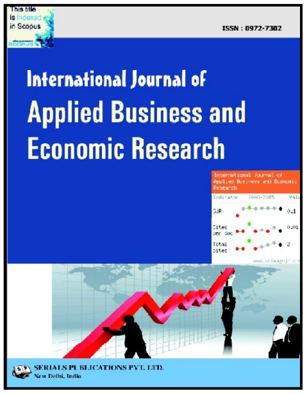

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Productivity Convergence at the Firm Level: Importance of Technology Diffusion

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Abtract: Productivity convergence between countries and regions has been extensively studied with mixed results. Much of this literature focuses on the macro-level data. This study uses Vietnam's annual enterprise survey data from 2000 to 2013 and a varying coefficient stochastic technology frontier framework to assess convergence among the manufacturing firms. The results support the convergence hypothesis, with the diffusion of technology from high tech firms to low-tech firms being the driving force. The results showed that technology diffusion by high-tech firms of the stochastic technology frontier led to a faster speed of convergence than the spillover effects among firms on the other technology frontiers.

Keywords: Channels of technology diffusion, varying coefficient stochastic technology frontier, speed of convergence, semi-parametric method.

1. INTRODUCTION

There has an extensive literature exploring the convergence of productivity across countries, both nationally and at the sectoral levels. For example, Cornwell and *et al.* (1998) used a sample of 26 OECD countries from 1965-90, and found convergence and catch-up were quite strong among EU countries but not among the G-7. Considering productivity growth by sector from 1963-1989, Barro and Sala-i-Martin (1991) concluded that convergence was occurring in all sectors, although more rapidly in manufacturing than in other sectors. Dollar and Wolff (1988, 1994) found convergence in almost individual industries and concluded that productivity convergence in industries was the main cause for convergence in aggregate labour productivity. Bernard and Jones have published a series of articles on productivity convergence at the sectoral level (Bernard and Jones, 1996a, 1996b, 1996c). They argue that per capita GDP convergence in the sample countries is not due to productivity convergence in the manufacturing sector, but rather to convergence in the service sector.

Pascual and Westermann (2002) 's study of productivity convergence in European manufacturing has shown convergence in some sub-industries and absence of convergence of the entire manufacturing sector, suggesting that large technology disparities in the industry may be the reason for the lack of evidence of convergence in previous research. They argue that if technology is a source of convergence in productivity, it is necessary to compare similar industries that use the same technology. However, it should be noted that a country's growth is rooted in the growth of its industries, and the growth of industries is rooted in the growth of firms. Much of the previous research focuses on industry-level convergence. Nisshimura and his colleagues (2005) have examined productivity growth at the enterprise level in Japan. They found that productivity convergence across firms appeared in both manufacturing and non-manufacturing sectors. In addition, the convergence rate at the enterprise level is faster than the reported convergence rates at the national or sectoral level. So the question is the power behind the convergence of firms. One possible source of convergence is the diffusion of technology which can provide opportunities for low-tech firms, especially small and medium enterprises, to catch up with advance technology firms even if they can not afford to invest in R and D or buy new technology.

Some studies have shown that technological diffusion is an important explanatory variable for convergence. Carree and Klomp (1997) suggest that low knowledge barriers allow imitation of new technologies and may lead to convergence. High knowledge barriers make imitation difficult and can create technological gaps in long-term issues that can hinder convergence. Tveterεs (1999), in the study of the learning and technology, argues that producers can not only learn from their own production experience, but also from other producers. Nishimura and his colleagues (2005) have suggested that it has a convergence of productivity among Japanese enterprises due to technological diffusion.

The primary objective of this paper is to fill this gap in literature by assessing convergence among Vietnam's manufacturing enterprises and the role of technology diffusion and spillover effect from advanced technology firms to low technology one, and how we can quantify spillover effects.

This paper is structured into four sections. The following section presents the methodological framework used in this study to estimate total factor productivity (TFP) and the contribution of technology diffusion and spillover effects. Section 3 describes the data and presents the results. The final section provides some concluding remarks.

2. THE METHODOLOGY FRAMEWORK

2.1 The Model of Productivity Convergence Among Firm

The simple model of productivity convergence developed by Bernard and Jones (1996) has been widely used in studies on productivity convergence across countries. According to this model, the growth rate of TFP in industry *i* is expressed as:

$$\Delta \ln TFP_{i,final} = \frac{1}{T}[\ln TFP_{i,final} - \ln TFP_{i,initial}] = \beta_o + \beta_1 \ln TFP_{i,initial} + u_i \quad ..(1)$$

where T denotes the length of the period, "final" the final year, "initial" the initial year . The TFP convergence is shown by a negative value of the coefficient $\beta_1 = -\{1 - (1 - \lambda)^T\}/T$. We assume that $u_{it} \sim N(0, \sigma)$.

To control for technology diffusion equation 1 can be rewritten as:

$$\Delta \ln TFP_{iT} = \frac{1}{T}[\ln TFP_{i\_final} - \ln TFP_{i\_initial}] = \alpha + \beta \ln TFP_{i\_initial} + \delta f(LH) + \mu_{iT} \quad ..(2)$$

where *f* is the function of the technological diffusion variables (LHjt), both horizontal and vertical. To assess the convergence rate and diffusion of technology diffusing among the stochastic high-tech frontier firms (Ω_{ot}) and high-tech firms in technology frontiers (Ω_{5t}, Ω_{10t}, Ω_{25t}),, equation 2 can be rewritten as:

$$\Delta \ln TFP_{iT} = \frac{1}{T}[\ln TFP_{i\_final} - \ln TFP_{i\_initial}] = \alpha + \beta \ln TFP_{i\_initial} + \theta f(LHb^{s}, LHf^{s}, LHb^{s0}) + \mu_{siT} \quad (2.s)$$

where

$$\theta f(LHb^{s}, LHf^{s}, LHb^{s}) = \sum_{i=1}^{13} \theta_i LHb_i^{s} + \sum_{i=1}^{13} \theta_i LHf_i^{s} + \sum_{i=1}^{13} \theta_i LHb_i^{s}$$

$$LHb_0^{s} = LHb_{2000}^{s}, LHb_1^{s} = LHb_{2001}^{s}, ...LHb_{13}^{s} = LHb_{2013}^{s};$$

$$LHf_0^{s} = LHf_{2000}^{s}, LHf_1^{s} = LHf_{2001}^{s}, ...LHf_{13}^{s} = LHf_{2013}^{s};$$

$$LHb_0^{s} = LHb_{2000}^{s}, LHb_1^{s} = LHb_{2001}^{s}, ...LHb_{13}^{s} = LHb_{2013}^{s}$$

$$s = 0, 5, 10, 15$$

Equation (2.s) collapses to equation (2) when s is = zero. As such, equation (2) is used to estimate technology diffusion from high-tech firms in the stochastic technology frontier ($\Omega 0T$) to the low-tech firms as well as and speed of convergence of the model.

When s takes the value of 5, 10, or 25, equation (2.s) is referred to as equation (2.5), (2.10) or (2.25). These equations are used to estimate diffusion technology from the high tech firms in the technology frontiers (Ω_{5t}, Ω_{10t}, Ω_{25t}) to low-tech firms as weel as the convergence speed.

2.2 Study Variables

(a) Construction of TFP Series using Levinshon- Petrin approach

The semi-parametric estimation of the parameters of the production function proposed by Olley-Pakes (1996) is used to account for the endogeneity of firms' input choices. They use investment to control the correlation between input levels and specific firm productivity shocks that are not observed in estimating the parameters of production functions. Olley and Pakes' methods only apply to firms with a positive net investment. Unfortunately, in our sample, most firms do not meet this condition. Levinsohn and Petrin (LP) (2003) propose an alternative method, using intermediate inputs to address the simultaneity problem. The method allows the analysis to proceed without reducing the sample size to firms with a positive net investment. Our analysis uses a semi-parametric estimation according to the approach of Levinsohn and Petrin (2003). Here we present a step-by-step exposition of the estimation procedure. Consider the following Cobb-Douglas production function:

$$\ln VA_{it} = \beta_k \ln K_{it} + \beta_l \ln L_{it} + \varpi_{it} + \varepsilon_{it} \quad ..(3)$$

Where ln VA_{it} is the log of value added (VA_{it}), ln k_{it} is the log of capital (K_{it}), ln L_{it} is the log of labor (L_{it}). Consider the following version where small cases refer to variables in logs:

$$va_{it} = \beta_k k_{it} + \beta_l l_{it} + \varpi_{it} + \varepsilon_{it} \quad ..(3')$$

The terms ϖ_{it} and ε_{it} are not observable to the econometrician but ϖ_{it} is observed to firms. This leads to a simultaneity problem, since ϖ_{it} is likely to be correlated with the choice of capital and labor. Levinsohn and Petrin (2003) assume that $m_{it} = m_{it}(k_{it}, m_{it})$. Where *mit* is the intermediate input, and it is monotonically increasing in ς_{it}. Therefore, the intermediate input function can be inverted to obtain $\varpi_{it} = \varpi_{it}(k_{it}, m_{it})$.

$$va_{it} = \beta_l l_{it} + \varphi(k_{it}, m_{it}) + \varepsilon_{it} \quad ..(4)$$

Where $\phi(k_{it}, m_{it}) = \beta_k k_{it} + \omega_{it}(k_{it}, m_{it})$. Levinshon and Petrin estimation involves two steps. In the first step, equation (2) is estimated treating $\phi_{it}(k_{it}, m_{it})$ non-parametrically, which gives the estimates for the labor inputs. The second step identifies β_k. Assuming that ω_{it} follows a first-order Markov process:

$$\varpi_{it} = E[\varpi_{it} / \varpi_{it-1}] + \eta_{it},$$

and given that k_{it} is decided at $t-1$, then $E[\eta_{it}/k_{it}] = 0$, which implies that η_{it} and k_{it} are uncorrelated. This moment condition is the used to estimate the elasticity of capital β_k. In this study, consumption of electricity and other intermediate inputs are used as the intermediate inputs to estimate that allows the identification of the elasticity of capital. Finally TFP is calculated as

$$TFP_{it} = \exp(va_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}) \quad ..(5)$$

(b) Definition of technology frontiers

When studying the impact of FDI on the productivity or output of domestic firms, previous research focuses on technology diffusion firms from FDI enterprises. However, in this study, we consider firms that are capable of spreading technology as high-tech enterprises, ie, firms that are on technology frontiers. Therefore, the set of firms located on the technology frontiers includes both FDI and domestic firms. Before defining the technology frontiers we need to make the three assumptions underlying the technology frontiers explicit: According to the first assumption, technology and firm's (TFP) are strongly correlated, i.e. high-tech firm has high (TFP) productivity. The second assumption is that the technical changes take the form of Hicks neutral, with technical change shifting production function upwards over time as a greater efficiency in the use of inputs is achieved. According to the third assumption, a firm has the potential to technology diffusion if the firm is among the set of technological frontier firms.

In the existing literature, the typical approach to determining productivity frontier is to take the top 5%, 10% or 25% firms with the highest productivity level (see Andrews and *et al.*, 2015). In this study, our approach is different. We construct a varying coefficient stochastic technology frontier by estimating the stochastic frontier production function (SVCF) (see Kalirajan *et al.* (1996)).

Using the SVCF we build the technology frontier. Suppose that there are two periods, denoted as period t and $t + 1$, and that a firm faces production frontiers Ft and $Ft + 1$, respectively. If a given firm has been on the technological frontier, output would be greater than or equal y_t^* in period t and y_{t+1}^* in period $t + 1$.

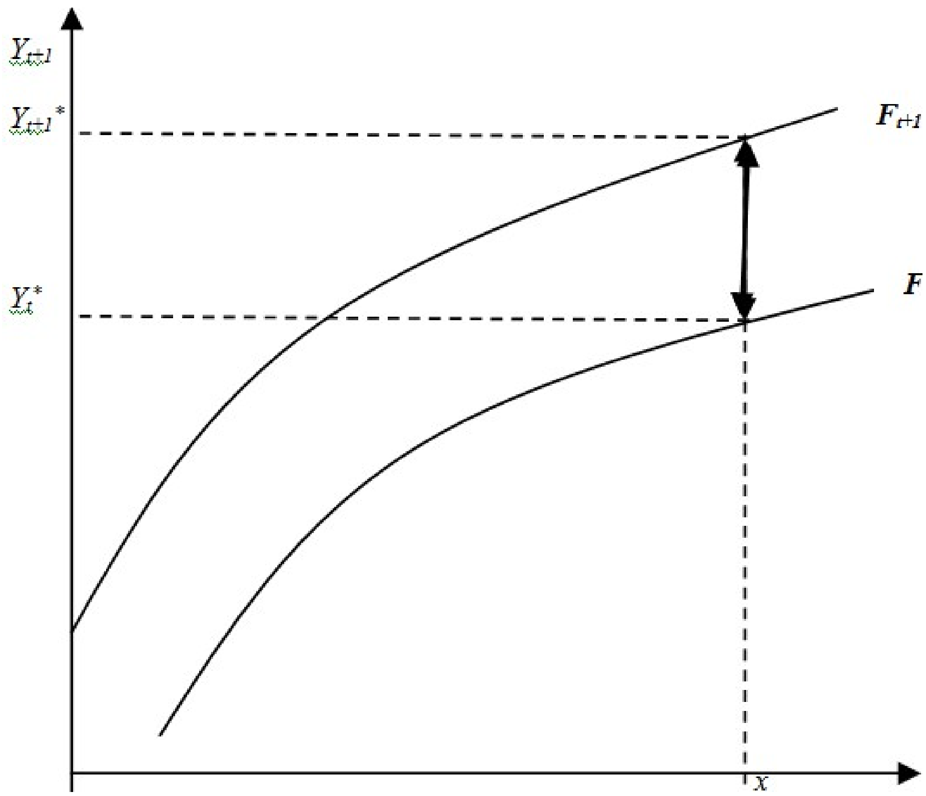

Figure 1: Technological progress in varying coefficient stochastic frontier production function

Technological progress is measured by the distance between frontier $F2$ and frontier $F1$, that is, $y^*_{t+1} - y^*_1$ using x input levels.

Definition 1: A set of varying coefficient stochastic technology frontier at time t (Ω_{0t}) can be defined as follows:

$$\Omega_{0t} = \left\{ i \in n : y_{i,t+1} \geq y^*_{i,t+1} > y^*_{i,t} \right\},$$

where n is the set of firms studying.

(Ω_{0t}) is called stochastic technology frontier).

Lemma: Ω_{0t} is a non-empty set.

Proof: According to assumption 2, the production function shifts up, over time then $y^*_{t+1} > y^*_t$, it means that there exists at least $i \in \Omega_{0t}$, so that $y^*_{i,t+1} > y^*_{i,t}$, then Ω_{0t} is the non-empty set.

Other definitions of the productivity frontier based on total factor productivity (TFP):

Definition 2: The productivity frontier includes the top 5% firms with the highest total factor productivity, within each industry and in year t (Ω_{5t}).

Definition 3: The productivity frontier includes the top 10% firms with the higest total factor productivity levels, within each industry and in year t (Ω_{10t}).

Definition 4: The productivity frontier includes the top 25% of firms with the highest total factor productivity levels, within each industry and in year t (Ω_{25t}).

Definition 5: A firm i is called a high-technology firm (high-tech firm) in year t if $i \in \Omega_{st}$ (s = 0, 5, 10 and 25) and a firm j is called a low-technology firm (low-tech firm) at year t if $j \notin \Omega_{st}$ (s = 0, 5, 10 and 25).

(c) The channels of technological spillovers from high tech firms to low tech firms

In the literature, the spillover effects of trade have been considered to be an important engine of TFP growth (Coe *et al.*, 1997; Crespo *et al.*, 2004; Engelbrecht, 1997; Frantzen *et al.*, 1998). Other studies show that the spillover channel through imports is less important.

In analyzing the productivity spillover effects of FDI on domestic firms, both within and across industries, two types of spillover are identified: spillover effects from FDI to domestic firms in the same industry (horizontal spillovers) and the spillover effect on firms in related industries (vertical spillovers). Schoors *et al.* (2002) and Smarzynska. J (2003, 2004) distinguish between vertical spillovers that occur through contacts between foreign firms and their local suppliers in upstream industries (backward spillovers) and those that occur through contacts between foreign firms and their downstream customers (forward spillovers).

However, in this paper we focus on the diffusion of technology from high-tech firms to low-technology firms, and consider a number of channels through which high-tech firms may have an impact on the low-technology firms and the productivity convergence. Here, we structure channels that allow the spread of technology from high-tech firms to low-tech firms in both horizontal and vertical spillovers.

Horizontal spillovers of technology (LHh) runs from a high tech firm to a low tech firm in the same industry. Technology spillovers can occur when low-tech firms improve TFP by imitating the technology of high-tech firms based on observation (imitation of technology) or by hiring workers, trained by high tech firms. Another kind of technology spillovers occurs if the presence of high-tech firms leads to more serious competition in the market and forces low-tech firms to use their existing resources more efficiently or to seek new technologies.

Influence of forward spillovers of technology (LHf) goes from high tech firms to low tech firms downstream through inputs. The availability of better inputs due to high-tech firms can improve the productivity of low-tech firms using these inputs.

Backward spillovers of technology (LHb) go from high-tech firms to low-tech through upstream supply firms. In this case, high-tech firms may want to support the input supply firms so that they can receive good quality inputs. In this case, high technology firms can transfer technology to firms that provide and encourage upstream technology diffusion. On the other hand, high-tech firms may impose stringent cost and quality requirements, which can be difficult for low-tech suppliers. In this case, the backward linkage effect could even damage the low-tech firms.

We use LH^s_{it} (s = 0, 5, 10, 25) as a variable to capture the existence of the firm i which has advanced technology in the industry in year t, and Ω_{0t} (or Ω_{5t}, Ω_{10t}, Ω_{25t}) is a set high tech firms.

$$LH^s_{it} = \begin{cases} 1 \text{ if } i \in \Omega_{st} \text{ and} \\ 0 \text{ if } i \notin \Omega_{st}, s = 0, 5, 10, 25 \end{cases} \quad ...(6)$$

The horizontal technological spillover variable LHh_{jt} indicates the level of involvement of high-tech firms in the industry and can be measured by the actual output of high-tech firms in the total output of the industry:

$$LHh_{it}^{s} = \frac{LH_{it}^{s} * X_{it}}{\sum_{j=1}^{n} X_{jt}}, \ s = 0, 5, 10, 25 \qquad ...(7)$$

where, X_{it} is the real output of firm i, n is the number of firms in the considered industry.

The variable LHb_{jt} measures the backward spillover effect, representing the association between suppliers with low technology and high technology clients. So we can measure LHb_{jt} as follows:

$$LHb_{jt}^{s} = \sum_{k \ if \ k \neq j} \gamma_{jkt} * LHh_{kt}^{s}, \ s = 0, 5, 10, 25 \qquad ...(8)$$

where, γ_{jkt} is the ratio of the output of the industry j sold to the industry k in the period t. Values of γ can be computed from I-O table. When computed γ, we remove the input of the firms sold in industry $(k \neq j)$ because this component has already been captured by LHh_{kt}.

In a similar way, we can define the forward spillover variable LHf_{it} as follows:

$$LHf_{jt}^{s} = \sum_{l \ if \ l \neq j} \delta_{jlt} LHh_{lt}^{s}, \ s = 0, 5, 10, 25 \qquad ...(9)$$

Here, the I-O table gives us δ_{jlt}, the input rate of the industry j purchased from the upstream industry l. Inputs purchased within the intra-industry $(l \neq j)$ are also removed because they are included in LHh.

3. EMPIRICAL RESULTS

3.1 Data Description

The micro-database is taken from the annual enterprise survey conducted by the General Statistics Office (GSO) from 2000 to 2013. This study uses data from all manufacturing firms for the period from 2000 to 2013.

The survey contains information on the type of firm, field of business, number of employees, assets, capital depreciation, fixed assets, labor's earnings, salary and bonus and social security contributions, financial obligations, and profits. Inputs and outputs are adjusted for inflation. This study uses balanced panel data, including all firms that appear for 14 years from 2000 to 2013. We exclude firms whose age, revenue, assets, and labor are not a positive value. In this study, value added is used to estimate total factor productivity. Since production cost data are not included in the data set, value added is measured in the sum of labor compensation and capital rental payment. The manufacturing industry includes food processing, apparel and textiles, leather and footwear, wood, paper, chemicals, rubber, plastics, non-metals, machinery, wood and furniture and recycling industries. The dataset includes 1284 observations per year and the entire sample is 14 years (17976 observations).

Table 2 provides a summary of distribution of foreign and domestic firms by the type of frontier. Type-1 frontier is the frontier including firms in the stochastic technology frontier (Ω_{0t}). Type-2 frontier is the frontier taking the top 5% of firms in terms of total factor productivity levels, within year t (Ω_{5t}). Type-3 frontier is the frontier taking the top 10% of firms in terms of total factor productivity levels, within year t (Ω_{10t}). Type-4 frontier is the frontier taking the top 25% of firms in terms of total factor productivity levels, within year t (Ω_{25t}).

Table 2
Summary of average of number of foreign and domestic firms and mean TFP in frontiers during the period of 2000-2013

	Ω_{0t}		Ω_{5t}		Ω_{10t}		Ω_{25t}	
Firms have advance technology	*Number of Firms*	*Mean TFP*	*Number of Firms*	*Mean TFP*	*Number of Firms*	*Mean TFP*	*Number of Firms*	*Mean TFP*
FDI firms	1739	8.134	1002	10.676	1662	8.533	2128	7.536
Domestic firms	2343	5.217	615	8.622	1429	6.432	2319	5.402
%	0.426		0.62		0.54		0.48	
Total Firms in Frontiers	4082	6.459	1617	9.895	3091	7.561	4447	6.423
Total firms in studying	17976	2.992	17976	2.992	17976	2.992	17976	2.992

Source: The authors estimate from business surveys of GSO.

The results show that average TFP of foreign firms is always higher than the average TFP of domestic firms in all technology frontiers. Moreover, the number of enterprises in the technology frontiers varying across the technology frontiers, with the proportion of FDI enterprises on the technology frontier in the " Stochastic technology frontier" being the lowest, accounting for only 42.6%.

(a) Estimated result of model (1)

We use a semi-parametric method proposed by Levinsohn and Petrin (LP) (2003) to estimate the production function. Underlying the LP approach is the assumption that the monotonic intermediate input increases with respect to TFP measured using strictly positive intermediate input observations. In order to test whether this assumption hold in case of our data, we estimated the fixed effects model at the firm level, in which the logarithms of intermediate inputs and TFP and dummy variables were used as explanatory variables in each period and they were adjusted for any set of variables.

Using a 4-digit industry code, the TFP logarithm estimate was 0.7 for the entire sample and statistically significant at 1%, indicating that a 1% TFP shock at company level cause intermediate inputs to increase by 0.7 within the sample. This suggests that using the LP method to estimate the production function is an appropriate method. Using TFP as estimated from equation (5), we estimate equation (1) to test whether there exists productivity convergence between firms in the manufacturing sector. Table 3 provides the OLS regression results of models (1). To compute the speed of convergence, we estimated b and, then computing $\lambda(\beta = -\{1 - (1 - \lambda)^T\}/T$. The estimated result presents in table 3.

The estimated coefficient β is negative and statistically significant, indicating a clear evidence of productivity convergence. The convergence speed is 6.0%, which higher than than the convergence speed

Table 3
Estimation results of convergence model (1)

	Const	*B*
	0.0365*** (0.0021)	–0.0414*** (0.0019)
R^2	0.2699	
F-Statistic	473.86	
Speed of convergence (%)	6.00%	
Half-life time	11.56	(year)

Source: The authors estimate from business surveys of GSO.

achieved at the national level. For example, while Dorwick and Nguyen (1989) report a convergence speed of 2.5% per year in their cross country study. However, these results are lower than those provided by Nisshimura *et al.* (2005), indicating a higher convergence speed at the national level than at the firm level. This difference between the speed of TFP convergence at national and firm level can be explained by the differences in diffusion of technology at the firm and national levels. Technology diffusion can be much faster at firm level in the same country than between different countries due to so-called "border impacts." Trade flows in the same country are much larger than transactions between different countries. For example, McCallum (1995), Engel and Rogers (1996) find that trade flows across different provinces of the country are several times higher than interstate trade. These arguments can be applied to the diffusion of technology. Since we focus on the diffusion of technology in a domestic industry, we hope that convergence rates between local companies are much faster than transnational studies.

(b) Compare the speed of convergence of models

Table 3 shows the convergence rate and half-life time, derived from the estimated results of the four convergence models under the influence of diffusion technology. There are models (2,0), (2,5), (2,10 and (2,25). Two prominent findings compared to this table. Firstly, in the four models (2.0), (2.5), (2.10) and the model (2.25), we observe strong evidence of productivity convergence. However, the speed of convergence is different among them. The fastest convergence rate in the model (2.0) compared to other models, Secondly, the convergence rate from the four models is significantly faster than the reporting rate in the model (1) in the previous section.

Table 4
The speed of convergence across models

	Model (2.0)	*Model (2.5)*	*Model (2.10)*	*Model (2.25)*
β	–0.0492 *** (0.002)	–0.0477*** (0.019)	–0.0469*** (0.020)	–0.0475*** (0.0020)
Speed of convergence (%)	8.00%	7.57%	7.35%	7.51%
Half-life time	8.66	9.16	9.43	9.22

Source: The author estimates from business surveys of GSO.

The results in Table 3.2 should be explained.

(i) The convergence rate of the models (2.0), (2.5) (2.10) and (2.25) is higher than the convergence ratio from the model (1). Estimated on the same convergence data set, but model (1) does not have the variables representing the diffusion channels of the technology.

(ii) The convergence rate of the model (2.0) is higher than the model (2.5), (2.10) and (2.25) because of the technology frontier of the model (2.0) is stochastic technology frontier. By definition, the stochastic technology frontiers only include those companies that have real technological advances, so the diffusion of technology from it is likely to generate better diffusion of technology from the other technology frontiers.

(c) Comparing spillover effects from different technology frontiers.

Table 5
Estimation results of convergence models (2.0) and(2.25)

	Model (2.0) *Coef.*	*Model (2.25)* *Coef.*		*Model (2.0)* *Coef.*	*Model (2.25)* *Coef.*
β	–0.0492 *** (0.002)	–0.0475*** (0.002)	θ_{21h}	0.6955 (0.7707)	2.3797*** (0.7913)
θ_0	–0.8668*** (0.2902)	–0.2803 (0.2177)	θ_{31h}	–0.1209 (0.1408)	–0.6050** (0.284)
θ_2	0.5384*** (0.2597)		θ_{4f}	–0.9516 (0.9779)	–0.6156 (0.6456)
θ_3	0.2944 (0.3856)		θ_{5f}	1.8561*** (0.552)	0.5293 –0.6979
θ_4	0.1634 (0.1482)	0.6041 (0.4777)	θ_{7f}	3.3173** (1.3869)	1.4633* (0.8159)
θ_5	2.9441*** (0.5646)	0.7611 (0.5272)	θ_{8f}	–2.5963*** (1.3688)	
θ_6	–1.7179** (0.6537)		θ_{9f}		0.8056** (0.4383)
θ_7	–1.0111** (0.5463)	0.697 (0.5206)	θ_{11f}		0.9936 (0.6799)
θ_8		–1.4649 (0.8159)	$\theta_{0\beta}$	0.4522*** (0.141)	
θ_9		1.3386** (0.5405)	$\theta_{1\beta}$	0.1571*** (0.0545)	
θ_{10}	3.2551*** (0.5619)		$\theta_{2\beta}$	–1.2689** (0.5647)	0.0805** –0.3949

Contd. table 5

	Model (2.0) Coef.	*Model (2.25) Coef.*		*Model (2.0) Coef.*	*Model (2.25) Coef.*
θ_{11}		–1.2271*** (0.4717)	$\theta_{3\beta}$	–0.6340** (0.2827)	
θ_{12}	–1.0128** (0.4932)		$\theta_{4\beta}$		0.4091* (0.2346)
θ_{13}	1.4006*** (0.4841)		$\theta_{8\beta}$	1.1922** (0.6353)	
θ_{1h}	0.2909 (0.211)	0.4219** (0.2255)	$\theta_{9\beta}$	–3.9497** (1.4147)	
θ_{2h}	–0.3778** (0.2049)	–0.1577 (0.1695)	$\theta_{10\beta}$	2.4211 (2.541)	
θ_{4h}		–0.6992** (0.3175)	$\theta_{11\beta}$	–0.6038 (0.8288)	–1.8194** (0.7597)
θ_{8h}	1.0126** (0.5492)		$\theta_{12\beta}$	3.8277*** (1.461)	3.5923*** (1.1536)
θ_{9h}	–2.0381 *** (0.5832)		$\theta_{13\beta}$	–0.7258** (0.5192)	–1.0812 (0.7172)
θ_{10h}		0.2219* (0.1823)		0 .0245*** (0.0079)	0.0166** (0.0083)
θ_{11h}	–0.3864 (0.5805)	–1.2512* (0.7058)			

Source: The authors estimate from business surveys of GSO.

The estimated results of the models (2.0), (2.5), (2.10) and (2.25) are presented in three tables (Table 3, Table 4 and Table 1A in the appendix). Table 3 is only for comparison purposes with model (1), so this table only shows convergence, speed of convergence and half-life time. Since the estimated results are longer than expected, we have separated the remainder of this estimate into Table 4 and Table 6 in the annex. For the purpose of comparing the spillover effects of the model (2.0) and the remaining models, Since the models (2.5), (2.10) and (2.25) have the same sample structure, while the model (2.25) has a convergence rate greater than the other models, (2.25) should be presented in the same table as (2.0).

Most of coefficients of technological spillover in all four models are statistically significant at 1%-10%, however, their signs varies across the models. All estimated values of β are negative and statistically significant at 1% level, confirming the existence of TFP convergence in Vietnam's manufacturing sector. The estimated coefficients of the spillover parameters (qs) vary greatly across the four models. However, the total value of all spillover parameters is positive, indicating the presence of the technology frontier benefits other firms based on spillover variables are calculated with the time-varying I-O tables show the impact of variables representing spillover effects on the models. The impact of the presence of firms on the technology frontier of the models (2.0),(2.5), (2.10) and (2.25) vary over time but their significantly positive total effects (total coefficients of θ_i (i = 0, 1, ...13)) are positive. It leads to conclusion that the presence of firms on the technology frontier of the models (2.0), (2.5), (2.10) and (2.25) is positive.

Horizontal spillovers are negative and statistically significant except the coefficient of θ_{h8}. This shows that the spread of technology through demonstration effects is limited. The sign of LH variable in 2000 is negative in three models ((2.0), (2.25) and (2.10) (in appendix 1A)) but not significant in model (2.25). It is also negative in 2006 and 2007 and significant at 5% and 10%, respectively in the model (2.0). The backward spillover is found to be mainly negative. Backward spillovers carry a significantly negative sign in years 2003, 2009 and 2013 but positive sign in years 2000, 2001, 2008 and 2012 but its totall effect (total coefficients of θ_i (i = 0, 1, .13)) is negative. Forward spillover exhibits a positive and significant in years 2005 and 2007and coefficients of θ_{f4} and θ_{f5} are positive and very high. We also recalculate the spillover effects using the I-O table for models (2.5), (2.10) (in appendix 6) and (2.25).

Although the complexity of the effects of diffusion of technology across channels and years is shown in table 3 and table 6 (in appendix), however, the overall impact of technology diffusion is positive. This can be demonstrated by comparing the results in Table 2, Table 3 and Table 4. It shows strong evidence for the impact of diffusion on convergence productivity among firms in those models. The model without variable denoting the technology spillover that has lower speed of convergence than other models. This again confirms the positive impact of technology spread.

4. CONCLUSIONS

This study examines the impact of technological diffusion on productivity convergence among Vietnamese manufacturing enterprises using the annual enterprise survey conducted by the GSO from 2000 to 2013. Rather than defining high-tech firms as 5%, 10 %, or 25% of enterprises with the highest productivity as done in previous research, this paper we identifies as a set of high-tech enterprises located at the frontier of the stochastic frontier production function with time-varying coefficients. We estimate convergence models without variables that represent technology diffusion and models with variables that denote diffusion of technology. The results indicates that the speed of convergence is greater when we control for the variables representing the technology spillover over from high tech enterprises to low tech enterprises and the rate of convergence of the model with stochastic technology frontier (2.0) is faster than that of the other models.

Two policy implications may be suggested from our analysis. Firstly, policymakers should know that not only technological innovation but technology diffusion also plays an important role in productivity growth so whenever the opportunity should facilitate the dissemination of technology. Secondly, research indicates that companies with strong technological spillovers must be those with real technological progress. Therefore, when building technology frontier, firms have made real technological advances.

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APPENDIX

Table 6
Estimated results of the models (2.5) and (2.10)

	Model (2.5) *Coef.*	*Model (2.10)* *Coef.*		*Model (2.5)* *Coef.*	*Model (2.10)* *Coef.*
B	–0.0477*** (0.019)	–0.0469*** –0.02	θ_{10h}	–0.2424 (0.208)	–0.2475 (0.1966)
θ_0		–0.6328** –0.2545	θ_{11h}	–1.4905** (0.6304)	–1.2757** (0.5985)
θ_2		0.5335* –0.19	θ_{12h}	2.8165*** (0.8162)	1.8064*** (0.6701)
θ_4	0.5727*** (0.2332)		θ_{13h}	–0.8063** (0.3633)	–0.3864 (0.2581)
θ_5		0.639 –0.4148	θ_{4f}		1.1357 –1.0597
θ_6	0.6597** (0.3561)		θ_{9f}	1.4543*** (0.5469)	0.6185** (0.3325)
θ_8	–0.8441** (0.4254)		θ_{1f}	2.3029*** (0.5528)	2.3189*** (0.5625)
θ_9		0.7397 (0.5122)	θ_{21f}		–1.2199*** (0.709)
θ_{10}		0.9254** (0.4548)	$\theta_{4\beta}$		0.5582** (0.2917)
θ_{11}		0.6101** (0.311)	$\theta_{5\beta}$	–0.2803 (0.3141)	– 0.8021*** (0.2513)
θ_{12}	–0.9913 (0.8122)		$\theta_{8\beta}$	–1.2778 (0.8671)	–1.4047** (0.7227)
θ_{13}	1.2396*** (0.7167)		$\theta_{9\beta}$	1.0605 (0.8937)	‘1.5055 (0.9766)
θ_{1h}	0.6286** (0.282)	0.6129** –0.2741	$\theta_{10\beta}$	–0.4273 (0.3666)	
θ_{2h}	–0.2932 (0.1941)	–0.3817** –0.1951	$\theta_{11\beta}$		–1.7734** (0.7173)
θ_{4h}	0.2493 (0.2709)		$\theta_{12\beta}$	5.6309*** (1.3304)	3.4821*** (1.0547)
θ_{9h}		0.6224* (0.3685)	$\theta_{31\beta}$	–2.9803*** (0.8689)	–1.1254** (0.5276)