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Abstract

This paper investigates the role of absorptive capacity in the diffusion of global technology with sector and firm heterogeneity. We construct the FDI-intensity weighted global R&D stock for each industry and link it to Chinese firm-level panel data relating to 53,981 firms over the period 2001-2005. Non-parametric frontier analysis is employed to explore how absorptive capacity affects technical change and catch-up in the presence of global knowledge spillovers. We find that R&D activities and training at individual firms serve as an effective source of absorptive capability. The contribution of absorptive capacity varies according to the type of FDI and the extent of openness.

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Key Words: Absorptive Capacity, FDI, R&D spillovers, productivity

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Abstract

This paper investigates the role of absorptive capacity in the diffusion of global technology with sector and firm heterogeneity. We construct the FDI-intensity weighted global R&D stock for each industry and link it to Chinese firm-level panel data relating to 53,981 firms over the period 2001-2005. Non-parametric frontier analysis is employed to explore how absorptive capacity affects technical change and catch-up in the presence of global knowledge spillovers. We find that R&D activities and training in individual firms serve as an effective source of absorptive capability. The contribution of absorptive capacity varies according to the type of FDI and the extent of openness.

I. Introduction

International technology transfer and spillovers through foreign direct investment (FDI) have long been regarded as an important channel for knowledge diffusion and acquisition. However, empirical evidence on the productivity effects of knowledge spillovers is mixed[2]. Many studies argue that the absorptive capacity of firms is a major determinant of the benefits that a firm can gain from global technology diffusion (Cohen and Levinthal, 1989; Xu, 2000; Griffith et al., 2003; Keller, 2002; Girma, 2005; Kneller and Stevens, 2006).

There are two streams of literature within this field. One stream examines the technology spillovers from FDI using firm-level data from developed and developing countries. Foreign technological knowledge is proxied by the share of assets, employment or sales of foreign-owned firms in total assets/employment/sales in the same industry/region in the host economy or by the productivity of foreign-owned firms. Empirical results from this strand of literature are, however, mixed (eg., Blomstrom and Kokko, 1998; Aitken and Harrison, 1999; Görg and Greenaway, 2004; Javorcik, 2004). These studies suffer from the limitation that foreign share of assets, employment or sales may not reflect the knowledge content of FDI, and they are also affected by government policy, attractiveness and competitiveness of the local economy.

The second stream of studies assesses knowledge diffusion through international trade and direct investment using aggregate country- or industry-level data (eg. Coe and Helpman, 1995; Keller, 2002; Kneller and Stevans, 2006). These studies link the

[2] See Görg and Strobl (2001) for a review of FDI spillovers and Keller (2004) for an excellent review of the process of international technology diffusion.

constructed global stock of R&D knowledge to country- or industry-level data, weight the global stock using bilateral trade or investment data, and explicitly test the benefits from technology spillovers at the country- or industry-level. Such studies also provide useful insights for our understanding of international knowledge diffusion. However, they fail to take into account heterogeneity amongst firms within an industry and differences in absorptive capacity among the firms.

This paper explores the role of absorptive capacity in terms of its possible impact on the benefits which firms might derive from global knowledge spillovers, using linked China-OECD data relating to 53,981 Chinese firms over the 2001-2005 period. The paper contributes to the literature in two ways. First, it makes a first attempt to link global industry-specific knowledge stocks to firm-level panel data and explores how a firm's absorptive capacity and openness to FDI affects the extent to which a firm can benefit from knowledge spillover. Second, we utilize a non-parametric frontier analysis using the Malmquist index to estimate total factor productivity (TFP) and decompose the index into technical change and catch-up. As Kneller and Stevens (2006) note, the frontier approach a relatively new technique in this area of research. It allows the study of absorptive capacity to be conducted in a framework that closely matches the idea of a technical frontier found in growth theory. The decomposition also allows the study to explore in depth the different role of absorptive capacity in the assimilation of a range of qualities of knowledge in various channels for productivity growth.

The remainder of the paper is organised as follows. Section II reviews the literature and develops the model. Section III discusses data and methodology. Section IV presents empirical evidence. Section V concludes.

II. Theoretical framework for analysis

With increasing openness to the world economy, a country may benefit from spillovers from global reservoirs of knowledge. Foreign direct investment is widely regarded as one of the major channels that facilitate the transfer of advanced knowledge from the global knowledge pool to the host countries. There are several ways in which FDI can serve as an effective vehicle for global knowledge transfer. First, a considerable proportion of FDI is brought into the host country in the form of imported machines and equipment. The advanced technology embedded in this imported machinery and equipment and the tacit knowledge brought into the host country by the foreign investors can lift the production technology level of the host economy and be transferred to local workers at foreign-owned firms through training (Lichtenberg and Pottelsbergh de la Potterie, 2001). Second, MNEs (Multinational Enterprises) are major players in global innovation activities. Advanced knowledge may spill over to local firms through the training of local staff in subsidiaries and joint ventures; skilled labour turnover from foreign to local-owned firms; demonstration effects when local firms learn by imitation; and knowledge transfer within the supply chain from foreign affiliates to their local suppliers and customers (Rodriguez-Clare, 1996; Fosuri, et al., 2001).

However, the adaptation and operation of foreign technology requires complementary skills. The benefits from international knowledge transfer are, therefore, subject to the absorptive capacity of the local firms and organisations (Cohen and Levinthal, 1989; Girma, 2005; Balasubramanayam, et al., 1996; Fu, 2008a). Absorptive capacity is the ability of an organisation to identify, assimilate and exploit knowledge from its surrounding environment (Cohen and Levinthal, 1989). The R&D intensities of local firms and, secondly, human capital are widely regarded as two major components of absorptive capacity. R&D activities of organisations are regarded as having two faces (Aghion and Howitt, 1992 and 1998; and Griffith et al., 2003). One is the widely acknowledged knowledge creation function; another is the role in learning and promoting 'absorptive capacity', given the fact that innovation is cumulative and path-dependent. It is argued that a certain level of R&D intensity is needed before firms benefit from FDI-generated externalities. Moreover, a threshold level of human capital has been found to be necessary if FDI is to generate growth-promoting effects (Balasubramanyam et al., 1996; Eaton and Kortum, 1996; Xu, 2000). Smaller plants or plants with a low share of skilled workers in the workforce lack the necessary absorptive capacity to benefit from FDI (Girma et al. 2001; Girma 2005). Using industry-level data relating to OECD countries, Kneller (2005) and Kneller and Stevens (2006) find that human capital is quantitatively more important to absorptive capacity than R&D, and that R&D matters only for the smaller OECD countries: in any case, here the evidence is less robust. Finally, absorptive capacity has also been proxied by the technology gap between the foreign and the domestic firms. Some studies find that spillovers are present when the technology gaps are moderate (Kokko et al, 1996). Girma and Gorg (2007) argue that the efficiency gap matters for productivity spillover benefits and that the relationship follows an inverted-U shape.

To analyse how a firm's absorptive capacity may affect the extent of the benefits which it might derive from global knowledge spillovers through FDI, following Jones (1995), we start from a standard production function as follows

$$Y = K^{1-\alpha}(AL_y)^{\alpha} \qquad (1)$$

and

$$\frac{\dot{A}}{A} = \delta L_A \quad (2)$$

where Y is output, A is productivity or knowledge, and K is capital. Labour is used either to produce output (L_y) or to search for new knowledge (L_A). Equation (2) reflects the R&D-based endogenous growth models.

Since the probability of producing new knowledge may increase with the level of A where A generates externalities, or decrease with the level of knowledge, we have

$$\dot{A} = \delta L_A^{\lambda} A^{\varphi} \quad (3)$$

where φ > 0 corresponds to positive external returns, φ < 0 represents the probability of innovation decreasing with the level of knowledge, and φ = 0 corresponds to constant returns to scale. λ reflects the possible overlap in research or the externalities occurring because of duplication in the R&D process. Rewriting (3) we have

$$\frac{\dot{A}}{A} = \delta L_A^{\lambda} A^{\varphi-1} \quad (4)$$

Labour dedicated research (L_A) can be proxied by a firm's investment in R&D, the spillovers of knowledge to the firm from other firms in the country, and spillovers of knowledge to the firm from other countries through trade and FDI. Therefore our extension of (4) will be

$$\frac{\dot{A}}{A} = \delta (L_{Am}^{\lambda} L_{Asd}^{\lambda} L_{Asf}^{\lambda}) A^{\varphi-1} \quad (5)$$

where L_{Am}^{λ} represents R&D investment in the firm and L_{Asd}^{λ} and L_{Asf}^{λ} represent assimilated knowledge spillovers from domestic and then foreign sources, respectively.

The possibility of imperfect spillovers of external knowledge, whether domestic or international, the degree of openness of both the firm and the industry to foreign trade and investment, and the varying absorptive capacities of different firms all affect the extent of the knowledge spillovers that are ultimately assimilated by a firm. In other words, the actual assimilated knowledge spillovers are a function of the R&D knowledge stock that may be spilled over, the openness of the firm and industry, and the absorptive capacity (*C*) of the firm. Hence, foreign R&D stock embodied in FDI is measured by an FDI-intensity weighted global R&D stock

$$S^f = R_f P \tag{6}$$

Assimilated foreign technological knowledge is therefore

$$L^{\lambda}_{Asf} = \eta (R_f P) C \tag{7}$$

where R_f is global knowledge stock; *P* is FDI-intensity at the firm and industry level; and *C* is the absorptive capacity of the firm. Grossman and Helpman (1991) predict that countries trading with R&D intensive countries will benefit more from international technology spillovers. It is probable that FDI from high-R&D home countries is likely to bring in relatively more technology than FDI from low-R&D countries. Distinguishing FDI by country of origin, we have

$$L^{\lambda}_{Asf} = \eta \sum_{k=1}^{n} P_k R_f C \tag{8}$$

where *k* denotes home country of FDI. Taking the logarithm of equation (5), our empirical model is therefore as follows[3],

$$\dot{p} = \delta' + \lambda_1' L_{Am} + \lambda_2' L_{Asd} + \lambda_3' L_{Asf} + \psi p_{t-1} + \tau_1 X + \tau_2 D + \varepsilon \tag{9}$$

Combining equations (8) and (9), we have

[3] According to Zheng (2008), equation (5) can be linearized around (1,1) following the Taylor expansion at first order approximation.

$$\dot{p} = \delta' + \lambda_1' L_{Am} + \lambda_2'(A_{Asd}) + \lambda_3' \sum_{k=1}^{n} P_k R_f C + \psi p_{t-1} + \tau_1 X + \tau_2 D + \varepsilon \tag{10}$$

where $\dot{p}$ is TFP growth, P is foreign investment to total asset ratio at firm and industry levels, X is a vector of control variables, D is the full set of time and sector dummies and ε is a random error term.

III. Methodology and data

We employ a two-step approach for the empirical test. First, we estimate total factor productivity (TFP) growth via a non-parametric frontier approach using the Malmquist index, and decompose it into technical progress and efficiency change. TFP is estimated for each industry separately allowing for different technology and production functions for different industries. Second, the impact of absorptive capacity is examined using econometric regressions. The estimated Malmquist TFP growth index and a decomposition of technical change and efficiency change are alternatively used as the dependent variable.

Estimation of TFP growth

The conventional technique for estimating TFP is the Solow residual method. It defines TFP growth as the residual of output growth after the contribution of labour and capital inputs have been subtracted from total output growth, based on a set of various assumptions. However, if these assumptions do not hold, TFP measurements will be biased (Coelli, 1996; Arcelus and Arocena, 2000). Given these limitations of the conventional approach, this paper estimates TFP growth by using a non-parametric programming method developed by Fare et al. (1994). Following Fare's approach, a production frontier is constructed based on all the existing observations. The distance of each of the observations from the frontier is estimated by using non-parametric programming methods. Technical efficiency is defined as the distance of each observation relative to the frontier. TFP growth is defined as a geometric mean of two Malmquist productivity indices. This approach, which is capable of measuring productivity in a multi-input, multi-output setting, does not require the assumptions of the Solow method (for example, the assumption that the production function is homogeneous across firms and industries) and hence avoids the corresponding problems of measurement.

The approach suggested by Fare et al. (1994) has another advantage in that it allows for the decomposition of productivity growth into two mutually-exclusive and exhaustive components: (1) efficiency change in movements towards (or away from) the frontier, which is a measurement of catching-up; and (2) technical change measured by shifts in the technological frontier. This decomposition of TFP growth enables us to investigate the impact of foreign and indigenous innovation efforts on technical progress and technological catch-up. Finally, according to Zheng (2008), the measurement of TFP in this approach coincides with the TFP growth rate defined in Jones (1995) which provides a natural way in which to bring the Malmquist TFP index into the growth function. The methodologies of estimation and decomposition are as follows.

Assuming a production technology S^t which produces a vector of outputs, $y^t \in R_+^M$, by using a vector of inputs, $x^t \in R_+^N$, for each time period t=1,…, T.

$$S^t = \left\{ \left(x^t, y^t\right): x^t \; can\; produce\; y^t \right\} \tag{11}$$

The output-based distance function at t is defined as the reciprocal of the 'maximum' proportional expansion of the output vector y^t, given inputs x^t

$$D_0^t\left(x^t, y^t\right) = \inf\left\{\theta : \left(x^t, y^t / \theta\right) \in S^t\right\} = \left(\sup\left\{\theta : \left(x^t, \theta y^t\right) \in S^t\right\}\right) \tag{12}$$

$D_0^t(x^t, y^t) \leq 1$ if and only if $\left(x^t, y^t\right) \in S^t$. $D_0^t(x^t, y^t) = 1$ if and only if $\left(x^t, y^t\right)$ is on the frontier. The output-based Malmquist productivity change index is defined as the geometric mean of two Malmquist productivity indices as follows

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\left(\frac{D_0^t\left(x^{t+1}, y^{t+1}\right)}{D_0^t\left(x^t, y^t\right)}\right)\left(\frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^t, y^t\right)}\right)\right]^{\frac{1}{2}} \tag{13}$$

Equation (13) represents the productivity of the production point $\left(x^{t+1}, y^{t+1}\right)$ relative to the production point $\left(x^t, y^t\right)$. A value greater than 1 indicates positive TFP growth in period t+1. When performance deteriorates over time, the Malmquist index will be less than 1.

Equation (3) can be rewritten as

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^t\left(x^t, y^t\right)} \times \left[\left(\frac{D_0^t\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_0^t\left(x^t, y^t\right)}{D_0^{t+1}\left(x^t, y^t\right)}\right)\right]^{\frac{1}{2}} \tag{14}$$

where technical change (TECHCH) $= \left[\left(\frac{D_0^t\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_0^t\left(x^t, y^t\right)}{D_0^{t+1}\left(x^t, y^t\right)}\right)\right]^{\frac{1}{2}}$ (15)

and catch-up (CATCH) $= \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^t\left(x^t, y^t\right)}$ (16)

Thus TFP change is decomposed into two components: technical change and catch-up. Technical change captures the shift in technology between the two periods. It indicates whether or not technical progress occurred at the input-output combination for a particular industry. Catch-up measures whether the production is getting closer to or farther away from the frontier. A value of more than 1 indicates catch-up with the frontier or technical progress. A value of less than 1 indicates deterioration in performance.

The Malmquist productivity index is estimated by using non-parametric linear-programming techniques, assuming k = 1,…., K industries using n = 1,…, N inputs $x_n^{k,t}$ at each time period t=1,…..T. Here inputs are used to produce m=1,……, M outputs $y_m^{k,t}$. To estimate the productivity change of each industry between t and t+1, we need to solve four different linear-programming problems for $D_0^t(x^t, y^t)$, $D_0^{t+1}(x^t, y^t)$, $D_0^{t+1}(x^{t+1}, y^{t+1})$ and $D_0^t(x^{t+1}, y^{t+1})$. The output-oriented LP problem for estimation of $D_0^t(x^t, y^t)$ under variable returns to scale is as follows[4]

$$
\begin{aligned}
&\left[d_0^t(x_t, y_t)\right]^{-1} = \max_{\phi,\lambda} \theta, \\
&\text{st} \quad -\theta y_{it} + Y_t\lambda \geq 0, \\
&\qquad x_{it} - X_t\lambda \geq 0, \\
&\qquad \lambda_i \geq 0, \qquad\qquad (17) \\
&\qquad \sum \lambda_i = 1, \quad i=1,\ldots,n.
\end{aligned}
$$

[4] The output distance function is reciprocal to the output-based Farrell measure of technical efficiency.

where θ is a scalar and λ is a nx1 vector of constants. The linear-programming problems for estimation of $D_0^{t+1}(x^t, y^t)$, $D_0^{t+1}(x^{t+1}, y^{t+1})$ and $D_0^t(x^{t+1}, y^{t+1})$ are similar to the above formulation with corresponding adjustments[5]. Output in our production function is measured by total firm output, inputs are capital as measured by net fixed assets, labour is measured by number of employees, and intermediate inputs are measured by variable costs. We use the output-oriented model under variable returns to scale in our estimation. Finally, to allow for the differences in production technologies across industries, TFP is estimated for each industry separately. Within each industry, each firm faces the same production frontier specific to this industry.

Empirical model

In its second stage, the empirical test examines the role of absorptive capacity in determining the benefits a firm may gain from international knowledge spillovers. Based on equation (10), the full empirical model is therefore as follows

$$\dot{p} = \delta' + \lambda_1' R_m + \lambda_2' R_d + \lambda_3' \sum_{k=1}^{n} P_k^m R_f C + \lambda_4' \sum_{k}^{n} P_k^{ind} R_f C + \psi p_{t-1} + \tau_1 X + \tau_2 D + \varepsilon \qquad (18)$$

where R_m is measured by firm-level R&D intensity, R_d is a vector of domestic R&D spillover variables at the industry level as measured by the proportion of R&D expenditure accounted for by different ownership types in each of the 171 three-digit industries. R_f is global R&D stock constructed from the OECD STAN database discussed below, P^m and P^{ind} are FDI intensity at firm- and industry-level, respectively. We conjecture that a firm might grow faster if it has easier access to foreign advanced knowledge through its foreign or ethnic[6] partners. We distinguish between foreign and ethnic capital because foreign and ethnic capital have different degrees of involvement in

[5] For details see Fare et al. (1994) and Coelli (1996).
[6] Ethnic capital refers to FDI from Hong Kong, Macao and Taiwan.

R&D and differential access to advanced technology in the global knowledge pool. Therefore, FDI is represented by two variables, the share of foreign and, secondly, ethnic capital at the firm-level.

C is the absorptive capacity variable. Following the normal measurement method used in the literature, *C* is measured by a firm's R&D intensity and training expenditure, alternatively. R&D intensity is proxied by the R&D to sales ratio; training expenditure is measured by the log of training expenditure per employee. The interaction terms of international industry-specific R&D stock, FDI intensity and absorptive capacity measure the international knowledge spillovers assimilated by the firms. We expect a significant positive coefficient for this variable if absorptive capacity is to exert a positive effect on knowledge spillovers. Note that, given the two faces of R&D as delineated by Griffith et al. (2003), R&D can also be viewed as a major tool for knowledge creation within a firm.

Other control variables consist of the initial level of technology efficiency, firm size, age, exports, intangible assets[7], and market concentration. These are hypothesised to affect the dependent variable. Such variables are chosen on the basis of the findings of the existing empirical literature (e.g. Bernard and Jensen, 1999; Aw, Chung and Roberts, 2000; Fu, 2005 and 2008b). Smaller firms and firms with exports are more likely to have faster TFP growth, technical change and efficiency improvements. Since technical efficiency is a relative performance measure, firms with higher levels of technical efficiency are less likely to grow as fast as other firms. There is no conclusive relationship between firm age/market concentration and firm's growth. For example, market competition may also

[7] According to Chinese *Accounting System for Business Enterprises*, costs to develop intangible assets are regarded as the R&D costs of autonomously-developed products that are registered giving rise to a legal right to the asset, such as a patent (Pacter and Yuen, 2001).

be a two-edged sword with respect to innovation. Geroski (1990) argues that a lack of competition in a market will give rise to inefficiency and result in sluggish innovative activity. On the other hand, the traditional Schumpeterian analysis claims that monopoly power makes it easier for firms to appropriate the returns from innovation and thereby provides the incentive to invest in innovation (Cohen and Levinthal, 1989; Symeonidis, 2001). Table 1 gives a precise definition of the variables used in the econometric analysis.

There are a number of control variables in the above specification that are arguably determined simultaneously with the dependent variable of TFP growth and its components. In other words, there might be a potential endogeneity problem, even after controlling for fixed effects. For example, firms with a relatively large number of R&D activities are more likely to have higher TFP growth and faster technical change than the others. However, it is possible that firms with higher growth rate might invest more in R&D activities to keep their technological advantages. Another example is the foreign capital share of a firm. Firms with a higher foreign capital share could have better access to foreign technology and therefore have higher growth rates, but there also might be a "cherry-picking" effect (Huang, 2003) in which foreign firms choose to invest in faster growing firms. Similar arguments can also be made in the case of export and ethnic capital participation.

In order to deal with the potential problem of endogeneity, we employ a fixed effects generalised method of moments (GMM) regression technique (see, inter alia, Hansen, 1982 and Arellano and Bond, 1991). The use of industry and region dummies in the regressions is designed to mitigate part of this potential endogeneity problem. Lagged values of the potentially endogenous variables are used as instruments. In addition, the shares of foreign and ethnic firms in the industry and region are also used as extra instruments. We assume that a sector might be more efficient than others if there are more foreign firms or ethnic firms participating in it, given the low level of competition from state-owned firms (Girma et al., 2009). We formally test whether the assumption of endogeneity is borne out by the data at hand and whether our instruments are relevant in the sense that they exhibit sufficiently strong correlations with the potentially endogenous variables. We also carefully test for the appropriateness of the instrumental variable candidates using Hansen's J test for overidentifying restrictions and use the Sargan test to examine the validity of the instruments. Reassuringly, we find that our instruments are appropriate on all counts.

Another issue to be taken into account is whether the residuals of the three equations are significantly associated with each other. Since the residuals are all performance indicators of the sampled firms, operating in one economic system, it is certainly possible for this to occur. If the residuals of the regressions are associated with each other, the three equations should be estimated in an equation system. Therefore, as a robustness check, we estimate the TFP, technical change and efficiency improvement regressions using a 3SLS equation systems technique which takes the endogeneity problem into account

Data

We draw on the Annual Report of Industrial Enterprise Statistics compiled by the State Statistical Bureau of China, covering all state-owned firms and other type of firms with annual turnover of over five million Renminbi ($0.6 million). The dataset includes variables such as firm ownership structure, industry affiliation, geographic location, year of establishment, employment, gross output, value added, fixed assets, exports, R&D and employee training expenditures[8]. The data currently available to us cover the 2001-2005 period, broadly classified into five ownership categories: (i) state-owned, (ii) collectively-owned, (iii) privately-owned, (iv) foreign-owned and (v) others. Foreign-owned firms are further sub-divided into, firstly, firms with investments from Hong Kong, Taiwan or Macao (so-called 'ethnic' firms) and, secondly, firms with investments from other foreign sources consisting mainly of investment from OECD countries. 'Other' firms (type (v) above) are mainly shareholding enterprises.

The final dataset consists of 269,905 observations from 53,981 firms. For our purposes, we select only those firms with a full set of observations during the sample period: estimation of TFP growth and its components using DEA analysis requires balanced datasets. The regression analysis of the technology spillovers from foreign firms through FDI includes only domestic firms. We do, however, use the full sample to construct various variables of interest: for example, the share of foreign firms in an industry or the Herfindahl index of market concentration.

Construction of global stock of knowledge

The global industry-specific knowledge stock is proxied by international research and development capital stock for each industry. It is estimated based on R & D expenditure data from the OECD's *Main Science and Technology Indicators.* Real R&D expenditures are nominal expenditures deflated by an R&D price index (PR), which is defined as PR = 0.5 P + 0.5W, where P is the implicit deflator for business sector output and W is an index of average business sector wages. This definition of PR implies that, half of R&D

[8] Nominal values are deflated using industry-specific ex-factory price indices obtained from the China Statistical Yearbook 2006.

expenditures are labour costs, which is broadly consistent with available data on the composition of R&D expenditures.

Following Coe and Helpman (1995), R&D capital stocks (R_f), which are defined here as stocks at the beginning of the period, were calculated from R&D expenditure (R) based on the following perpetual inventory model

$$R_{ft} = (1- \delta) R_{f(t-1)} + R_t$$

where δ is the depreciation or obsolescence rate, which was assumed to be 5, 10 and 15 percent, alternatively. The benchmark for R_f was calculated as $R_{f0} = R_0 / (g + \delta)$, following the procedure suggested by Griliches (1992), where g is the average annual logarithmic growth of R & D expenditures over the period for which published R & D data was available, R_0 is the first year for which the data was available, and R_{f0} is the benchmark for the beginning of the year. The domestic R&D capital stocks were converted into Euros at constant prices for the year 2000. The R&D stocks of the 22 OECD countries are then summed to proxy the world R&D stock. The estimated international industry-specific R&D stock is then linked to the Chinese firm-level data by industry and by year. The foreign R&D stock embodied in inward FDI is measured by FDI-intensity weighted R&D stock as discussed earlier.

Figure 1 reports the evolution of absorptive capacity in terms of R&D and training intensity of the Chinese firms over the 2001-2005 period. Evidence from the figure shows that there is a modest increase in absorptive capacity among Chinese firms over this period. R&D intensity among firms with R&D investment has risen from 1.6 to 2 percent.

Training expenditure per employee has increased from 206 RMB to 266 RMB within five years.

IV. Results

Figure 2 presents the estimated TFP growth, technical change and catch-up rates over the sample period. Overall, the Chinese manufacturing industries have experienced considerable TFP growth over the 2001-2005 period at an average annual growth rate of 4.5%. The main driver of this growth is the shift of technical frontier at an average annual rate of 4.3%, rather than any catch-up by follower firms. The electronics, transport equipment, special purpose machinery, chemical, petroleum, leather and textiles sectors are the leading industries that have experienced significant technical change of more than 10% average annual growth. Garments and furniture industries are the two sectors with the least technical change.

Table 2 reports both the OLS and the General Method of Moments (GMM) estimates of the base model including indicators of absorptive capacity and the control variables. Results from the Wu-Hausman specification test suggest significant endogeneity between R&D, exports and FDI on the one hand and the dependent variable on the other hand. The GMM estimation result is therefore preferred to the OLS estimates. The GMM estimates of both the R&D and training intensity variables are positive and statistically significant at the 1% level suggesting that these factors play a significant role in firm TFP growth. This may be due not only to the absorptive capacity function of R&D and training in terms of enabling firms to assimilate and operate new technologies, but also due to the knowledge-creation function of R&D activities.

With regard to the coefficients of the control variables, firms with better initial technical efficiency tend to grow slower. Smaller firms appear to enjoy faster TFP growth. Firms with high export-intensity and greater intangible assets have higher TFP growth than those who lack these characteristics. These estimated results are robust and statistically significant across different estimation methods. Firms with greater FDI intensity from foreign countries appear to enjoy faster TFP growth than other firms. However, the estimated coefficient is only statistically significant at the 10% level. Ethnic investment does not show any significant effect. Firm age does not appear to be a significant factor. Interestingly, high industry concentration and low levels of competition seem to increase firm productivity.

Table 3 reports the GMM estimates of the determinants of TFP growth using four alternative models. These four models are distinguished by the assumption made about the R&D stock in the production function. Model (1) assumes that there are no cross-border knowledge spillovers. Model (2) assumes that the global stock of R&D in the industry is common across countries. Model (3) assumes that the amount of knowledge inflow is moderated by an industry's and a firm's openness to FDI, but the FDI-intensity weighted global R&D stock is common to all firms, i.e., there is no difference in absorptive capacity among firms. As a robustness check, estimated results of international R&D spillovers at three alternative depreciation rates were applied. The estimated coefficients from different model specifications are consistent, suggesting that the estimated results are robust. Model (4) assumes heterogeneity in firms' absorptive capacity, i.e. firms' ability in assimilation and implementation of new technology are different and the international spillovers of foreign technology are therefore incomplete[9].

Estimated coefficients of the absorptive capacity variables, R&D intensity and training expenditure, are positive and statistically significant. These results are robust across the four models and with different R&D capital depreciation rates. Results from the four models also indicate that, without openness to FDI and absorptive capacity, the global knowledge stock does not have a significant effect on firm TFP growth (Model 2). With only openness to FDI but no absorptive capacity in local firms, international knowledge will impose a negative competitive pressure on the TFP growth of local firms (Model 3). The estimated coefficients of the FDI-intensity weighted global R&D stock variable are negative and statistically significant at the 5 or 1 percent significance level. This result is robust across regressions with different R&D depreciation rates.

Taking absorptive capacities of local firms into account, the negative competitive effect of the spillovers is reduced substantially or even turned into significant positive benefits (Model 4). The estimated coefficients of the interaction terms of absorptive capacity and FDI-weighted R&D stock change from negative to positive but remain statistically insignificant. Most interestingly, when R&D intensity is interacted with industry FDI-weighted R&D stock, the estimated coefficient not only changes to positive but is also statistically significant. This suggests that, in the presence of greater openness to FDI from high-R&D countries in an industry, the higher the absorptive capacity of a firm in terms of R&D intensity, the greater the benefits from international knowledge spillovers to a firm's TFP growth. Training expenditure also has the effect of reducing the negative

[9] Due to space limitations we will only report the results with a 10 percent R&D depreciation rate in later tables. Results of all the estimations are available from the authors subject to request.

competitive pressure on local firms brought about by inflows of foreign advanced technology embodied in FDI. Its effect, however, does not seem to be as strong as that of R&D intensity. On the other hand, in industries with a higher proportion of ethnic investment, R&D activities do not appear to be able to reduce the negative competition pressure. This may be explained by the fact that most ethnic investment goes into labour-intensive industries. R&D activities in these industries are not necessarily the most efficient way to promote TFP growth.

The effects of the control variables are similar to those in the basic model discussed earlier for Table 2. Moreover, R&D spillovers from other domestic industries appear to have a positive and significant effect on TFP growth, while R&D spillovers from foreign affiliates in China have exerted a significant depressing effect on the TFP growth of local firms. This is likely due to the competition effect discussed in Hu and Jefferson (2002) and Fu and Gong (2008).

Table 4 reports the estimated results of the role of absorptive capacity in technical change and catch-up. Section A reports the estimated results in the technical change equation and section B reports the results of the catch-up equation. Given the way in which technical change (frontier shift) and catch-up are estimated from decomposed TFP, the estimated coefficients of the same explanatory variable are often of different signs. This is because if one factor plays a significant role in pushing up the frontier, it will consequently have an opposite effect on closing the gap between the frontier and the followers (the catching-up effect).

Results from Table 4 suggest that both R&D-intensity and training expenditure in individual firms, on their own, contribute significantly to the catch-up process but not to any upward shift of the technology frontier. This suggests that the type of R&D and training activities in China in individual firms serve mainly as a driver of absorptive capacity, enabling firms to absorb frontier technology and catch-up with the leaders. The common global R&D stock, which is assumed universal to all industries and all firms, has not shown significant effect on technical change and catch-up. In one case, it even shows a significant negative effect on catch-up of the indigenous firms. However, taking into account the openness of the industry to FDI[10] and the absorptive capacity of individual firms, the estimated results suggest that absorptive capacity has enabled firms in industries with greater openness to FDI from high-R&D countries to produce major technical change and shift up the technology frontier. The interaction term of absorptive capacity and industry foreign FDI-weighted R&D stock bears a positive sign and is statistically significant at the 1% level. This is the case for both R&D and training as sources of absorptive capacity. The magnitude of the estimated coefficients is around 0.02 to 0.06, which is not a small value compared to the estimated coefficients of other variables included in the model. On the other hand, R&D and training have also enabled firms in industries with greater FDI intensity from ethnic investors to absorb superior (though not most advanced) technology to catch-up with the leaders on the frontier. The estimated coefficient of the interaction term of absorptive capacity and industry ethnic FDI-weighted R&D stock is positive and statistically significant.

With regard to the control variables, larger firms appear to enjoy greater technical change. Firms with more exports are doing better in the catch-up process. Moreover, greater

[10] Since the estimated coefficients of the firm-level FDI-intensity weighted R&D stock are not significant with a very small magnitude of almost zero, we drop the two interaction terms involving firm-level FDI intensity from the regression.

competition fosters innovation and therefore greater technical change. Finally, collective R&D activities by indigenous firms serve as a significant driver of technical change for indigenous firms while R&D activities in foreign affiliates have exerted a significant negative impact on technical change and frontier movement in local firms. There are two possible reasons for this. First, foreign R&D labs have imposed strong competitive pressures on local firms by attracting talents which lead to an internal problem of brain drain for local firms. Second, these top local talents are mostly employed to undertake R&D into ways of adapting the existing products of MNEs to local markets. These research activities into the adaptation of existing technology, however, do not contribute to the development of the technology frontier. On the other hand, the created technologies may be superior to existing local technology and so could have a positive effect on catch-up in follower firms.

Robustness check using equation systems

Table 5 reports the results of robustness checks using simultaneous equation systems for the TFP, technical change and catch-up equations. The estimated results are broadly consistent with the estimates using GMM; the sign, magnitude and level of statistical significance of the estimated coefficients are very similar to those of the GMM estimates. All this evidence reinforces our earlier findings that absorptive capacity has played an important role in capturing the benefits from global knowledge spillovers, although the exact role of such benefits in technical change and catch-up depends on the type of FDI since this determines what type and quality of knowledge may spill over.

V. Conclusions

This paper attempts to explore the role of absorptive capacity in determining the ultimate benefits to firms of global knowledge spillovers, using a linked China-OECD database. The paper uses non-parametric frontier analysis for the estimation and decomposition of TFP growth. Findings from this research suggest that, in a developing country such as China, although collective indigenous R&D serves as a major driver of technical progress of indigenous firms, R&D activities in individual firms mainly serve as a source of absorptive capability. The contribution of R&D to productivity growth varies according to the type of FDI and hence level of advancement of spilled-over knowledge, as well as the extent of FDI openness. With greater absorptive capacity, firms can effectively assimilate the spillovers of the most advanced knowledge which has been generated through greater openness to FDI from industrialized countries. These benefits will result in major technical change that pushes out the production frontier. On the other hand, greater absorptive capacity will also enable firms to benefit significantly from assimilating superior technological knowledge spilled over from the international knowledge pool through ethnic FDI which accelerates the catch-up process.

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Figure 1. Dynamics of the absorptive capacity of Chinese firms: 2001-2005

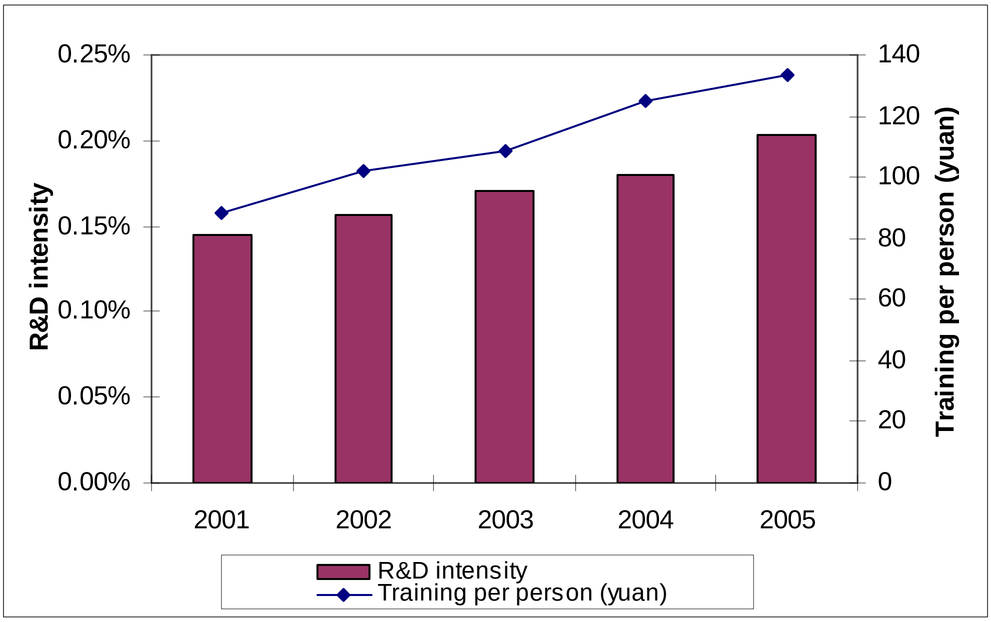

Figure 2. TFP changes of Chinese firms by industry, 2001-2005

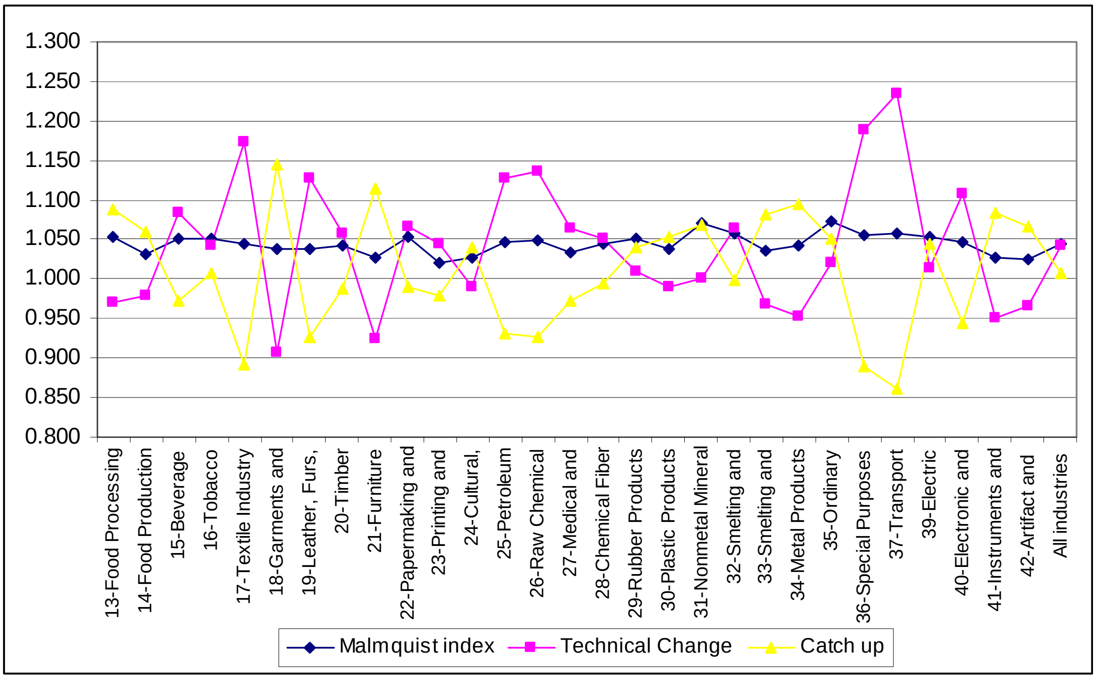

TABLE 1
Summary statistics of the variables

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
R&D intensity	The ratio of R&D expenditure to total sales	269,905	0.0017	0.0118	0	1
Training expenditure per person	Log value of training expenditure per person	269,891	0.0834	0.1734	0	4.0108
Age	Log value of age	269,905	2.6242	0.6989	0.6931	5.1874
Employment	Log value of employment	269,905	5.2039	1.1096	0.6931	11.9031
Intangible asset per person	Log value of intangible assets per person	269,900	0.9052	1.3799	0	9.0027
Exports	Log value of export sales	269,905	3.3919	4.7273	0	18.0558
Foreign MNE	Share of foreign capital	269,905	0.0905	0.2610	0	1
Ethnical MNE	Share of ethnic capital	269,905	0.1053	0.2841	0	1
Domestic R&D spillovers from local firms	Proportion of R&D expenditure accounted for by local firms	269905	10.74963	1.824661	0	15.47567
Domestic R&D spillovers from foreign invested firms	Proportion of R&D expenditure accounted for by foreign invested firms	269905	7.762833	2.658609	0	13.82531
Domestic R&D spillovers from ethnic invested firms	Proportion of R&D expenditure accounted for by ethnic invested firms	269905	8.142533	2.704527	0	14.67106
Market concentration	Herfindahl index (three-digit industry)	269905	0.0196	0.0266	0.0017	1
TFP growth		269905	0.8811	0.5825	0	11.391
Catch up rate		269905	0.9924	0.9231	0	16.25
Technical change		269905	1.0258	0.9639	0	7.905
TE_initial	Initial technical efficiency level	269905	0.3965	0.2043	0.013	1

TABLE 2
Absorptive capacity and TFP growth: the base model

	GMM		OLS	
	R&D	Training	R&D	Training
Initial TE	-0.196***	-0.200***	-0.159***	-0.164***
	(0.007)	(0.007)	(0.0046)	(0.0046)
Age	-0.0208***	-0.0201***	-0.0177***	-0.0182***
	(0.0012)	(0.0012)	(0.0008)	(0.0008)
Employment	0.001	0.001	0.002	0.001
	(0.0017)	(0.0017)	(0.0011)	(0.0011)
Market Competition	0.181***	0.189***	0.159***	0.158***
	(0.0536)	(0.0536)	(0.039)	(0.0389)
Intangible Asset	0.0054***	0.0052***	0.0050***	0.0041***
	(0.0009)	(0.0009)	(0.0006)	(0.0006)
Exports	0.0012***	0.0011***	0.0024***	0.0023***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Foreign Share	0.0564*	0.0573*	0.036	0.0374*
	(0.0299)	(0.03)	(0.0219)	(0.0217)
Ethnic Share	0.012	0.011	0.001	0.002
	(0.0214)	(0.0214)	(0.016)	(0.016)
R&D Intensity	1.050***		-0.359***	
	(0.291)		(0.0674)	
Training		0.0670***		0.0654***
		(0.008)		(0.0066)
Constant	1.265***	1.260***	0.152***	0.155***
	(0.0087)	(0.0086)	(0.0054)	(0.0053)
Observations	158280	158265	197918	197908
R-squared	0.014	0.017	0.573	0.574
Exogenous test	0	0		
Hansen J test	0.452	0.413		

Notes: 1. Robust standard errors in parentheses
2. *significant at 10%; ** significant at 5%; *** significant at 1%
3. All specifications include the full set of time and two-digit industry dummies.

TABLE 3

Absorptive capacity, technology spillovers and TFP growth

	Model 1	Model 2	Model 3			Model 4	
	No cross border spillovers	Common spillovers	Common spillovers of FDI-weighted global R&D stock			Imperfect international spillovers	
			5% depreciation	10% depreciation	15% depreciation	R&D	Training
Initial TE	-0.203***	-0.199***	-0.188***	-0.193***	-0.199***	-0.194***	-0.201***
	(0.0071)	(0.0071)	(0.0073)	(0.0072)	(0.0071)	(0.007)	(0.0071)
Age	0.0004	0.0005	0.0027	0.0015	0.0011	0.0007	0.0015
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Employment	-0.0220***	-0.0209***	-0.0218***	-0.0216***	-0.0215***	-0.0207***	-0.0189***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Competition	0.161***	0.158***	0.133**	0.135**	0.135**	0.151***	0.153***
	(0.056)	(0.056)	(0.059)	(0.058)	(0.058)	(0.0561)	(0.0564)
Intangible Asset	0.0047***	0.0049***	0.0050***	0.0050***	0.0050***	0.0057***	0.0060***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Exports	0.0011***	0.0013***	0.0015***	0.0014***	0.0014***	0.0014***	0.0014***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Foreign Share	0.246***	0.0591**	0.556***	0.561***	0.560***	0.0505*	0.0573*
	(0.073)	(0.0301)	(0.21)	(0.2)	(0.2)	(0.0306)	(0.0314)
Ethnic Share	0.171**	0.0128	0.473**	0.491**	0.484**	0.0190	0.0131
	(0.075)	(0.0214)	(0.21)	(0.22)	(0.21)	(0.0219)	(0.0219)
Domestic R&D %	0.0042***	0.0042***	0.0030***	0.0034***	0.0031***	0.0041***	0.0040***
	(0.001)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
Ethnic R&D %	-0.0007	-0.0007	0.0001	0.0000	0.0001	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Foreign R&D %	-0.0024***	-0.0023***	-0.0016**	-0.0019**	-0.0016**	-0.0023***	-0.0021***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
R&D Intensity	0.937***	1.122***	1.059***	0.943***	0.943***	1.353***	
	(0.28)	(0.371)	(0.34)	(0.29)	(0.28)	(0.418)	
Training	0.0727***	0.0763***	0.0739***	0.0726***	0.0730***		0.125***
	(0.0083)	(0.0084)	(0.0087)	(0.0084)	(0.0083)		(0.0109)
R_f		-0.0020**					
		(0.0010)					
$R_f * P_{firm(foreign)}$			-0.0130**	-0.0145**	-0.0148**		
			(0.0065)	(0.0069)	(0.0071)		
$R_f * P_{firm(Ethnic)}$			-0.0176**	-0.0198**	-0.0201**		
			(0.0081)	(0.0095)	(0.0096)		
$R_f * P_{industry(foreign)}$			-0.0060***	-0.0053***	-0.0059***		
			(0.0018)	(0.0018)	(0.0018)		
$R_f * P_{industry(Ethnic)}$			-0.0012	-0.0006	-0.0009		
			(0.0019)	(0.0018)	(0.0018)		
$R_f * P_{firm(foreign)} * C$						0.0000	0.0000
						(0.0000)	(0.0000)
$R_f * P_{firm(Ethnic)} * C$						-0.000**	0.0000
						(0.0000)	(0.0000)
$R_f * P_{industry(foreign)} * C$						0.0085***	-0.0024
						(0.0026)	(0.0017)
$R_f * P_{industry(Ethnic)} * C$						-0.0142***	-0.0019
						(0.0035)	(0.0018)
Constant	1.277***	1.271***	1.336***	1.325***	1.333***	1.241***	1.236***
	(0.011)	(0.0114)	(0.023)	(0.022)	(0.022)	(0.0119)	(0.0118)
Observations	158272	157640	150851	155885	158272	157693	156973
R-squared	0.01	0.015	0.01	0.01	0.01	0.014	0.018
Exogenous test	0	0	0	0	0	0	0
Hansen J test	0.5962	0.5113	0.4766	0.6451	0.4231	0.4324	0.4156

Note: 1. Robust standard errors in parentheses

2. *significant at 10%; ** significant at 5%; *** significant at 1%

3. All specifications include the full set of time and two-digit industry dummies.

TABLE 4

The role of absorptive capacity in technical change and catch up

	Section A: Technical change				Section B: Catch up effect			
	R&D		Training		R&D		Training	
	Common	Incomplete	Common	Incomplete	Common	Incomplete	Common	Incomplete
Initial TE	-0.187***	-0.189***	-0.184***	-0.185***	-0.484***	-0.483***	-0.489***	-0.489***
	(0.0077)	(0.0076)	(0.0077)	(0.0077)	(0.0105)	(0.0105)	(0.0105)	(0.0106)
Age	0.0031	0.0022	0.0033	0.0027	0.0034	0.0038	0.0032	0.0040
	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Employment	0.0160***	0.0155***	0.0161***	0.0151***	0.0020	0.0025	0.0017	0.0032*
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Competition	-0.0935	-0.125*	-0.0957	-0.125*	0.0409	0.0542	0.0568	0.0666
	(0.064)	(0.0647)	(0.064)	(0.0655)	(0.0936)	(0.0938)	(0.0934)	(0.0942)
IntangibleAsset	-0.0043***	-0.0045***	-0.0040***	-0.0046***	0.0004	0.0007	-0.0002	0.0007
	-0.0010	-0.0010	-0.0010	-0.0010	-0.0013	-0.0013	-0.0013	-0.0014
Exports	-0.0003	-0.0003	-0.0003	-0.0002	0.0014**	0.0014***	0.0012**	0.0012**
	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005
Foreign Share	0.046	0.043	0.0457	0.0442	-0.0148	-0.0137	-0.013	-0.0109
	-0.0316	-0.0314	-0.0316	-0.0316	-0.0457	-0.0456	-0.0458	-0.0459
Ethnic Share	-0.0157	-0.0149	-0.0161	-0.0155	-0.0568*	-0.0575*	-0.0545	-0.0555
	-0.0239	-0.0239	-0.0239	-0.024	-0.0343	-0.0343	-0.0343	-0.0345
Domestic R&D share	0.0064***	0.0054***	0.0065***	0.0056***	-0.0053***	-0.0049***	-0.0051***	-0.0049***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Ethnic R&D share	-0.0005	0.0007	-0.0005	0.0005	0.0000	-0.0004	-0.0002	-0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Foreign R&D share	-0.0086***	-0.0088***	-0.0086***	-0.0091***	0.0031***	0.0034***	0.0031***	0.0036***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
R&D Intensity	-0.239	-0.194			1.681***	1.824***		
	(0.212)	(0.217)			(0.451)	(0.492)		
Training			-0.0411***	-0.0616***			0.0506***	0.0882***
			(0.0081)	(0.0103)			(0.0116)	(0.0149)
R_f	-0.0002		-0.0002		-0.0033***		0.0000	
	(0.0008)		(0.0006)		(0.0012)		(0.0007)	
$R_f * P_{industry(foreign)} * C$		0.0630***		0.0196***		-0.0357***		-0.0127***
		(0.0036)		(0.0022)		(0.0043)		(0.0028)
$R_f * P_{industry(Ethnic)} * C$		-0.0729***		-0.0191***		0.0338***		0.0102***
		(0.0046)		(0.0025)		(0.0054)		(0.003)
Observations	157648	157693	157633	156973	157648	157693	157633	156973
R-squared	0.689	0.689	0.689	0.689	0.407	0.407	0.408	0.409
Exogenous test	0	0	0	0	0	0	0	0
Hansen J test	0.286	0.312	0.347	0.211	0.4471	0.4504	0.4132	0.3856

Note: 1. Robust standard errors in parentheses. 2. *significant at 10%; ** significant at 5%; *** significant at 1%.
3. All specification include the full set of time and two-digit industry dummies. 4. Results for the constant are not reported here due to space limitations.

TABLE 5
Estimated results using equation systems method

	TFP Growth				Technical Change		Catch Up Effect	
	R&D		Training		R&D	Training	R&D	Training
Initial TE	-0.195***	-0.195***	-0.201***	-0.203***	-0.188***	-0.184***	-0.484***	-0.490***
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0075)	(0.0075)	(0.0096)	(0.0097)
Age	0.0010	0.0009	0.0005	0.0017	0.0021	0.0025	0.0039	0.0040
	(0.0017)	(0.0017)	(0.0016)	(0.0017)	(0.0020)	(0.0020)	(0.0026)	(0.0026)
Employment	-0.0216***	-0.0212***	-0.0219***	-0.0196***	0.0158***	0.0154***	0.0023	0.0030
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0018)	(0.0018)
Competition	0.158***	0.151***	0.165***	0.152***	-0.125**	-0.124**	0.0555	0.0618
	(0.0455)	(0.0455)	(0.0454)	(0.0456)	(0.0557)	(0.0559)	(0.0717)	(0.0718)
Intangible Asset	0.0056***	0.0058***	0.0050***	0.0059***	-0.0044***	-0.0045***	0.0006	0.0008
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0013)	(0.0013)
Exports	0.0013***	0.0013***	0.0011***	0.0013***	-0.0001	-0.0001	0.00130**	0.00113**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Foreign Share	0.249***	0.245***	0.237***	0.241***	-0.0991	-0.1	0.137	0.13
	(0.0649)	(0.0646)	(0.0648)	(0.0647)	(0.079)	(0.0794)	(0.102)	(0.102)
Ethnic Share	0.162***	0.162***	0.172***	0.162***	-0.112	-0.116	-0.0198	-0.0067
	(0.0593)	(0.0593)	(0.0592)	(0.0592)		(0.0727	(0.0934	(0.0725)
Domestic R&D share	0.0045***	0.0042***	0.0045***	0.0040***	0.0053***	0.0056***	-0.0050***	-0.0051***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0012)	(0.0012)	(0.0017)	(0.0017)
Ethnic R&D share	-0.0008	-0.0005	-0.0008	-0.0004	0.0008	0.0006	-0.0005	-0.0006
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Foreign R&D share	-0.0024***	-0.0023***	-0.0024***	-0.0022***	-0.0088***	-0.0091***	0.0034***	0.0037***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0011)	(0.0011)
R&D Intensity	1.173***	1.358***			-0.197		1.838***	
	(0.175)	(0.183)			(0.223)		(0.287)	
Training			0.0767***	0.136***		-0.0614***		0.0975***
			(0.0067)	(0.0085)		(0.0104)		(0.0134)
R_f	-0.0010		0.0008					
	(0.0007)		(0.0005)					
$R_f * P_{industry(foreign)} * C$		0.0084***		-0.0026	0.0631***	0.0197***	-0.0357***	-0.0126***
		(0.0030)		(0.0017)	(0.0037)	(0.0021)	(0.0050)	(0.0027)
$R_f * P_{industry(Ethnic)} * C$		-0.0141***		-0.0018	-0.0731***	-0.0192***	0.0338***	0.0101***
		(0.0040)		(0.0019)	(0.0044)	(0.0023)	(0.0057)	(0.0030)
Observations	157648	157693	157633	156973	157693	156973	157693	156973
R-squared	0.014	0.013	0.016	0.017	0.689	0.689	0.407	0.409

Note: 1. Robust standard errors in parentheses. 2. *significant at 10%; ** significant at 5%; *** significant at 1%
3. All specifications include the full set of time and two-digit industry dummies. 4. Results for the constant are not reported here due to space limitations.