating total output with respect to time i.e., $\frac{\delta lny}{\delta t}$. The scale economy change (SC) measure is estimated as follows;

$$SC = (RTS - 1)\{(\textstyle\sum_{j=1}^{k} \lambda_j \dot{x}_j)\}; \tag{7}$$

$RTS = \sum_{j=1,..k} \varepsilon_j$, $\lambda_j = \varepsilon_j / RTS$, and $\dot{x}_j$ = input growth

where return to scale (RTS) represented by summation of kth ε_i input-elasticity. The second term of the RHS of Eq. (7) is a summation ratio of output elasticity to input growth variation or percentage change in input usage. As Kumar and Russell (2002) mentioned, productivity change can occur due to (i) a shift in the production function, (ii) change in efficiency, and (iii) scale economies (dis-economies). Alternatively, TFP growth is also predicted by excluding the scale economies (dis-economies) component. The TFP growth is estimated as follows:

$$T\dot{F}P = SC + TC + T\dot{E}$$

We differentiate the SF model according to three different setup of u_{it} function. The SF0 is specified assuming $\delta_1 = 0$. The SF1 specified with $\delta_1(iniFRDL_{i\underline{t}})$ and the SF2 specified with $\eta_1(iniTPL_{i\underline{t}})$. Our *SC* estimate shows that a majority of the developing countries suffer from diseconomies of scale, meaning that costs of inputs hugely dominate output growth in the production process (refer to Table 2, PART [A]). In general, the production processes are highly input driven with per capita output elasticity from per capita capital dominating the production technology at a value of 0.3884 and 0.3899 for SF1 and SF2 respectively. This therefore squeezes the overall $\dot{TFP}$ measure.

DATA

Details of variables used in this research are described in Table 1. This research optimizes secondary data compiled from various trusted databases (Data descriptions are presented in Table 1). This study focuses on a total of 36 developing and emerging economies over the period 1990-2010. Due to missing observations, we only manage to compile an unbalanced panel of 747 observations over the stipulated time frame. The chosen time frames of 1990-2010 are due to several reasons. Observations on foreign R&D imports from the OECD Science and Technology database only started in 1988 with latest observation in 2011, but due to large missing values for data in 1988 and 1999 and also for observation in 2011 especially among the developing economies, we decided to use observation 1990 to 2010 as our final time frame. In fact, data on triadic patent statistics only appear starting in 1990 in the OECD Patent statistics database.

The output and physical capital variable are measures of GDP at US constant 2005 prices and the physical capital stock measured by gross capital formation (GCF) at constant 2005 US price derived using the perpetual inventory method (PIM) with 5% depreciation rate. The estimations of the physical stock at the cross-country level use the earliest available observation i.e., 1960. Total labor is measured by total labor force, human capital measures adopted from the dataset of Barro and Lee (2013) measured by average number of years of schooling for population aged 25 and above.

The measure of R&D is the imported capital from 20 OECD countries. The imported capital is measured by a ratio of imported capital goods on machinery and equipment over the 20 OECD countries GDP, extracted from STAN Bilateral trade database-ISIC4 (OECD) and weighted by the R&D stock of 20 OECD countries. The imported R&D stock is estimated using the PIM methods with 5% depreciation rate.

The triadic patent family counts are gathered from the OECD Patent Statistics[10]. The use of triadic patent family counts to measure domestic technological capabilities is basically referring to the total number of patents observed at the earliest priority filing for each country i.e., based on *inventor's country of residence* or *residence country of the applicant* observed at the earliest priority date. The measure of technological capabilities as defined by the triadic patent family is of importance to avoid home country bias when using the locally counted or foreign counted patents in the domestic market. The triadic patent family is basically a count of patents of the identical invention of each country with applications made and/or granted outside their territorial economic boundaries. Unlike the traditional counted patent statistics, which suffers from home country biases, the triadic patent count, is basically counted in the triad region, the region known to be at the forefront in the world technological provider. The use of triadic patent family counts is basically referring to the total number of patents observed at the earliest priority filing for each country i.e. based on *inventor's country of residence* or *residence country of the applicant* observed at the earliest priority date.

Due to unavailable observations, the triadic patent family counts only cover 36 developing countries in the sample set, which altogether determine the total number of countries in our samples and thus limit the time series observations. The data is then transformed into logarithm using the following procedure; ln(1 + (TPL)) to represent *triadic patent propensity*; triadic patent per million labor force. The applied procedure i.e., adding a constant as for the transformation is needed to preserve the "zero" observation figure observed across countries within the time period.

ANALYSIS OF RESULTS AND DISCUSSION

As in Table 1, all variables in our datasets are in per capita real constant 2005 US price (except for per capita human capital and triadic patent propensity). Data presented in Table 1 is the average estimates for the period of 1990-2010. The average per capita real GDP recorded at 12 billion US dollar, capital stock stood at 31 billion US dollar, whereas foreign R&D at 0.1 million US dollar. Human capital ratio is recorded at an average of 1.75 per million-labor force. The average ratio of triadic patent per million labor force is recorded around 2.294.

At the regional level, countries that reside in the Asian region records the highest average ratio of triadic patent per million labor force at 6.260, contributed largely by South Korea, Singapore, Taiwan and Hong Kong. The Asian region records highest average per capita foreign imported R&D at 0.219 million but lowest in terms of human capital per million ratio (0.628) compared to other regions. The Asian region also scores second highest on average per million ratios for real capital stock and real output, where both ratios a mounted at 12.9 billion US dollar and 34 billion US dollar respectively. As our sample is an unbalanced panel consisting of developing countries from four different regions, the average ratios of output, capital stock, human capital, foreign R&D and triadic patent propensity at the regional level need to be cautiously interpreted especially figures for African and Middle East and Eastern Mediterranean.

The empirical model comparing the three-translog SFA production function is shown in Table 2. All models are specified with added inputs of foreign R&D and triadic

TABLE 1. Data Descriptions (N=747)

		Output (YL)	Capital Stock (KL)	Human capital (HL)	Foreign R&D (FRDL)	Triadic patent propensity (TPL)
Mean		12114.100	31096.720	1.750	0.110	2.294
Std. dev		12900.630	33447.800	4.235	0.275	9.674
Min		557.428	371.353	0.011	0.001	0.000
Max		62575.910	153782.200	28.684	4.047	82.734
REGION (Mean)	1 [3]	5705.673	10919.180	1.702	0.069	0.239
	2 [8]	15843.710	43071.890	4.226	0.065	0.412
	3 [13]	10903.850	27118.010	1.256	0.043	0.194
	4 [12]	12989.680	33865.670	0.628	0.219	6.260

Source: Authors' computations.
Notes: Data on output, capital stock and foreign R&D are measured in million US dollar
All data are in per million total labor force.
YL: per capita real GDP at constant 2005 US price; World Development Indicator (WDI), the World Bank.
KL: per capita Gross Capital Formation; United Nation Statistical Department, National Account.
HL: per capita Human capital; Barro and Lee (2013) datasets.
FRDL: per capita Foreign R&D: Gross Expenditure on Research and Development (GERD), OECD S&T Database.
TPL: Triadic patent propensity (per million labor force); OECD patent statistics.
L: Total labour force (in million); WDI database, the World Bank.
Region: 1: Africa, 2: Middle East and Eastern Mediterranean, 3: Latin America, 4: Asia.
Value appear in [ ] refer to total number of countries in the respective region.

patent propensity in determining frontier technology. In the first model (SF0), all countries are assumed to have a common inefficiency as specified by δ_0. In the second model (SF1), log of initial foreign R&D-to-labour (*iniFRDL*) ratio is fitted into the inefficiency equation, to capture the initial conditions or capacity of foreign R&D towards inefficiency. Whereas, in the third model (SF2), the inefficiency function is fitted with log of initial triadic patent propensity (*iniTPL*), capturing the capacity of homegrown technology efforts.

Generally, in all specifications the production technology is considered as capital-intensive where capital per labour dominates all other inputs to determine the output growth (See PART [A] of Table 2). It is estimated that elasticity of capital-to-labour ratio, human capital-to-labour ratio, foreign R&D-to-labour ratio and patent triadic propensity with respect to output growth is consistent across all specification in determining output growth.

Our estimates also portray evidence on the potential in inefficiency reduction as predicted by countries heterogeneity estimate from log of initial foreign R&D capacity (*iniFRDL*) and log of initial triadic patent propensity (*iniTPL*). The potential inefficiency reduction predicted from utilizing foreign R&D in model SF1 is around 0.29% and 0.26% reduction in inefficiency as predicted from initiative of domestic homegrown technology in SF2 model. The potential technical efficiency is predicted by the G_t function (country-specific temporal variation). For example, to gain the potential technical efficiency resulting from utilizing foreign R&D and triadic patent propensity, Turkey's technological catch-up rate needs to be sustained annually at an average of 7.4% and 7.6% respectively (see PART [B] of Table 2). Our results on the effect of foreign imported R&D in improving technical efficiency is comparable to Henry et al. (2009), where their model estimates the effect of capital imports in improving efficiency to around 0.239%. As for the effect of triadic patent propensity to efficiency improvement, we are unable to compare our results with any previous empirical finding since there is no empirical research (to the best of our knowledge) using the similar variable as we did, except the study by Mastromarco and Ghosh (2009). In fact, Mastromarco and Ghosh (2009) however use a totally different approach from ours. The authors uses total patent applications for non-residents in their developing countries sample to proxy imported R&D as one of the channel for technology diffusion and found that total patent application from non-residents is positively related to developing economies efficiency.

The estimates on country-specific temporal variation show that nearly 52% of the samples exhibit movement towards the frontier (technological catch-up) with Turkey being the highest and Brazil being the lowest (results for Brazil is not shown in Table 2 due to space constraints and in fact the technological catch-up rate is less significant). Only 10 countries out of 19 show a significant technological catch-up rate (i.e., evidence of convergence) as predicted from all models, namely Argentina, China, Indonesia, India, Iran, Thailand, Trinidad and Tobago, Tunisia, Turkey and Uruguay. Unfortunately, for the purposes of comparison on the incidence of technological catch-

TABLE 2. Estimation Results Comparing Three Inefficiency Function of SF Model

PART [A]: Frontier Elasticity (evaluated at the mean value of each input)						
	SF0	*p*-value	SF1	*p*-value	SF2	*p*-value
θ_{KL}	0.3996	0.000	0.3884	0.000	0.3899	0.000
θ_{HL}	0.1295	0.000	0.1067	0.000	0.1134	0.001
θ_{FRDL}	0.0983	0.000	0.0973	0.000	0.0974	0.000
θ_{TPL}	0.0249	0.000	0.0254	0.000	0.0252	0.000
CRS	-0.3476	0.000	-0.3823	0.000	-0.3739	0.000
TC	0.0126	0.000	0.0132	0.000	0.0130	0.000
PART [B]: Inefficiency Function						
			iniFRDL		iniTPL	
δ_0	0.7465	0.002	-0.9409	0.258	1.6239	0.000
δ_1	-	-	-0.2890	0.017	-0.2649	0.048
Technological “catch-up” rate, $G_t = \xi_i(t - \underline{t})$						
ARG	-0.0093*	-0.053	-0.0088**	-0.024	-0.0089**	-0.032
CHN	-0.0379***	0.000	***-0.0386****	0.000	-0.0384***	0.000
IDN	-0.0101**	-0.014	***-0.0119****	-0.002	-0.0116***	-0.003
IND	-0.0187***	0.000	***-0.0209****	0.000	-0.0205***	0.000
IRN	-0.0149***	0.000	-0.0151***	0.000	-0.0151***	0.000
THA	-0.0159***	-0.002	***-0.0185****	0.000	***-0.0179****	0.000
TTO	-0.0136**	-0.023	-0.0111**	-0.049	-0.0116**	-0.043
TUN	-0.0204***	0.000	-0.0187***	0.000	-0.0192***	0.000
TUR	-0.0833**	-0.013	-0.0743***	0.000	-0.0757***	-0.001
URY	-0.0105*	-0.064	-0.0091***	-0.008	-0.0095**	-0.032
σ_u^2	-0.484	-0.256	-0.7540**	-0.042	-0.6732*	-0.079
σ_v^2	-6.3408***	0.000	-6.3426***	0.000	-6.3425***	0.000
No. of Obs	747		747		747	
Log likelihood	1160.5		1163.7		1162.8	
PART [C]: Production Function Specification test (Loglikelihood Ratio, LR test)						
CD specification	64.4***	23.21 (10)	65.8***	23.21 (10)	65.4***	23.21 (10)
Non-neutral TP	51.4***	13.28 (4)	55.8***	13.28 (4)	54.6***	13.28 (4)
#H_0: $\delta_1 = 0$*	-	-	6.4***	5.41 (1)	4.6**	2.70 (1)

Source: Authors' estimation.
Notes: * 0.1, ** 0.05, *** 0.01 significant level.
CD: Cobb-Douglas specification and Non-neutral TP specification test critical value based on Chi-Square distribution.
[#] The LR test critical value is based on Kodde and Palm (1986).
Bold italic in the function denotes increase in technological catch-up rate compared to SF0.
Value appearing in the parentheses in PART C denotes number of degrees of freedom.

up at the individual country level, we have yet to find comparable previous empirical studies. Even though Henry et al. (2009) and Mastromarco and Ghosh (2009) did use samples from a group of developing countries in their studies, both studies however use a different approach of SFA technique. Both studies employ the time varying approach of Battese and Coelli (1995) to estimate each developing countries technical efficiency level but not the technical catch-up effect as conducted in this research.

The suitability of translog specification is reported in PART [C]. We test both the hypothesis of Cobb-Douglas (CD) specification form and non-neutral technological progress. In both SFA specifications function, we reject the hypothesis of CD specification and non-neutrality for technological progress at 1% level, which tell us the suitability of the chosen non-linear functional form. The test statistics follows a χ^2 distribution. In addition, we also test the null hypothesis of log initial foreign R&D per capita and log initial triadic patent propensity in the inefficiency function. Both test reject the null hypothesis at 1% and 5% significant level in the respective SF1 and SF2 specification.

Evidence of convergence predicted from SF1 and SF2 is compared to SF0. This comparison is to further classify whether the technological catch-up rate predicted from SF1 (i.e., potential technical efficiency gain from utilizing foreign R&D) and SF2 (i.e., potential efficiency gain from utilizing triadic patent) may improve the technological catch-up rate (i.e., an evidence of *pure TEC* gain) and lead to *pure TFP* growth. These two concepts of *pure TEC* gain and *pure TFP* growth are our own prerogative, a concept to describe the positive (monotonic) effect on TEC and TFP.

The classifying process for *pure TEC* gain is solely based on a comparison to a predicted TEC estimate of Eq. (5) of SF1 and SF2 specifications (i.e., TEC estimate on foreign R&D and TEC estimate on triadic patent propensity) to TEC estimate of specification SF0. If the TEC estimate from Eq. (5) of SF1 and SF2 is higher than the TEC estimates of SF0, then a *pure TEC* gain is observed. This concept in fact only applies to a significant coefficient predicted by the time-varying function as in Eqs. (4) and (5).

The *pure TFP* growth however is related to a summation of *pure TEC* gain estimates plus other estimates on TC and scale economies. A *pure TFP* growth again is compared to the estimates of TFP growth of SF1 and SF2 to SF0, a similar approach to *pure TEC* gain procedure. For example, an estimate of *pure TEC* gain observed from either SF1 or SF2 is the key consideration of pure TFP growth incidence. A *pure TFP* growth from SF1 or SF2 is observed if the TFP growth estimate is higher than estimates from SF0.

Detailed estimates of the TFP growth decomposition is appended in Appendix 3. Our results identify five countries (i.e., China, Indonesia, India, Iran and Thailand) with incidence of *pure TEC* gain both in SF1 and SF2 but found no incidence of *pure TFP* growth due to strong scale diseconomies effect in these economies. The highest incidence of *pure TEC* gain is recorded in China (7.24% in SF1 and 7.05% in SF2) and Iran (1.58% in SF1 and 1.56% in SF2) being the lowest for both specifications. The explanations for such improvement are possibly due to the embarkation of new industrial policy in which the imported foreign R&D suits the targeted sector and liberalization of economic policy being undertaken in those countries.

These arguments are also plausible for countries with subsequent main economic contribution derived from newly embarked product innovation-based activities, for example, high-tech and heavy industries, which mainly characterize emerging economies such as China, Indonesia, India and Thailand especially in the automotive industries (Biswajit et al., 2007). These four economies largely received huge foreign investment from big multinational automobiles players in the world especially from Japan, United States and Germany. As a hub for car assembling and parts distributors in the Asian region, the impact of triadic patent in this instance may also possibly play a complete mix and match or *pseudo-complementary* effect in the respective sector.

We also observe a significant divergence rate for Hong Kong, Taiwan, Chile, Colombia, Costa Rica, Ecuador, Guatemala, Kenya, El Salvador, Venezuela and Zimbabwe in our analysis. All listed countries are driven by non-manufacturing sectors, which portray why foreign specific capital and triadic patent are unsuccessful in showing a convergence (classical examples of *miss-match* technology needs), except for Hong Kong and Taiwan. These observations are also possibly due to fundamental economic structure as a majority of the listed countries is driven by agriculture rather that manufacturing. This therefore points to our argument that, specific foreign R&D imports are sector specific and does not suit the policy embarked on agricultural strategy. An improvement may probably be observed if general capital such as foreign direct investment (FDI) is considered in the analysis. We also observed anomalies in the catch-up rate from Saudi Arabia[11].

The economies of Hong Kong and Taiwan are largely supported by high-tech industries such as electronic components and lately innovation-driven companies play a vital role in shaping and developing their electronic sectors specifically in designing and manufacturing the *state of the art* technology in the information and communication technology (ICT) sector. As big players in the ICT sector at the international level, stiff competition from locally grown experts and technology is the key answer why specific foreign technology imports has failed to generate a sign of convergence in the analysis. This divergence effect is also observed from the inclusion of triadic patent propensity measure.

As primary manufacturers and suppliers of computer components and peripherals at the global platform, a sign of convergence may be witnessed if a form of specific measures of triadic patent propensity for ICT sector is used rather than the general triadic patent measure, as we did in this analysis[12]. In addition a less significant divergence incidence is also predicted in our analysis especially observed in Cyprus, Jordan, Mexico, Malaysia and Singapore.

The insignificant catch-up rates are observed from Brazil, Egypt, South Korea, Sri Lanka, Morocco, Pakistan, Peru and the Philippines. For the case of Brazil and South Korea, the role of foreign imported R&D is unlikely to improve technical efficiency due to the homegrown technology initiative being undertaken in those countries especially in the ICT sector. This also may possibly be due to the diminishing marginal effect of the existing accumulated foreign R&D stock, which sees why foreign technology has produced insignificant efficiency effect in this respect.

South Korea is actively involved in patenting activities for the two decades especially in the ICT sector and lately gain momentum as a competitive producer of ICT products and peripherals at the global market place especially for the brand Samsung and LG. Similar to our earlier argument, a sign of convergence may be witnessed if a form of specific measures of triadic patent propensity for ICT sector is used rather than general triadic patent count measure. However, for the case of Egypt, Sri Lanka, Morocco, Pakistan, Peru and the Philippines, the specific category of foreign imported R&D have minimal impact on the efficiency improvement as these countries probably require more general investment type such as FDI to promote growth and efficiency.

The estimate of TFP growth components of four regions is presented in Table 3, with details at the individual country presented in Appendix 2. We classify the region for each country based on classification made by the United Nations Country Grouping. Two regions show scale diseconomies change with the remaining two regions showing otherwise. The measure of scale economies/diseconomies change (SC) is estimated using Eq. (7) for each country at the respective regional classifications. Negative estimates of SC represent scale diseconomies change whereas scale economies change states otherwise. Scale economies are observed higher in the Asian region in both specifications, with scale diseconomies higher in Latin America region. A positive TC is observed in all regions, an evidence of positive transmission of knowledge over time. A mix between convergence and divergence of technical efficiency change across all regions is observed in both SF1 and SF2 model. A divergence of TEC is observed in two regions i.e., Africa and Latin America as a result of utilizing foreign R&D as well as from the triadic patent propensity. This evidence re-emphasizes our earlier argument of technological *miss-match* between agriculture and manufacturing sector in both regions. All regions show positive growth on TFP led by the Asian region in both specifications. This is a clear indication of foreign technology spillover effect with domestic capacity of homegrown technology having similar capacity in achieving the growth momentum.

We also include tests of absolute and conditional β- and σ-convergence in our analysis. Readers are not to confuse with the term convergence when we discussed about the speed of convergence related to improvement on technical efficiency earlier, even though the estimate is related to TFP. This test is purely a two-stage approach, meaning that TFP measure estimated from the stochastic frontier technique in stage one is used in the second-stage. The alternative test on absolute and conditional β- and σ-convergence of TFP employed in this study is owed to Miller and Upadhyay (2002). Miller and Upadhyay (2002) uses growth-accounting framework for a panel of 83 countries (mixed between developed and developing for the years 1960 to 1989) to estimate TFP but ours uses the stochastic frontier technique to produce more refined values of TFP for a panel of 36 developing and emerging economies (i.e., observed between 1990 to 2010).

There is a huge literature highlighting the long-standing debates on growth convergence especially within the neo-classical devotees. A symposium discussing the "Controversy on the Convergence and Divergence of Growth Rates" as documented in "The Economic Journal" in 1996, hinges on the issue of appropriateness of neo-classical estimation approach in predicting growth convergence or divergence. Despite strong empirical support (Sala-i-Martin 1996), the neo-classical approach is also subject to criticism. Bernard and Jones (1996) argue that the existence of technological diffusion and the role of capital accumulation in understanding issues of convergence and divergence estimated by the cross-section technique are likely to be less accurate. Quah (1996) however argue in order for convergence to be highly likely observed, time series data on real income per capita distribution need to be observed instead of cross-section. However, as pointed by Sala-i-Martin (1996), despite its criticisms, the classical approach to convergence has survived such challenges.

We use an alternative approach of TFP growth measures by excluding the scale economies component

TABLE 3. TFP Growth Decomposition by Region: The effect of Initial Foreign R&D and Triadic Patent Propensity

Region	SF1 ($u_i = \delta_0 + \delta_1 lnFRDL$)				SF2 ($u_i = \eta_0 + \eta_1 lnTPL$)			
	SC	TC	TEC	TFPG	SC	TC	TEC	TFPG
1 [3]	0.0015	0.0245	-0.0177	0.0082	0.0011	0.0236	-0.0172	0.0076
2 [8]	-0.0061	0.0123	0.0056	0.0118	-0.0059	0.0120	0.0059	0.0120
3 [13]	-0.0068	0.0151	-0.0049	0.0040	-0.0065	0.0147	-0.0046	0.0041
4 [12]	0.0818	0.0105	0.0104	0.1026	0.0011	0.0106	0.0100	0.0218
Total [36]	0.0244	0.0137	0.0015	0.0389	-0.0025	0.0152	-0.0015	0.0113

Source: Authors' estimation.
Notes: All value is in mean.
Value appear in [ ] referring to total number of countries.
1: Africa, 2: Middle East and Eastern Mediterranean, 3: Latin America, 4: Asia.

TABLE 4. β- and σ-convergence Analysis Across Regions

Conditional -convergence					
SF Equations	Overall	Region 1	Region 2	Region 3	Region 4
SF1	TFPG [334]	TFPG [0]	TFPG [93]	TFPG [89]	TFPG [152]
	-0.2442***	-	-0.2064*	0.3906***	-0.3676***
	(0.000)	-	(0.074)	(0.005)	(-0.000)
Dummy *t*	yes	-	yes	yes	yes
Dummy *i*	yes	-	yes	yes	yes
SF2	TFPG [331]	TFPG [0]	TFPG [93]	TFPG [86]	TFPG [152]
	-0.3031***	-	-0.1220	-0.1063	-0.3892***
	(0.000)	-	(0.296)	(0.294)	(0.000)
Dummy *t*	yes	-	yes	yes	yes
Dummy *i*	yes	-	yes	yes	yes

Absolute Convergence						
		Overall [36]	Region 1 [3]	Region 2 [8]	Region 3 [13]	Region 4 [12]
SF1	1991-1995	0.0196	0.0146	0.0122	0.0106	0.0239
	1996-2000	0.0181	0.0214	0.0108	0.0120	0.0181
	2001-2005	0.0204	0.0331	0.0099	0.0137	0.0169
	2006-2010	0.0240	0.0458	0.0114	0.0138	0.0194
	1991-2010	0.0209	0.0323	0.0111	0.0127	0.0197
SF2	1991-1995	0.0189	0.0141	0.0117	0.0104	0.0230
	1996-2000	0.0181	0.0214	0.0108	0.0120	0.0181
	2001-2005	0.0199	0.0326	0.0094	0.0135	0.0164
	2006-2010	0.0237	0.0458	0.0108	0.0135	0.0188
	1991-2010	0.0204	0.0320	0.0106	0.0125	0.0189

Source: Authors' estimation.
Notes: Dummy *t*: time dummy
Dummy_*i*: country dummy
[ ]: number of observations/countries
( ): p-value
*, ** and ***: referring to 10%, 5% and 1% significant level.
Region 1: Africa; 2: Middle East & Eastern Mediterranean, 3: Latin America; 4: Asia.

in conducting this convergence test. The estimate of conditional β-convergence and absolute σ-convergence is depicted in Table 4. We are unable to test the absolute β-convergence due to large missing observations in the process of transforming the TFP growth into logarithm form. The estimate for conditional β-convergence does not include any exogenous variables but only time trend and country dummy, an approach similar to Miller and Upadhyay (2002). This approach is adequately less restricted considering that TFP generated in stage-one is flexibly captured within the translog production function. We differentiate our test for the four regions i.e., Africa, Middle East & Eastern Mediterranean, Latin America and Asia[13], however; again due to missing observations, testing of conditional β-convergence for the African region cannot be conducted.

Evidence of conditional β-convergence is significant at least at 10% level in two regions i.e., Middle East & Eastern Mediterranean and Asian region except for the Latin American region as predicted in SF1. The Asian region records highest convergence as predicted by the SF2 model with other two regions showing insignificant convergence. It is observed that triadic patent propensity among countries in the Asian region has the capacity to accelerate the conditional TFP growth with convergence of 0.02% faster compared to foreign technology import. This evidence implies that both sources of technology are equally important for growth and efficiency.

A mixture of σ-convergence and divergence are observed across regions in both estimated models. The estimate of σ-convergence in SF1 and SF2 model shows a complete divergence over time except for two regions i.e., the Asian and Middle East & Eastern Mediterranean. In addition, a similar observation pattern of σ-convergence appear in both SF1 and SF2 for Asian and Middle East & Eastern Mediterranean as the value show some increment within the period of 2006-2010. The empirical findings from both tests not just add some view into the issue of technological and regional growth disparities but most importantly it may dictate the choice of technological policy that may be relevant to developing economies.

CONCLUSION

This research highlights the endogenous role of foreign R&D embodied in capital imports and domestic technology initiative principally dictated by triadic patent propensity towards the convergence process for a group of 36 developing and emerging economies. Our estimates show some variation on individual convergence rate once foreign R&D and triadic patent propensity is taken into account using the recent approach of stochastic frontier analysis. A sign of significant improvement on technological catch-up rate is found to be of importance in determining the efficient frontier. Out of a group of 36 developing and emerging economies, only five economies i.e., China, Indonesia, India, Iran and Thailand show signs of *pure TEC gain* as a result of utilizing foreign imported technology and domestic homegrown technology into the production process. Our results only confirm the evidence of monotonicity effect of both foreign imported technology and domestic homegrown technology to technical efficiency growth with no indication of *pure TFP growth*. We also add to our analysis the estimates of β- and σ-convergence of TFP growth, to provide an alternative view on speed of convergence to the earlier TEC analysis. The evidence in this research not only confirms that imported technology from advanced trade partners play a significant role in achieving a higher efficient frontier but it also predicts that domestic capacity of homegrown technology has the momentum to achieve a similar capacity.

Even though evidence of *pure TFP growth* is not shown in our analysis, foreign imported capital is indeed important in achieving higher growth. This impact is significant in laying a platform to at least initiate or embark on the innovating effort to produce quality novel research (triadic patent), specifically for the latecomer countries in the Asian region such as China, South Korea, Singapore, Taiwan, Hong Kong and India. This also applies to countries in Latin America such as Brazil and Argentina. Triadic patent describes a country's ability to compete in terms of the creation of the latest technology. Although this study is limited to 36 developing and emerging countries, but the implications of the result from this study in terms of capacity of domestic technology compared to foreign imported capital is critical to be highlighted.

As part of the policy recommendation, the triadic patent propensity may in fact be able to boost efficiency once proper initiatives and strategies are in place. It is also found that triadic patent may in fact possibly speed-up the process to at least achieve *pure TFP gain* if stronger *pure TEC gain* is witnessed from the triadic patent propensity effect at lower scale diseconomies. This argument is also relevant for foreign imported capital as well. As larger scale diseconomies is witnessed across all countries and regions, the speed up effect to reach higher growth through the triadic patent (or foreign imported capital) has at least slowed down. Therefore, policy targeted to improve input usage efficiency through proper human resource policy is highly recommended. In this respect we recommend restructuring the policy targeted to human capital. A higher quality of human capital may in fact trigger higher complementary impact on the technology usage both from foreign and domestic sources (Mastromarco & Ghosh 2009).

We also suggest some ideas for future research. First, in this study we only used total triadic patent to portray each country's domestic technology capacity without segregating the triadic patent into its specific sector due to serious data unavailability. Distinguishing the triadic patent into its specific technology sector, i.e., pharmaceutical, nanotechnology, biotechnology, Information and Communication technology (ICT) and medical patent may in fact produce more rigorous results (subject to data availability for developing countries) as far as country and sectoral heterogeneity is concerned. If data are sufficiently observed among the developing and emerging countries, this may probably be an interesting issue to be highlighted especially the TEC effect. As far as the triadic patent data is concerned, we observed a huge improvement in triadic patent protection from China, South Korea, Singapore, Brazil and Argentina in the triadic region especially from three categories of triadic patent, i.e., ICT, biotechnology and pharmaceutical patents. Second, we also have not distinguished between foreign trade partners especially the bilateral trade or the free trade agreement (FTA) among developing countries and its trade counterpart. This also will be an interesting issue to consider and we leave this for future research.

ENDNOTES

1 The home-country bias in patent statistics appears when using domestic patent statistics as a measure of technological capability. Therefore, to reduce the bias, most researchers used either foreign patent application/ registered in the domestic countries or the triadic patent count measure that we will use in this research. The use of triadic patent family counts is basically referring to the total number of patents observed at the earliest priority filing for each country, i.e., based on inventor's country of residence or residence country of the applicant observed

at the earliest priority date. The priority date is the earliest date that one invention appears at the IP office records once the application was made. See Sternitzke (2009) for detail discussions on triadic patent.

2 See footnote 1 above.

3 The list of developing and emerging countries is shown in Appendix 1.

4 Coe et al. (2009) finds significant evidence that productivity also tend to increase when factors such as ease of doing business, quality of tertiary education system, improvement on patent system and the origin of legal system are included in determining the productivity function.

5 Foreign technology could be in the form of FDI or imported capital goods. However, in this article we limit the discussion of foreign technology to foreign imported capital because it reflects a more direct measure of foreign technology penetration compared to FDI.

6 The interpretation of the residual as technical change as proposed by the growth-accounting approach is only valid if all countries are producing on their frontier, meaning that each country is producing at constant return to scale (CRS). In this research, since the sample are drawn from a group of developing and emerging countries, the assumption of CRS is found to be less valid as countries differ in rates of physical, human capital and population growth. These differences may deviate the initial conditions, which determine heterogeneous preferences and technology usage.

7 Kumbhakar and Wang (2005) only predict common-time temporal variation to partially determine the convergence process and control the heterogeneity by assuming country-specific fixed effect intercept in the production function.

8 If no endowment variables are specified in the U_i function, then the function only consists of an autonomous constant term i.e., the mean of inefficiency are homogenous across country.

9 The conditional technical inefficiency score used in this article follows the method suggested by Jondrow et al. (1982). In this estimate, the initial level of technical inefficiency, u_i, is country-specific.

10 Triadic patent family in this study uses the current definitions of patent triadic region where all application of patent files should appear in the registration records in each IP office simultaneously i.e., the EPO, USPTO and the JPO respectively.

11 We consider the figure as anomalies because the unusual estimates keep on appearing as we attempt to re-estimate the frontier function by inserting different initial starting value for the function.

12 The triadic patent count that we apply in this study is a summation of triadic patent counted from five specific categories, i.e., triadic patent on ICT, triadic patent on biotechnology, triadic patent on medical, triadic patent on nanotechnology and triadic patent on pharmaceutical patents.

13 We lost the 1990 and 1991 observations in this processes. All observation is lost for 1990 due to mathematical operation in measuring Scale economies as in Eq. (6). We also lost the 1991 data due to lag operation to measure growth.

REFERENCES

Allred, B. B., & Park, W. G. 2007. The influence of patent protection on firm innovation investment in manufacturing industries. *Journal of International Management* 13(2): 91-109.

Ang, J. B. 2010. Financial reforms, patent protection, and knowledge accumulation in India. *World Development, 38*(8), 1070-1081.

Barro, R. J., & Lee, J. W. 2013. A new data set of educational attainment in the world, 1950-2010. *Journal of Development Economics* 104: 184-198.

Basberg, Bjorn, L. 1987. Patents and the measurement of technological change: a survey of the literature. *Research Policy* 16(2): 131-141.

Battese, G. E., & Coelli, T. J. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20(2): 325-332.

Bayoumi, T., Coe, D. T., & Helpman, E. 1999. R&D spillover and global growth. *Journal of International Economics 47*: 399-428.

Bernard, A. B., & Jones, C. I. 1996. Technology and convergence. *The Economic Journal* 1037-1044.

Biswajit, N., Saikat, B., & Rittwik, C. 2007. Changing Features of the Automobile Industry in Asia: Comparison of Production, Trade and Market Structure in Selected Countries. *ARTNeT Working Paper Series, 37*(July 2007).

Bitzer, J., & Geishecker, I. 2006. What drives trade-related R&D spillovers? Decomposing knowledge-diffusing trade flows. *Economics Letters 93*(1), 52-57.

Coe, D. T., & Helpman, E. 1995. International R&D spillovers. *European Economic Review 39*(5): 859 - 887.

Coe, D. T., Helpman, E., & Hoffmaister, A. W. 1997. North-South R&D Spillovers. *The Economic Journal 107*(440): 134-149.

Coe, D. T., Helpman, E., & Hoffmaister, A. W. 2009. International R&D spillovers and institutions. *European Economic Review 53*(7): 723-741.

Cuesta, R. 2000. A Production Model With Firm-Specific Temporal Variation in Technical Inefficiency: With Application to Spanish Dairy Farms. *Journal of Productivity Analysis 13*(2): 139-158.

Eaton, J., & Kortum, S. 1996. Trade in ideas Patenting and productivity in the OECD. *Journal of International Economics 40*(3-4): 251-278.

Eaton, J., & Kortum, S. 1997. Engines of growth: Domestic and foreign sources of innovation. *Japan and the World Economy 9*(2): 235-259.

Eaton, J., & Kortum, S. 1999. International Technology Diffusion: Theory and Measurement. *International Economic Review 40*(3): 537-570.

Eaton, J., & Kortum, S. 2001. Trade in capital goods. *European Economic Review, 45*(7), 1195-1235.

Fung, M. K., & Chow, W. W. 2002. Measuring the intensity of knowledge flow with patent statistics. *Economics Letters 74*(3): 353-358.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. 2006. Do alliances promote knowledge flows? *Journal of Financial Economics 80*(1): 5-33.

Griliches, Z. 1990. Patent statistics as economic indicators: a survey. *Journal of Economic Literature, 28*(4), 1661-1707.

Grossman, G. M., & Helpman, E. 1991. Trade, knowledge spillovers, and growth. *European Economic Review 35*(2-3): 517-526.

Henry, M., Kneller, R., & Milner, C. 2009. Trade, technology transfer and national efficiency in developing countries. *European Economic Review 53*(2): 237-254.

Hu, A. G., & Jaffe, A. B. 2003. Patent citations and international knowledge flow: the cases of Korea and Taiwan. *International Journal of Industrial Organization 21*(6): 849-880.

Hu, A. G., & Jefferson, G. H. 2009. A great wall of patents: What is behind China's recent patent explosion? *Journal of Development Economics 90*(1): 57-68.

Hu, M. C., & Mathews, J. A. 2005. National innovative capacity in East Asia. *Research Policy 34*(9): 1322-1349.

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics 19*(2-3): 233-238.

Keller, W. 1998. Are international R&D spillovers trade-related? Analyzing spillovers among randomly matched trade partners. *European Economic Review 42*(8): 1469-1481.

Kodde, D. A., & Palm, F. C. 1986. Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica 54*(5): 1243-1248.

Kumar, S., & Russell, R. R. 2002. Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. *American Economic Review*: 527-548.

Kumbhakar, S. C., & Lovell, C. K. 2003. *Stochastic Frontier Analysis*. Cambridge: Cambridge University Press.

Kumbhakar, S. C., & Wang, H.-J. 2005. Estimation of growth convergence using a stochastic production frontier approach. *Economics Letters 88*(3): 300-305.

Lach, S. 1995. Patents and productivity growth at the industry level: A first look. *Economics Letters 49*(1): 101-108.

Lee, G. 2006. The effectiveness of international knowledge spillover channels. *European Economic Review 50*(8): 2075-2088.

MacGarvie, M. 2005. The determinants of international knowledge diffusion as measured by patent citations. *Economics Letters 87*(1): 121-126.

Madsen, J. B., Saxena, S., & Ang, J. B. 2010. The Indian growth miracle and endogenous growth. *Journal of Development Economics 93*(1): 37-48.

Mastromarco, C. 2008. Foreign capital and efficiency in developing countries. *Bulletin of Economic Research 60*(4): 0307-3378.

Mastromarco, C., & Ghosh, S. 2009. Foreign Capital, Human Capital, and Efficiency: A Stochastic Frontier Analysis for Developing Countries. *World Development 37*(2): 489-502.

Miller, S. M., & Upadhyay, M. P. 2002. Total factor productivity and the convergence hypothesis. *Journal of Macroeconomics 24*(2): 267-286.

Park, W. G. 2013. International Patenting, Patent Rights, and Technology Gaps. *Review of Economics & Institutions/ Economia, Societa e Istituzioni 4*(1).

Quah, D. T. 1996. Twin peaks: growth and convergence in models of distribution dynamics. *The Economic Journal* 1045-1055.

Sala-i-Martin, X. X. 1996. The classical approach to convergence analysis. *The Economic Journal*: 1019-1036.

Sternitzke, C. 2009. Defining triadic patent families as a measure of technological strength. *Scientometrics 81*(1): 91-109.

Sternitzke, C., Bartkowski, A., & Schramm, R. 2008. Visualizing patent statistics by means of social network analysis tools. *World Patent Information 30*(2): 115-131.

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APPENDIX 1. List of Countries and Residing Region

Region	Ctry ID	Country	Ctry Code	Region	Ctry ID	Country	Ctry Code
3	1	Argentina	ARG	2	19	Morocco	MAR
3	2	Brazil	BRA	3	20	Mexico	MEX
3	3	Chile	CHL	4	21	Malaysia	MYS
4	4	China	CHN	4	22	Pakistan	PAK
3	5	Colombia	COL	3	23	Peru	PER
3	6	Costa Rica	CRI	4	24	Philippines	PHL
2	7	Cyprus	CYP	2	25	Saudi Arabia	SAU
3	8	Ecuador	ECU	4	26	Singapore	SGP
2	9	Egypt	EGY	3	27	El Salvador	SLV
3	10	Guatamala	GTM	4	28	Thailand	THA
4	11	Hong Kong	HKG	3	29	Trinidad & Tobaggo	TTO
4	12	Indonesia	IDN	2	30	Tunisia	TUN
4	13	India	IND	2	31	Turkey	TUR
2	14	Iran	IRN	4	32	Taiwan	TWN
2	15	Jordan	JOR	3	33	Uruguay	URY
1	16	Kenya	KEN	3	34	Venezuela	VEN
4	17	South Korea	KOR	1	35	South Africa	ZAF
4	18	Sri Lanka	LKA	1	36	Zimbabwe	ZWE

Notes: 1: African region,
2: Middle East & Eastern Mediterranean
3: Latin America region
4: Asia region

APPENDIX 2. Time-varying SF results

	SF0	p-val	SF1	p-val	SF2	p-val
Frontier Function						
lnKL	0.6183	-0.246	0.5479**	-0.017	0.5822	-0.131
lnHL	-0.1788	-0.213	-0.1801	-0.206	-0.1769	-0.219
lnFRDL	0.1043	-0.364	0.1028	-0.248	0.1008	-0.309
lnTPL	0.1851***	0.000	0.1867***	0.000	0.1857***	0.000
lnKL_sq	-0.0069	-0.907	0.0000	-0.999	-0.0036	-0.933
lnHL_sq	0.0249	-0.381	0.0265	-0.29	0.0267	-0.322
lnFRDL_sq	0.0062	-0.54	0.0055	-0.552	0.0055	-0.568
lnTPL_sq	-0.0000	-0.237	-0.0000	-0.162	-0.0000	-0.176
lnKL_lnHL	0.0274*	-0.097	0.0232	-0.116	0.0241	-0.123
lnKL_lnFRDL	-0.0044	-0.706	-0.0044	-0.634	-0.0042	-0.681
lnKL_lnTPL	-0.0174***	0.000	-0.0176***	0.000	-0.0175***	0.000
lnHL_lnFRDL	-0.0147***	-0.001	-0.0147***	-0.002	-0.0147***	-0.001
lnHL_lnTPL	0.0013	-0.146	0.0013	-0.143	0.0013	-0.15
lnFRDL_lnTPL	0.0021*	-0.055	0.0022**	-0.044	0.0021**	-0.047
lnKLt	-0.0063*	-0.059	-0.0074***	0.000	-0.0071***	-0.009
lnHLt	0.0060*	-0.08	0.0079***	-0.001	0.0074***	-0.007
lnFRDLt	0.0013	-0.328	0.0014	-0.226	0.0014	-0.25
lnTPLt	0.0008***	0.000	0.0009***	0.000	0.0009***	0.000
t	0.0662*	-0.07	0.0774***	0.000	0.0742**	-0.01

t_sq	0.0008***	-0.003	0.0009***	0.000	0.0008***	0.000
Constant	3.9700*	-0.074	4.3177***	0.000	4.1639**	-0.01
Mu : Inefficiency function						
iniFRDL	-		-0.2891**	-0.017		
iniTPL	-				-0.2649**	-0.048
Constant	0.7465**	-0.014	-0.9409	-0.258	1.6239***	0.000
Gamma Function: Time-varying function (individual technological "catch-up" rate)						
ARG	-0.0093*	-0.053	-0.0088**	-0.024	-0.0089**	-0.032
BRA	-0.0009	-0.892	-0.0048	-0.427	-0.0041	-0.519
CHL	0.0269	-0.121	0.0304***	-0.001	0.0291**	-0.025
CHN	-0.0379***	0.000	-0.0386***	0.000	-0.0384***	0.000
COL	0.0152**	-0.026	0.0161***	0.000	0.0158***	-0.002
CRI	0.0221*	-0.058	0.0265***	0.000	0.0252***	-0.005
CYP	0.0086	-0.491	0.0158	-0.143	0.0138	-0.241
ECU	0.0101	-0.243	0.0133***	-0.007	0.0124*	-0.06
EGY	-0.0054	-0.385	-0.0037	-0.31	-0.0042	-0.378
GTM	0.0132	-0.16	0.0162***	-0.001	0.0153**	-0.029
HKG	0.0207*	-0.06	0.0262***	-0.005	0.0247**	-0.015
IDN	-0.0101**	-0.014	-0.0119***	-0.002	-0.0116***	-0.003
IND	-0.0187***	0.000	-0.0209***	0.000	-0.0205***	0.000
IRN	-0.0149***	0.000	-0.0151***	0.000	-0.0151***	0.000
JOR	0.0013	-0.875	0.0051	-0.337	0.0041	-0.541
KEN	0.0124	-0.102	0.0139***	0.000	0.0134**	-0.015
KOR	-0.0264	-0.307	-0.0267	-0.206	-0.0269	-0.234
LKA	-0.0026	-0.653	-0.0022	-0.55	-0.0024	-0.602
MAR	-0.0034	-0.464	-0.0030	-0.317	-0.0032	-0.385
MEX	0.0068	-0.4	0.0025	-0.701	0.0035	-0.618
MYS	0.0014	-0.771	0.0013	-0.671	0.0012	-0.739
PAK	-0.0014	-0.768	-0.0023	-0.514	-0.0022	-0.587
PER	-0.0016	-0.738	-0.0019	-0.583	-0.0018	-0.634
PHL	-0.0028	-0.525	-0.0023	-0.411	-0.0025	-0.477
SAU	-5.5037	-0.835	-5.9246	-0.847	-6.4850	-0.876
SGP	0.0139	-0.284	0.0218*	-0.064	0.0198	-0.113
SLV	0.0162	-0.171	0.0206***	-0.002	0.0193**	-0.033
THA	-0.0159***	-0.002	-0.0185***	0.000	-0.0179***	0.000
TTO	-0.0136**	-0.023	-0.0111**	-0.049	-0.0116**	-0.043
TUN	-0.0204***	0.000	-0.0187***	0.000	-0.0192***	0.000
TUR	-0.0833**	-0.013	-0.0743***	0.000	-0.0757***	-0.001
TWN	0.0076***	0.000	0.0078***	0.000	0.0077***	0.000
URY	-0.0105*	-0.064	-0.0091***	-0.008	-0.0095**	-0.032
VEN	0.0285***	0.000	0.0265***	0.000	0.0269***	0.000
ZAF	0.0063	-0.285	0.0045	-0.374	0.0049	-0.357
ZWE	0.0903***	0.000	0.0864***	0.000	0.0872***	0.000
σ_u^2	-0.484	-0.256	-0.7540**	-0.042	-0.6732*	-0.079
σ_v^2	-6.3408***	0.000	-6.3426***	0.000	-6.3425***	0.000
No. Obs	747		747		747	
loglikehood	1160.5		1163.7		1162.8	

Source: Authors' estimation

APPENDIX 3. TFP growth Decomposition: The effect of initial FRDL and TPL

	SF0		SF1				SF2			
CODE	TEC	TFPG	SC	TC	TEC	TFPG	SC	TC	TEC	TFPG
ARG	0.0069	0.0057	-0.0102	0.0078	0.0067	0.0042	-0.0099	0.0077	0.0067	0.0046
BRA	0.0005	-0.0056	-0.0076	-0.0018	0.0027	-0.0067	-0.0073	-0.0013	0.0022	-0.0064
CHL	-0.0107	-0.0021	-0.0077	0.0170	-0.0116	-0.0022	-0.0073	0.0165	-0.0113	-0.0021
CHN	0.0649	0.0124	-0.0530	-0.0096	***0.0724***	0.0098	-0.0517	-0.0085	***0.0705***	0.0104
COL	-0.0110	-0.0005	-0.0007	0.0119	-0.0118	-0.0006	-0.0007	0.0117	-0.0116	-0.0006
CRI	-0.0178	0.0011	-0.0053	0.0275	-0.0200	0.0023	-0.0051	0.0265	-0.0194	0.0020
CYP	-0.0092	0.0165	0.0000	0.0318	-0.0146	0.0172	0.0000	0.0303	-0.0134	0.0170
ECU	-0.0110	0.0148	0.0081	0.0221	-0.0140	0.0162	0.0078	0.0212	-0.0132	0.0158
EGY	0.0070	0.0166	-0.0076	0.0177	0.0048	0.0150	-0.0072	0.0172	0.0055	0.0155
GTM	-0.0132	-0.0031	-0.0121	0.0235	-0.0157	-0.0044	-0.0115	0.0226	-0.0151	-0.0039
HKG	-0.0069	-0.0006	-0.0111	0.0182	-0.0076	-0.0004	-0.0108	0.0178	-0.0074	-0.0005
IDN	0.0129	0.0003	-0.0132	-0.0041	***0.0166***	-0.0006	-0.0128	-0.0034	***0.0158***	-0.0004
IND	0.0267	-0.0023	-0.0275	-0.0081	***0.0337***	-0.0020	-0.0269	-0.0071	***0.0321***	-0.0020
IRN	0.0150	0.0143	-0.0042	0.0016	***0.0158***	0.0132	-0.0040	0.0019	***0.0156***	0.0135
JOR	-0.0018	0.0151	-0.0076	0.0281	-0.0068	0.0137	-0.0073	0.0269	-0.0055	0.0141
KEN	-0.0173	-0.0038	-0.0098	0.0250	-0.0196	-0.0044	-0.0093	0.0241	-0.0189	-0.0041
KOR	0.0066	0.0369	0.0071	0.0330	0.0077	0.0479	0.0046	0.0331	0.0076	0.0453
LKA	0.0035	0.0094	-0.0101	0.0164	0.0030	0.0092	-0.0097	0.0158	0.0032	0.0093
MAR	0.0037	0.0053	-0.0079	0.0083	0.0034	0.0038	-0.0076	0.0082	0.0036	0.0042
MEX	-0.0026	-0.0046	-0.0047	0.0002	-0.0011	-0.0056	-0.0045	0.0007	-0.0015	-0.0053
MYS	-0.0010	-0.0010	-0.0116	0.0104	-0.0010	-0.0023	-0.0113	0.0104	-0.0010	-0.0019
PAK	0.0018	0.0035	-0.0050	0.0046	0.0032	0.0028	-0.0048	0.0048	0.0030	0.0030
PER	0.0015	-0.0024	-0.0144	0.0089	0.0019	-0.0037	-0.0140	0.0088	0.0019	-0.0033
PHL	0.0040	0.0118	-0.0055	0.0131	0.0033	0.0110	-0.0053	0.0129	0.0036	0.0112
SAU	0.0011	0.0068	-0.0010	0.0065	0.0008	0.0062	-0.0010	0.0065	0.0005	0.0060
SGP	-0.0061	0.0460	1.1443	0.0441	-0.0082	1.1803	0.1747	0.0435	-0.0077	0.2105
SLV	-0.0166	0.0102	-	0.0320	-0.0199	0.0121	-	0.0306	-0.0191	0.0115
THA	0.0209	-0.0027	-0.0205	-0.0099	***0.0270***	-0.0034	-0.0200	-0.0088	***0.0255***	-0.0033
TTO	0.0147	0.0210	-0.0130	0.0211	0.0112	0.0193	-0.0126	0.0203	0.0119	0.0196
TUN	0.0229	0.0252	-0.0075	0.0091	0.0210	0.0226	-0.0072	0.0089	0.0216	0.0233
TUR	0.0149	0.0009	-0.0134	-0.0046	0.0207	0.0027	-0.0132	-0.0039	0.0194	0.0023
TWN	-0.0251	-0.0196	-0.0129	0.0175	-0.0259	-0.0213	-0.0124	0.0173	-0.0256	-0.0207
URY	0.0227	0.0328	-0.0089	0.0200	0.0198	0.0309	-0.0086	0.0193	0.0207	0.0315
VEN	-0.0122	-0.0094	-0.0047	0.0066	-0.0121	-0.0102	-0.0046	0.0067	-0.0122	-0.0100
ZAF	-0.0028	-0.0045	-0.0093	0.0063	-0.0021	-0.0051	-0.0092	0.0064	-0.0023	-0.0050
ZWE	-0.0275	0.0281	0.0235	0.0421	-0.0313	0.0342	0.0218	0.0403	-0.0303	0.0318

Source: Authors' estimation.
Notes: Bold TEC figure denote *pure TEC gain*.