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Abstract

This paper explores the drivers of technology upgrading in emerging economies using a recent Chinese firm-level panel dataset over the 2001-2005 period. It extends the Directed Technical Change theory by considering differences in technology intensities across industries within a country; examines the drivers of technical change, efficiency improvement and TFP growth in Chinese manufacturing firms; and explores the roles of indigenous innovations and foreign technology. It finds that FDI contributes to static industry capabilities by advanced technologies embedded in imported machineries, but not to dynamic technological capabilities of indigenous firms in developing countries. Collective indigenous R&D activities at industry level are the major driver of technology upgrading of indigenous firms that push up the technology frontier. Policy implications are discussed.

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I. Introduction

Technology upgrading is a key element of industrialisation in developing countries. Technology transfer through foreign direct investment (FDI) has for long been regarded as a major engine of this process. Many developing countries joined the competition for FDI with the expectation that advanced technological and managerial knowledge embedded in FDI can build up the technological capabilities in their country and drive the technological upgrading in these economies. Although studies in favour of openness and globalisation argue that FDI can serve as an important catalyst for technological change in developing countries, the advocates of globalisation seem to assume that the private interests of multinationals do not diverge from the social interests of the host countries. (Lall and Urata, 2003). In fact, higher up a country moves up the industrial ladder, the more important would be local capabilities and innovation. While FDI can facilitate the development of basic operational capabilities, they "may be less efficient means of deepening capabilities" (Lall, 2003).

There is also a crucial issue of the "appropriateness" of the technologies. The Appropriate Technology (AT) theory suggests that technologies are specific to particular combinations of inputs (Stewart, 1983; Basu and Weil, 1998; Los and Timmer, 2005), and technological progress is "localized learning by doing" (Atkinson and Stiglitz, 1969). New technology is only 'appropriate' for countries that produce according to technologies similar to the innovator's technology, whereas other countries will not benefit from the new technology. Moreover, the Directed Technical Change (DTC) theory argues that technologies will be designed to make optimal use of the conditions and factor suppliers in the country where the technology is developed. These technologies are often capital or skilled-labour augmenting. Therefore, these advanced technologies, transferred to the developing countries through trade or FDI, will be inappropriate to the conditions in the South and therefore less productive (Acemoglu, 2002). Therefore, the debate on the importance of foreign versus indigenous innovation efforts is inconclusive.

Can the developing countries reply on foreign technology to catch up with the industrialised countries? What are the major drivers of technological upgrading in developing countries? This paper attempts to address this question by extending the DTC theory to the industry level. It assumes that (1) developing countries, especially middle-income countries, are not only users but also creators of new technology in certain industrial sectors; and (2) the industry structure in these countries is far less specialised than the Heckscher-Ohlin trade model suggests and it often consists of a diverse mixture of industries of different technology intensities. These assumptions are valid because middle-income countries have large domestic markets, substantial volumes of human capital, and a strong desire for economic independence. The study uses China as a case study. China provides a good case for this study giving the huge FDI inflows into her economy and a renewed emphasis on indigenous innovation for technology capabilities building in developing countries in recent years.

The paper uses a firm-level panel dataset of 56,125 Chinese firms over the 2000-2005 period. Non-parametric frontier technique is used to decompose TFP growth of firms into technical change and efficiency improvement. The drivers of these changes and catch-up will be explored with special reference to the impact of indigenous and foreign R&D efforts. Unlike most of the existing studies that estimate total factor productivity (TFP) using a single unchanging production function across industries, this study allows for the differences in production technology across industries, and TFP is estimated for each industry separately. We consider three types of R&D efforts: R&D by individual firms, R&D spillovers from foreign and indigenous firms in the same industry, and international R&D spillovers through FDI. To test the third type of foreign R&D efforts, international industry specific R&D stock is linked to the Chinese firm-level data in corresponding industry and adjusted by industry- and firm-level openness.

This paper is organised as follows: Section II presents the theoretical framework for understanding the drivers of technological upgrading in a middle income developing country. Section III provides a brief overview of FDI and innovation in China. Section IV discusses data, model and methodology. Section V presents empirical evidence. Section VI concludes with some policy implications.

II. Theoretical framework

Existing literature focuses almost exclusively on "aggregate technological change", ignoring the bias and direction of technology. According to the Directed Technical Change theory (Acemoglu, 2002), technologies will be designed to make optimal use of the conditions and factor suppliers in the country where the technology is developed. Most new technologies are invented and developed in industrial countries, e.g. OECD countries, which are abundant in skilled labour. Therefore, these new technologies developed in industrialised countries are "optimised" for their factor proportions and use and rely on the skilled labour, e.g., engineers, managers and other professionals. In other words, technology developed in industrialised countries may be capital augmented or skilled-labour augmented. Many developing countries use technologies developed in the North, but the factor endowments in the South are significantly different from that in the North. Therefore, these advanced technologies, no matter whether imported or transferred through FDI, will be inappropriate to the conditions in the South and therefore less productive (Acemoglu and Zilibotti, 2001; Acemoglu, 2002). This is also consistent with the argument by Atkinson and Stiglitz (1969), David (1975), Stewart (1978) and Basu and Weil (1998) that imported technologies may not be "appropriate" to the needs of the developing countries (South). The extent of directed technical change will determine how inappropriate technologies used by the South are to their needs.

Moreover, as endowments in the developing countries are different across countries and across regions within a nation, and the demand for skills varies across industries, the degree of appropriateness of foreign technology for productivity growth in the developing countries depends on the characteristics of the country, the region and the specific industry sector that we study. In a country that is abundant with unskilled and semi-skilled labour, foreign technology maybe the least appropriate for the labour-intensive low-technology sector. The appropriateness of foreign technology may increase along the technology hierarchy in the industry categories, and become relatively appropriate in the high-technology (technology-intensive) industry. Since developing countries possess abundant unskilled and semi-skilled labour, indigenous technology will be biased towards that which is labour and labour-augmenting.

Both the theories on appropriate technology and direct technical change provide an in-depth explanation of the productivity/growth differences between countries. However, they focus on either the capital-labour ratio or the unskilled-skilled labour ratio of a country and neglect the industry structure of an economy which may have different technology and skills intensity. In reality, countries are far less specialised in particular sorts of goods than 'old' trade theory (Richardian as well as Heckscher-Olin) suggests. The economies, especially in the middle-income economies, may have upgraded to undifferentiated or differentiated sectors featured by specialisation and economies of scale, and hence a diverse mixture of goods being produced. This requires an extension of the direct technical change theory to industry/sector level.

Technologies created in labour-abundant countries may be un-skilled labour augmenting. In low-technology industries that use un-skilled labour intensively, labour-augmenting indigenous technology will be more pro-productivity than foreign technology. Moreover, foreign technology from industrial countries will be skilled-labour augmenting. In the high-technology sector that uses technology intensively, foreign technology may be more pro-productivity than indigenous technology.

For the same relative factor prices, the gains from introducing new techniques is higher the larger the volume of demand. This would indicate that countries such as China, Brazil and India are more likely to generate 'intermediate' technology than smaller economies with the same degree of capital scarcity (Findlay, 1978). Moreover, the middle-income countries have accumulated a pool of knowledge and skills, which distinguishes their factor endowments from that of the least developing countries as well as that of the industrialised countries. Therefore, the middle-income large economies are more likely to generate 'intermediate' innovations with medium-level technology intensity. These middle-income countries can reap the gains from investment in such technologies by sale of patents, payment of royalties or South-South direct foreign investment in smaller developing countries. Given the disparities in financial and human capital across different regional or economic / social groups in these large middle-income countries, this intermediate technology will be generated by the relative skill and capital-rich group of firms in these economies.

Foreign innovation efforts and knowledge spillovers through FDI

With increasing openness to the world economy, a country may benefit from foreign technology transfer. Foreign direct investment (FDI) is one of the major channels for it. FDI contributes to technological upgrading in the host economy in several ways. First, advanced technology embedded in the imported machinery and equipments can lift the level production technology of the host economy. Second, R&D and other forms of innovation generated by foreign firms and R&D labs of MNEs increases the innovation outputs in the country directly (Athreye and Cantwell, 2007). When the operations of MNEs in host countries move from cost-based towards the supply of higher-value parts, their R&D activities may eventually accede to locally integrated laboratory status. Moreover, successful innovation requires more than just brilliant scientists. It involves, from top management to employees in its R&D, finance, production and marketing divisions. It requires high-quality decision-making, long-range planning, motivation and management techniques, coordination, and efficient R&D, production and marketing. Therefore, the innovation performance of a firm is determined not only by 'hard' factors such as R&D manpower and R&D investment, but also by certain 'soft' factors such as management practices and governance structures (Aghion and Tirole, 1994; Bessant et al., 1996; and Cosh, et al., 2004). MNEs are more experienced in innovation management. They may contribute to the local innovation system by bringing in advanced management practices and thus improve the innovation efficiency of local innovation system (Fu, 2008). Finally, technological spillovers from foreign innovation activities may influence technical change and catch-up of the indigenous firms. Knowledge spillovers from foreign to local firms may take place through knowledge transfer within the supply chain; skilled labour turnovers; demonstration effects when local firms are learning by imitation; and competition effects when the competitive pressure caused by foreign presence forces the local firms to improve their production technology and management.

However, foreign R&D activities may also crowd out domestic innovation activities as they attract the most talented researchers and compete in the markets of innovation products which threaten local firms, SMEs in particular (Aghion et al., 2005; Fu, 2004a and 2007; UNCTAD, 2005b). In the Chinese electronics industry, Hu and Jefferson (2002) find significant productivity depression rather than positive spillover effects of FDI on domestic firms. Moreover, knowledge transfer via supply chain requires effective linkages between foreign firms and local suppliers and customers (Balasubramanayam, et. al., 1996; Fu, 2004b). Thirdly, significant spillovers from FDI on local firms are also subject to sufficient absorptive capacity of the local firms and organisations (Cohen and Levinthal, 1989; Girma, 2005; Fu, 2008). The efficiency gap matters for productivity spillover benefits where the relationship follows an inverted-U shape (Girma and Gorg, 2007). Finally, the type of FDI has markedly different productivity spillover effects (Driffield and Love, 2007). Empirical evidence on the actual extent of spillovers from MNEs to domestic firms is, however, mixed (Blomstrom and Kokko, 1998; Aitken and Harrison, 1999; Kathuria, 2000; Liu et al, 2000; Gorg and Greenaway, 2001; Jovorcik, 2004). Given the fact that foreign investors in China are mostly market- or resource- or cheap labour-seeking processing types, R&D spillovers from foreign invested firms are likely to be limited.

III. FDI and innovation in China

Since it launched the economic reforms and invited foreign capital participation in its economy in 1979, China has received a large volume of international direct investment flows and stands as the second largest FDI recipient in the world. In 2004 FDI inflows into China reached a historical peak of US60.63 billion[1]. The sources of inward FDI in China have also evolved over time. While investment from overseas Chinese in Hong Kong, Macao and Taiwan were the major sources of inward FDI in the 1980s, the 1990s has seen increasing inward FDI from the major industrialised countries and other OECD countries.

As one of the important drivers of competitiveness, innovation efforts in China have grown rapidly during the past two decades. The total R&D expenditure in China has grown from 7.4 billion Yuan in 1987 to 300.3 billion Yuan in 2006, with an average annual growth rate of 15 percent[2]. Since late 1990s, with the increasing globalisation in innovation, R&D activities of foreign firms in China have been increasing, at a

[1] Source: Chinese Statistical Yearbook, various issues.
[2] Source: Ministry of Science and Technology of China, www.most.org.cn.

faster pace than that of the domestic firms. The average annual growth of R&D expenditure over the 1998 to 2004 period was 38 and 33 percent in foreign invested enterprises and Ethnic Chinese invested firms[3], respectively. This is much higher than that in indigenous firms at 25 percent over the same time period. In 2004, the number of foreign firms was about one third of China's total number of enterprises. Although the R&D expenditure and R&D staff of the foreign firms accounted for only 27 percent and 18 percent of China's total industrial R&D expenditure and R&D staff, innovation outputs by foreign firms in terms of percentage of total sales of new products and the percentage of invention patent application by foreign firms were both more than 40 percent[4].

IV. Data and methodology

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 data set includes variables such as firm ownership structure, industry affiliation, geographic location, establishment year, employment, gross output, value added, fixed assets, exports, R&D and employee training expenditures.[5] The data currently available to us cover the period 2001 to 2005 broadly classified under five ownership categories: (i) state-owned (ii) collectively-owned (iii) privately-owned (iv) foreign-owned and (v) others. Foreign-owned firms are further divided into firms that with investments from

3 Ethnic Chinese invested firms refer to foreign firms which have owners from Hong Kong, Macao and Taiwan.

4 Source: The First Economic Census of China, 2004.

5 Nominal values are deflated using industry-specific ex-factory price indices obtained from China Statistical Yearbook 2006.

Hong Kong, Taiwan and Macro investors (so-called Ethnic firms) and from other foreign sources (FIEs). "Other" firms are mainly shareholding enterprises. Following the standard used by the Eurostat Dataset, we divided the technological categories into four groups; High-tech, Middle-High, Middle-low and Low-tech[6].

The final data set consists of 269,905 observations from 53,981 firms, we include only those firms with the full set of observations during the sample period as 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 the domestic firms. We, however, use the full sample to construct various variables of interest, for example the share of foreign firms in an industry-region or the Herfindahl index of market concentration.

International industry specific R&D stock is linked explicitly to the Chinese firm-level data. The estimates of international research and development capital stocks are based on R & D expenditure data from the OECD's *Main Science and Technology Indicators.* Real R & D expenditure 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 index of average business sector wages (the same source as for Y). This definition of PR implies that, half of R & D expenditures are labor costs, which is broadly consistent with available data on the composition of R & D expenditures.

6 Technological group is divided according to the standard used in Eurostat Dataset, which is based on the NACE Rev 1.1 Classification at 3-digit level, which is converted into SIC 2-digit level. Details of industries under each category are given in Tables 1 and 3.

Following Coe and Helpman (1995) and Park (2004), research and development capital stocks (S), which are defined here as beginning of period stocks, were calculated from R & D expenditure (R) based on the perpetual inventory model

$$S_t = (1- \delta) S_{t-1} + R_t$$

where δ is the depreciation or obsolescence rate, which was assumed to be 5, 10 and 15 percent, alternatively. The benchmark for S was calculated following the procedure suggested by Griliches (1980), as $S_0 = R_0 / (g + \delta)$, 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 S_0 is the benchmark for the beginning of the year. The domestic R & D capital stocks were converted into Euros at 2000 constant price. The R&D stocks of the 22 OECD countries are then summed to proxy the world R&D stock. Table 1 gives the definitions of the variables used in the analysis along with some summary statistics.

Methodology

The empirical study is conducted in the following steps. First, we estimate total factor productivity (TFP) growth via a non-parametric frontier approach by using the Malmquist index, and decompose it into technical progress and efficiency change (Fare, et al., 1996). TFP is estimated for each industry separately allowing for different technology and production function for different industry. Second, we identify the firms that are located on the technology frontier measured by firm's technical efficiency. Third, we use econometric techniques to estimate the drivers of TFP, technical change and efficiency improvement. In this exercise the estimated Malmquist TFP growth index and the decomposed technical change and efficiency change are used as the dependent variable. Estimations are also done for sub-samples by industry, technology and ownership group.

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 assumptions. If these assumptions do not hold, TFP measurements will be biased. (Coelli et al., 1998; Arcelus and Arocena, 2000). Because of the above 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 indexes, which is to be estimated as the ratios of distance functions of observations from the frontier. This approach is capable of measuring productivity in a multi-input, multi-output setting, does not require the assumptions of the Solow method, and avoids the corresponding measurement problems.

It also 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 technological frontier

(Fare, et al., 1994). This decomposition of TFP growth enables us to investigate the impact of foreign and indigenous innovation efforts on technical progress and technological catch-up. 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.

$$S^t = \{(x^t, y^t): x^t \text{ can produce } y^t \} \tag{1}$$

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.

$$D_0^t(x^t, y^t) = \inf\{\theta : (x^t, y^t/\theta) \in S^t\} = (\sup\{\theta : (x^t, \theta y^t) \in S^t\}) \tag{2}$$

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

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right)\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{3}$$

Equation (3) represents the productivity of the production point (x^{t+1}, y^{t+1}) relative to the production point (x^t, y^t). 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

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{4}$$

where efficiency change (EFFCH) = $\dfrac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t}\left(x^{t}, y^{t}\right)}$ (5)

$$\text{technical change (TECHCH)} = \left[\left(\frac{D_0^{t}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_0^{t}\left(x^{t}, y^{t}\right)}{D_0^{t+1}\left(x^{t}, y^{t}\right)}\right)\right]^{\frac{1}{2}} \qquad (6)$$

Thus TFP change is decomposed into two components: efficiency change and technical change. Efficiency change measures whether production is getting closer to or farther away from the frontier. It reflects the catch-up process. 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. A value of greater 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 $D_0^t(x^{t+1}, y^{t+1})$[7]. Output in our production is measured by total output of firm, inputs are capital measured by net fixed assets, labour measured by number of employees, and intermediate inputs measured by variable costs. We use the output-oriented model under variable returns to scale for estimation.

7 For details see Fare et al. (1994) and Coelli (1996).

Foreign and indigenous R&D efforts and TFP growth

Having decomposed productivity growth, the next step is to estimate the drivers of TFP growth, technical change and efficiency improvement using regression analysis. Following Findlay (1978), foreign and domestic capital are regarded as distinct factors of production in this model reflecting the fact that capital, management and technology are inextricably combined.

The empirical analysis of the indigenous and foreign technology spillovers on the technology upgrading of indigenous firms are based on the model as follows,

$$\Delta Y_{it} = \chi RD_{it} + \gamma FDI_{it} + \beta X_{it} + \delta D_{it} + \varepsilon_{it} \qquad (7)$$

where the dependent variable Y represents TFP growth, technical change and efficiency improvement respectively. RD is a vector of R&D variables, which include 3 types of innovation efforts: R&D investment of the firm, indigenous and foreign R&D investment of the industry and international foreign R&D investment. FDI is FDI intensity measured by foreign investment to total asset ratio. X is a vector of control variables; D is the full set of time, sector dummies and ε is a random error term.

The set of variables we are most interested in is the set of R&D variables. In our specification, there are three types of innovation efforts: firm level, industry level and international level. We construct the variables as follows: (1) at the firm level R&D intensity is used as the direct effect of innovation on firm's growth performance; (2) the industry level innovation effect in each of the 171 three-digit industries and 31 provinces are constructed as the proportion of R&D expenditure accounted for by different ownership types in the same industry and region; (3) the interaction terms of international industry specific R&D stock and FDI share at both firm and industry level are adopted to measure the international innovation effect through FDI spillover effects. The full empirical model is therefore as follows,

$$\Delta Y_{it} = \chi_1 RDF_{it} + \chi_2 RDI_{it} + \chi_3 RDW_{it} * FDIF_{it} + \chi_4 RDW_{it} * FDID_{it} + \gamma FDI_{it} + \beta X_{it} + \delta D_{it} + \varepsilon_{it}$$

where *RDF* is firm R&D intensity, *RDI* is a vector of industry level R&D spillovers variables measured by industry average R&D intensity by different ownership types, *RDW* is world R&D stock constructed from OECD STAN database as discussed earlier, *FDIF* and *FDID* are FDI intensity at firm and industry level, respectively.

Control variables consist of initial level of technology efficiency, age, firm size, export, intangible assets, labour training and market concentration that are hypothesised to impact on the dependent variable. These variables are chosen according to 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 and more labour training are more likely to have faster TFP growth, technical change as well as efficiency improvement. Firms standing at the frontier are less likely to grow as fast as other firms. There is no conclusive relationship between firm age, intangible assets[8] and market concentration. For example, market competition may also be a two-edged sword on innovation. Geroski (1990) argues that lack of competition in a market will give rise to inefficiency and result in sluggish innovative activity. On the other hand, the traditional Schumpeterians claim that monopoly

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

power makes it easier for firms to appropriate the returns from innovation and thereby provides the incentive to invest in innovation (Cohen and Levin, 1989; Symeonidis, 2001). Table 1 gives a precise definition of the variables used in the econometric analysis.

In the above specification, FDI is represented by two variables, the share of foreign and ethnic capital at the firm level. We conjecture that a firm might grow faster if they have easier access to foreign advanced technical and management knowledge through their foreign or ethnic partners. We distinguish between foreign and ethnic capital because we would like to take different motivations of foreign and ethnic capital into account. Foreign investors are more likely to be market-oriented while ethnic investors might look for cheaper labour and rent to lower costs and re-export the final products.

There are a number of variables in the above specification that are arguably determined simultaneously with the dependent variable, 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 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 technology advantages. Another example is the foreign 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) that foreign firms choose the faster growing firms to invest. Similar arguments can also be made in the case of export and ethnic capital participation.

In order to deal with the problem of endogeneity, we employ the fixed effects generalised method of moments 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, 2006). We formally test whether the assumption of endogeneity is borne out by the data at hand and whether our instruments are relevant in that they exhibit sufficiently strong correlation with the potential endogenous variables. We also carefully test for the appropriateness of the instrumental variable candidates using Hansen J's test for overidentifying restrictions and the validity of the instruments with Sargan test. Reassuringly we find that our instruments are appropriate on all counts.

V. Results

TFP growth, technical change and catch-up

Estimated technical efficiency and TFP growth as well as the decomposed components are reported in Figures 1 and 2. The foreign invested enterprises (FIEs) enjoy the highest level of average technical efficiency; while that of the SOEs is the lowest, about one-third lower than that of the FIEs. The average technical efficiency of the Ethnic firms comes to the 2nd, higher than those for the private- and collective-owned enterprises and the shareholding companies. Across technology groups, the FIEs enjoy some advantage in technical efficiency over the indigenous firms, but the gap is small in the low-technology industries, but becomes large with the increase of technology intensity. The high-technology sector sees the largest gap between the FIEs and the SOEs at about 30%. All these evidences indicate the gap in the level of technology between foreign and indigenous firms and suggest the contribution of the advanced technology embedded in FDI to the static technology capabilities in China (Figure 1).

In terms of growth dynamics, overall, the Chinese firms have experienced considerable TFP growth over the 2001-2005 period at an average annual rate of 4.8%. The growth is mainly due to technical change at an average annual growth rate of 5.1% rather than efficiency change. The average annual growth rate of efficiency improvement was only 0.7% over the sample period, which suggests limited catch-up process of the followers to the leaders in the Chinese manufacturing sector. The growth is widely spread across different sectors. But the indigenous firms have taken a lead in this growth process in comparison to the foreign invested firms (Figure 2).

The indigenous firms enjoy higher TFP growth in the low- and medium-technology sectors (Figure 2). The difference is less obvious in the high-technology sector. In terms of technical change, the indigenous firms grow faster in low- and medium-technology sectors, especially the private and collective-owned firms in the low-tech sector, and the SOEs and the shareholding companies (SHCs) in the medium/high-technology sector. The foreign firms enjoy faster technical change in the high-tech sectors such as pharmaceutical, electronic and communications industries. The difference between foreign and ethnic firms is not significant in this respect.

Drivers of technological upgrading

Despite the lower average technical efficiency of indigenous firms in comparison to the foreign invested firms, a large number of indigenous firms stand on the frontier in the low to medium/high-technology sectors (Figure 1). This advantage decreases with the increase in technology intensity. In the medium/high-technology sector, this difference becomes very small; and in the high-technology sector, relatively large foreign-firms stand on the technology frontier[9]. The performance of SOEs is not as bad as it is perceived by many based on the argument that the corporate governance structure of the SOEs fundamentally hinders innovation in these firms. There are a considerable number of SOEs on the technology frontier, especially in the medium/high-technology industries. This maybe explained by the historical fact that the Chinese science and technology system is to a certain degree influenced by the former Soviet Union model and the state has long taken a leading role in scientific research and technology progress.

Overall, technological upgrading in the Chinese economy is not dominated by any single sector. The foreign firms have some advantages in the high-technology sector, and the indigenous firms have taken the lead in technology progress in the low-and medium-technology sectors. Shareholding companies, who are relatively rich in

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[9] The industries that foreign firms have obvious dominance include electronic and telecommunications, instruments and meters, culture, educational and sports goods, as well as garments and leather products industries where ethnic firms have a clear lead. Indigenous firms have dominant presence in the low- and low-medium-technology industries such as food processing, paper making, smelting and processing of ferrous and nonferrous metals industries, although the lead may be contributed by different indigenous sectors in different industries. There are also a list of industries where foreign and domestic firms share the lead and push upward the frontier together.

capital and skilled labour, enjoy a lead in the medium-technology, especially the medium/high-technology industries. There are also areas, especially in the middle field where the foreign and indigenous firms are moving together towards the technology frontier.

Dynamically, the greatest amount of technical change in China has taken place in the medium/high-technology industries. This change is driven by both the indigenous and the foreign firms, although SOEs and shareholding companies have a high rate of change. In the low-technology industries, the POEs are the main drivers of technical change; and in the high-technology industries, the FIEs are the leading force (Figure 2). The high- and medium/high-technology industries have enjoyed impressive technical progress, but the average efficiency change rates are less than 1 suggesting the majority of followers have not been able to catch up with the fast technological progress pace of the innovation leaders. But in the medium/low-technology sector, most of the progress is made by the followers in efficiency change, while the leading firms have not made significant technical progress in the sample period.

Spillovers from foreign innovation efforts

Table 2 reports the GMM estimates of effects of technological spillovers from foreign innovation efforts on the TFP of indigenous firms. Results from the Wu-Hausman specification test suggest significant endogeneity between R&D, exports and FDI on one hand and the dependent variable on the other. The GMM estimation results are therefore preferred to the OLS estimates. For a robustness check, estimations of the basic model, models with industrial and international R&D spillovers at three alternative depreciation rates, both the OLS and GMM approaches, are all carried out.

The estimated coefficients from different model specifications are consistent in the main suggesting the robustness of the estimated results. We have only reported the GMM estimated for 10% R&D depreciation rate due to space limitation[10].

Indigenous R&D efforts have a significant positive impact on firm-level TFP growth. The estimated coefficients bear the expected positive sign and are statistically significant across different model specifications. R&D spillovers from SOEs and SHCs in the same industry exert a significant positive effect on the TFP growth of indigenous firms. However, R&D spillovers from POEs and FIEs are negative and statistically significant. Dividing the sample into 4 sub-samples according to the technology category shows that this effect is industry specific. Innovation efforts in the FIEs have shown a significant positive spillover on TFP growth of the indigenous firms in the high-technology industries, but negative and significant medium- and low-technology sectors. This is likely because of either the competition effects of foreign R&D on the indigenous firms, or the technologies developed by these sectors are not appropriate for the current technology frontier. R&D spillovers from POEs are not statistically significant in most industry groups except the medium/high-technology sector where the estimated spillover coefficient is significantly negative. This may be explained by the fact that in these industries such as transportation equipment and chemical materials, firms are normally large and capital-intensive. POEs in China are often in small scale and labour or skilled-labour intensive sectors which are difficult to excel in. The estimated coefficients on international R&D spillovers variable are mostly statistically insignificant. This is likely to be explained

[10] Results of all the estimations are available from the authors subject to request.

by their inappropriate nature in the developing country context and the strong intellectual property rights protection in the high-technology industries.

Smaller firms appear to be more productive. Firms with high export-intensity, high FDI-intensity, more training and greater intangible assets have higher TFP growth than those who lack these characteristics. These estimated results are robust and statistically significant across industry sectors and different model specifications. Firm age does not appear to be a significant factor. Interestingly, industry concentration and low levels of competition seem to increase firm productivity although the estimated coefficient loses its statistical significance when international R&D spillovers are controlled for.

Tables 3 and 4 report the estimated results on the impact of indigenous innovation efforts and foreign R&D spillovers on technical change and efficiency improvements of the indigenous firms. Indigenous R&D of individual firms has no significant impact on technical change. It has, however, contributed significantly to efficiency improvement which reflects the catch-up process. This is not surprising given the fact revealed from the First National Economic Census in 2004 that about 95% of total business R&D expenditure was spent on development and only 5% was spent on basic scientific research. Interestingly, spillovers from R&D at the industry level appear to be the main drivers of technological upgrading and technological catch-up. R&D activities in the POEs and SOEs at the industry level have shown significant and robust positive spillovers on the technical progress of indigenous firms. This evidence suggests that it is collective indigenous R&D activities, i.e. R&D at industry level, that push up the technology frontier and drives technology upgrading of indigenous firms. R&D activities of foreign invested firms at the industry level have shown a negative spillover effect on technical change of indigenous firms, especially in the medium/high- and low-technology industries, suggesting Foreign R&D activities may well intensity competition for the limited domestic talent pool (Change, et al., 2006) and crowd out indigenous firms from local labour, resource and product markets. Foreign technology may not be appropriate in these industries and Foreign R&D centers may have limited interested in sharing knowledge with domestic firms and R&D labs (Chen, 2006; Change et al., 2006, Zhou, 2007). This may also be explained by the strict intellectual property rights protection of these high-end FIEs against the indigenous firms, especially in the high-technology industry. Interestingly, the industry level R&D of FIEs has shown a significant positive effect on catching up process of the indigenous firms in the medium- and high-technology industries. This may be explained by findings of recent studies that the core technology development of MNEs still remain at the head quarters, while the applied research and adaptation are the main tasks of its affiliates in foreign countries. For example, the R&D labs of Intel in Santa Clara, Folsom and Austin remain primary locations for core technology development and applied research. Its R&D team in Shanghai focuses on applied research to identify new applications for China and other emerging markets. Therefore, these R&D activities may not contribute to technical change but their impact on catching-up is positive and statistically significant. The spillover effects of R&D investment in ethnic firms on technical change and catch-up have similar signs to those of FIEs but are insignificant in general, although estimates from different technology categories show some significant positive spillovers effect on catch up in the low- and medium/high-technology sectors. This is also likely due to similar reasons as those for the FIEs - that R&D activities of Ethnic firms focus on adaptation of advanced foreign technology to local production and market environment. Moreover, the sort of know-how provided by firms from the ethnic Chinese as opposed to firms from the non-Chinese consists of marketing know-how rather than production know-how (Buckley, et al., 2002).

Results from these tests also show that older and larger firms have high levels of technical change. Exports contribute to efficiency change and catch-up, but not the shift of the technology frontier. This result is consistent with the findings in Fu (2005) using Chinese industry-level panel data suggesting the focus on low-cost competitiveness based on cheap un-skilled labour and the dominance of process trading in the export structure provide no effective incentive for firms to innovate. Foreign ownership does not show a significant impact on either technical change or efficiency change. This is likely due to the spillover tests being focused on the indigenous firms, in which by definition, the share of foreign ownership is small, ranging from 0 to 25 percent. The estimated coefficients on the intangible assets variable are negative and statistically significant in the technical change equation. This is likely because intangible assets include, according to Chinese accounting practices, R&D investment in the development stage but not the research stage. For firms in the technology intensive industries, novel research activities may play a more important role in keeping them on the frontier and promoting TFP growth in these industries. The second reason may be that intangible assets are correlated with the fixed assets that we used for the TFP estimation. Therefore, technically there is a negative association between TFP and intangible assets. Training exerts a significant positive impact on efficiency improvement as expected, but surprisingly, bears a significant negative impact on technical change. Further investigation is needed with regard to the accounting definition of training expenditure in China, the purposes and contents of training, how they are expended and who are trained. They are likely to be conducted for teaching new or advanced practices but not for the creation of frontier technology. Finally, the estimated coefficients of market concentration are not significant. However, breaking down the sample by technology categories, market concentration appears to promote technical change and innovation, which is consistent with the Schumpeterian hypothesis. The lack of competition, however, deters efficiency improvements in most of the sectors.

The effects of the international R&D spillovers on indigenous Chinese firms vary between technical change and efficiency improvement. The interaction between international R&D stock and firm FDI-intensity exerts a positive and significant effect on technical change of indigenous firms at the 5% significance level. This suggests the importance of intra-firm technology transfer of the frontier technology through FDI. Foreign investors may transfer the most advanced technology when they have more control of the firm. On the other hand, the interaction between international R&D stock and industry FDI-intensity exerts a positive and significant effect on efficiency improvement of indigenous firms at 5% significance level. This evidence suggests that it is the openness of the industry rather than the foreign equity of one individual firm that facilitates the type of international technology transfer which can drive up technology upgrading of the indigenous firms.

VI. Conclusions

Findings from the current study can be summarised briefly. First, neither the foreign nor the indigenous firms dominate the technology frontier in China. In low- and medium-technology sectors, more indigenous firms are located on the frontier. The private-owned firms have taken a lead in the low-technology industries and the shareholding companies are the leaders in the medium-technology industries. In the high-technology sector, foreign firms dominate the frontier. The advanced technology embedded in foreign direct investment, especially in the core machinery and equipment imported by the foreign firms and the technology know how brought by the foreign investors created the high-technology frontier in China. Dynamically, they are leading the technology progress in these industries as well.

Secondly, there has been a real catch up by the indigenous Chinese firms. This growth is likely to be sustainable from the technological perspective as the indigenous innovation activities have played a key role in the recent wave of TFP growth. Over the 2001 to 2005 period, the Chinese firms have experienced considerable TFP growth at an average annual rate of 4.8%. The growth is mainly due to technical change with an average annual growth rate of 5.1% rather than efficiency change. The average annual growth rate of efficiency improvement was only 0.7% over the sample period, which suggests limited catch-up process among the followers to the leaders in the Chinese manufacturing sector. The growth is widely spread across different sectors, although the indigenous firms have taken a lead in this growth process in comparison to the foreign invested firms.

Collective indigenous R&D activities at industry level are the major driver of technology upgrading of indigenous firms that push up the technology frontier. R&D investment in POEs and SOEs has shown significant positive spillovers on the technical change of indigenous firms. R&D in FIEs have significant positive spillover effect on the catch-up process of indigenous firms suggesting R&D activities in the FIEs in China over the sampling period have been focusing on adaptation of current technology rather than creation of world frontier technology. Findings from this study also suggest that the intensity of foreign equity of individual firms facilitates intra-firm technology transfer of international frontier technology. On the other hand, it is the openness of the industry that promotes the international technology spillover of superior, though not the most advanced, technology for catching up.

Findings from this research have important implications for technology policy in developing countries. Developing countries may not only be users of new technology, but also the creators of new technology in some sectors. The effective technology development path may be country, region and industry specific. Technology acquisition through imports of advanced machineries and equipments and FDI may create static technological capabilities. It is, however, the collective indigenous innovation efforts that drive the real dynamic indigenous technological capabilities building in a developing country. This highlights the important role of technology and industrial policies in developing countries in encouraging indigenous innovation. Moreover, foreign R&D activities may well intensity competition for the limited domestic talent pool and generate negative spillover effects on indigenous innovation efforts. Therefore, rigorous policies must be in place to reduce the potentially high opportunity costs of inward R&D investment that may result from internal “brain drain”, when global firms are crowding out the local market for scarce skills.

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Figure 1: Technical efficiency by ownership and technology category

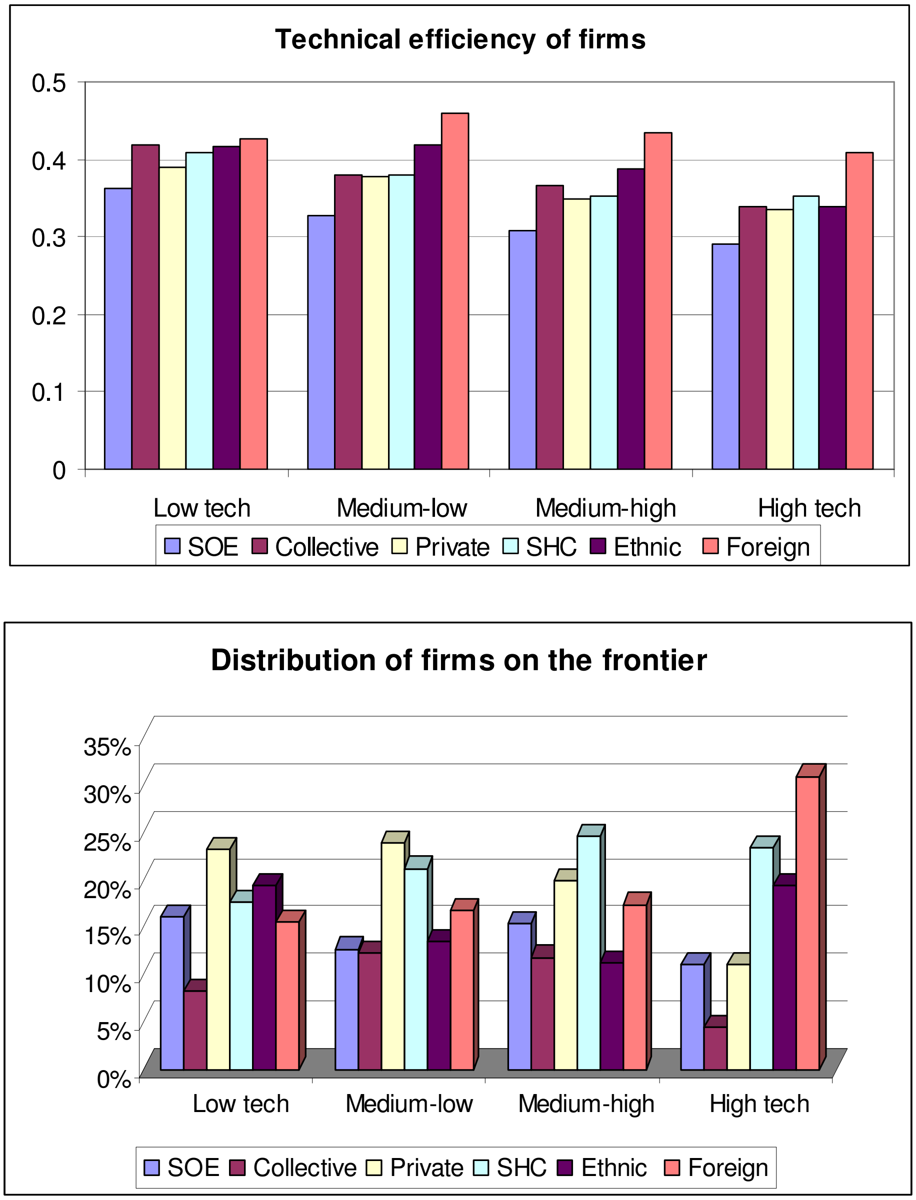

Figure 2: TFP growth, technical change and catch up

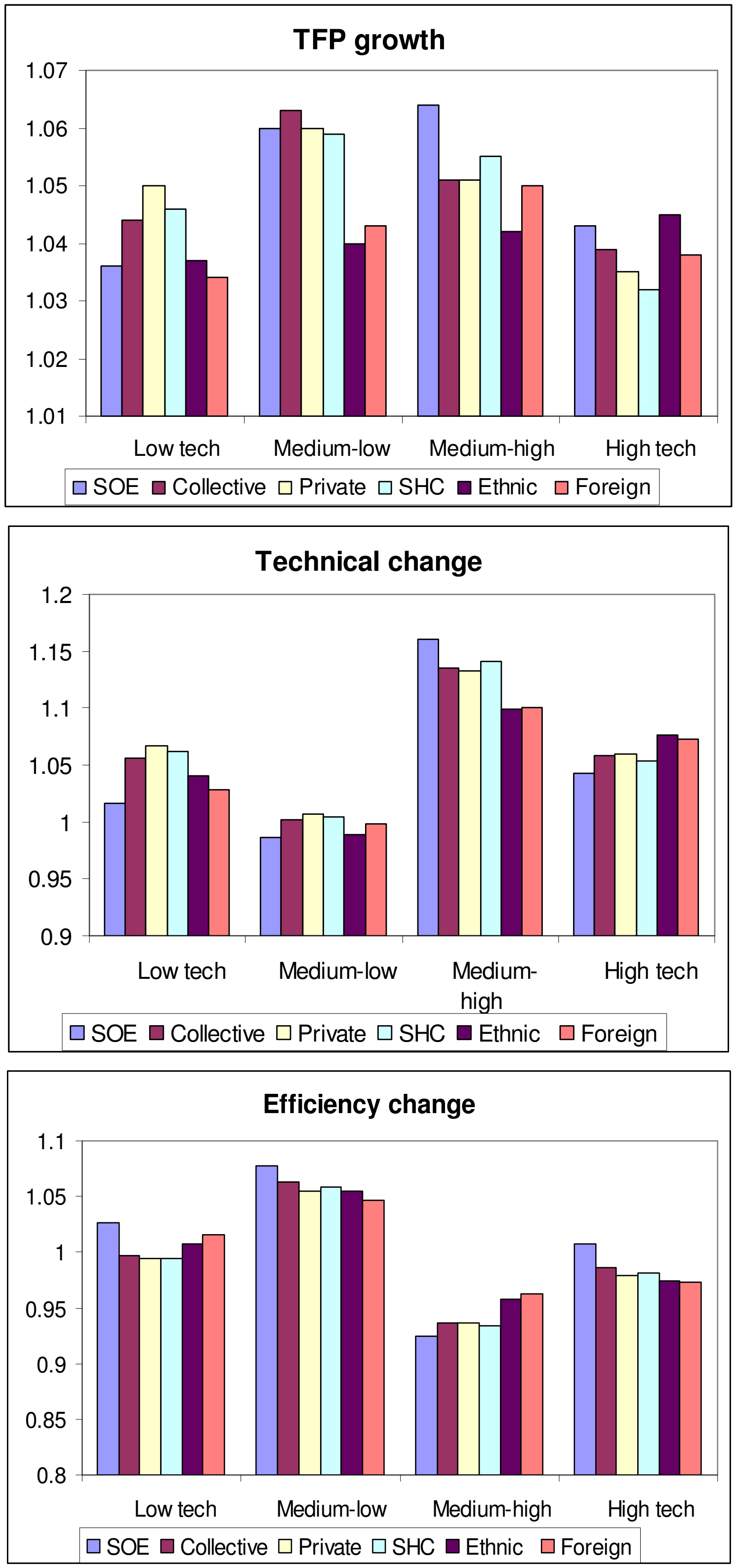

Table 1. Summary statistics of the variables

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Technical efficiency	TE based on variable returns to scale	269905	0.3836	0.2106	0	1
Scale efficiency	The ratio of technical efficiency under the assumption of constant returns to scale to technical efficiency calculated under the assumption of variable returns to scale	269903	0.8263	0.1886	0.005	1
TFP growth		269905	0.8811	0.5825	0	11.391
Efficiency change		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
Age	log value of age	269905	2.6242	0.6989	0.6931	5.1874
Employment	log value of employment	269905	5.2039	1.1096	0.6931	11.9031
Market concentration	Herfindahl index (three-digit industry)	269905	0.0196	0.0266	0.0017	1
Intangible asset per person	log value of intangible assets per person	269900	0.9052	1.3799	0	9.0027
Training expenditure per person	log value of training expenditure per person	269891	0.0834	0.1734	0	4.0108
Export	log value of export sales	269905	3.3919	4.7273	0	18.0558
R&D intensity	The ratio of R&D expenditure to total sales	269905	0.0017	0.0118	0	1
Foreign MNE	Share of foreign capital	269905	0.0905	0.2610	0	1
Ethnical MNE	Share of ethnic capital	269905	0.1053	0.2841	0	1
Ownership classifications	1 State-owned firms	269905	0.1115	0.3147	0	1
	2 Collective-owned firms	269905	0.1093	0.3120	0	1
	3 Private firms	269905	0.2638	0.4407	0	1
	4 Ethnic firms (investors are from Hong Kong, Taiwan, Macro)	269905	0.1449	0.3520	0	1
	5 Foreign firms (foreign MNE)	269905	0.1219	0.3271	0	1
	6 Others (mainly share holding companies)	269905	0.2488	0.4323	0	1
High tech	A dummy equals 1 for SIC 27 40 41	269905	0.0774	0.2672	0	1
Medium-high tech	A dummy equals 1 for SIC 26 28 36 37 39	269905	0.2343	0.4236	0	1
Medium-low tech	A dummy equals 1 for SIC 24 25 29 30 31 32 33 34 35 42	269905	0.3404	0.4739	0	1
Low tech	A dummy equals 1 for SIC 13 14 15 16 17 18 19 20 21 22 23	269905	0.3479	0.4763	0	1

Table 2: Determinates of the TFP growth

	All	High tech	Medium-high	Medium-low	Low tech
Firm R&D Intensity	0.941***	0.0640**	0.0746***	0.0648***	0.0767***
	(0.29)	(0.026)	(0.018)	(0.012)	(0.017)
Industry SOE R&D %	0.00110*	0.0002	-0.0002	0.0007	0.0013
	(0.0006)	(0.0034)	(0.002)	(0.0008)	(0.001)
Industry POE R&D%	-0.0045***	-0.0078	-0.0092***	-0.0019	-0.0024
	(0.001)	(0.0055)	(0.0024)	(0.0015)	(0.0018)
Industry Collective R&D %	0.0004	0.0053**	0.0025	-0.0005	0.0003
	(0.0006)	(0.0025)	(0.0016)	(0.0009)	(0.001)
Industry Ethnic R&D %	0.0004	-0.0035	0.0021	-0.0004	0.0015
	(0.0006)	(0.0038)	(0.0013)	(0.0008)	(0.0014)
Industry Foreign R&D %	-0.0015**	0.0076*	-0.0079***	0.0004	-0.0021
	(0.0007)	(0.0042)	(0.0022)	(0.001)	(0.0014)
Industry SHC R&D%	0.0031***	-0.0077	0.0053**	0.0019	0.0031**
	(0.0009)	(0.0053)	(0.0026)	(0.0014)	(0.0016)
Int'l R&D * Firm openness	-0.0160**	-0.0138	-0.0336	-0.0280*	-0.0011
	(0.0066)	(0.013)	(0.024)	(0.016)	(0.012)
Int'l R&D * Industry openness	-0.0053***	0.0015	-0.0042	-0.0013	-0.0071
	(0.0016)	(0.0058)	(0.0033)	(0.0025)	(0.0045)
Initial Technical Efficiency	-0.194***	0.0014	0.0021**	0.0014**	0.0002
	(0.0071)	(0.0012)	(0.0008)	(0.0006)	(0.0006)
Age	0.0008	0.108	2.033**	1.038*	3.36
	(0.0018)	(0.24)	(0.83)	(0.56)	(2.1)
Employment	-0.0223***	-0.244***	-0.172***	-0.166***	-0.235***
	(0.0013)	(0.031)	(0.016)	(0.011)	(0.012)
Market Size	0.0851	-0.0051	0.0027	0.0017	-0.0009
	(0.058)	(0.0073)	(0.0039)	(0.0028)	(0.0031)
Intangible Asset	0.0050***	-0.0236***	-0.0208***	-0.0220***	-0.0264***
	(0.0009)	(0.0055)	(0.0029)	(0.0021)	(0.0023)
Training Expenditure	0.0722***	0.0155	0.0491	0.122	0.111
	(0.0084)	(0.21)	(0.1)	(0.079)	(0.1)
Export Intensity	0.0013***	0.0031	0.0022	0.0055***	0.0071***
	(0.0004)	(0.003)	(0.0018)	(0.0015)	(0.0017)
Foreign Share	0.559***	0.558	1.4	0.983*	0.09
	(0.2)	(0.5)	(0.95)	(0.51)	(0.31)
Ethnic Share	0.183**	0.14	0.719	0.127	0.260*
	(0.075)	(0.18)	(0.53)	(0.14)	(0.13)
Constant	1.326***	1.373***	1.352***	1.275***	1.365***
	(0.019)	(0.09)	(0.041)	(0.029)	(0.047)
Observations	155885	9610	37377	56227	51997
Exogenous test	0	0	0	0	0
Hansen J test	0.7605	0.732	0.1442	0.4415	0.2515

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

Table 3: Determinants of technical change

	All	High tech	Medium-high	Medium-low	Low tech
Firm R&D Intensity	-0.219	-0.0128	0.166	-0.479	-0.457
	(0.17)	(0.17)	(0.28)	(0.34)	(0.92)
Industry SOE R&D %	0.0016**	0.0049**	0.0142***	-0.0020*	0.0012
	(0.0007)	(0.0023)	(0.0018)	(0.0012)	(0.001)
Industry POE R&D%	0.0125***	0.0071**	0.0172***	0.0045**	0.0137***
	(0.0013)	(0.0031)	(0.0029)	(0.002)	(0.0022)
Industry Collective R&D %	-0.0039***	0.0098***	0.0108***	-0.0111***	0.0114***
	(0.0007)	(0.0019)	(0.0013)	(0.0012)	(0.0011)
Industry Ethnic R&D %	-0.0007	-0.0067**	0.0096***	-0.0028***	-0.0031*
	(0.0008)	(0.0035)	(0.0016)	(0.001)	(0.0017)
Industry Foreign R&D %	-0.0082***	-0.0056	-0.0232***	0.0012	-0.0152***
	(0.0009)	(0.004)	(0.0021)	(0.0013)	(0.0017)
Industry SHC R&D%	-0.0009	0.0016	-0.0252	0.0084***	-0.0032
	(0.0012)	(0.0044)	(0.0025)	(0.0018)	(0.002)
Int'l R&D * Firm openness	0.0133**	-0.0086	0.0047	0.0267*	0.0040
	(0.0067)	(0.0074)	(0.011)	(0.015)	(0.016)
Int'l R&D * Industry openness	-0.0034*	0.0043	-0.017***	0.0200***	0.0016
	(0.0019)	(0.0056)	(0.0032)	(0.0029)	(0.0065)
Initial Technical Efficiency	-0.186***	0.00813	-0.222***	-0.222***	-0.176***
	(0.0077)	(0.02)	(0.015)	(0.013)	(0.013)
Age	0.0036*	-0.0008	-0.0057	0.0090***	0.0048
	(0.002)	(0.0052)	(0.004)	(0.0031)	(0.0034)
Employment	0.0164***	0.0021	0.0185***	0.0176***	0.0151***
	(0.0015)	(0.0041)	(0.0028)	(0.0023)	(0.0025)
Market Size	0.0342	0.303**	-0.0947	0.294***	0.796***
	(0.066)	(0.14)	(0.098)	(0.1)	(0.21)
Intangible Asset	-0.0045***	0.0024	-0.0067***	-0.0064***	-0.0001
	(0.001)	(0.0023)	(0.0018)	(0.0017)	(0.0019)
Training Expenditure	-0.0419***	-0.0156	-0.0473***	-0.0470***	-0.0486***
	(0.0081)	(0.014)	(0.015)	(0.013)	(0.016)
Export Intensity	-0.0002	0.0007	-0.0011	0.0006	0.0009
	(0.0004)	(0.0011)	(0.0009)	(0.0007)	(0.0007)
Foreign Share	-0.361*	0.326	-0.162	-0.737*	-0.0693
	(0.2)	(0.28)	(0.4)	(0.44)	(0.42)
Ethnic Share	-0.127*	-0.174*	-0.153	-0.109	-0.0817
	(0.071)	(0.1)	(0.26)	(0.15)	(0.12)
Constant	0.522***	0.703***	1.503***	0.799***	0.517***
	(0.022)	(0.077)	(0.036)	(0.036)	(0.064)
Observations	155,885	9,610	37,377	56,227	51,997
Exogenous test	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J test	0.5560	0.0511	0.0708	0.4589	0.5955

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

Table 4: Determinants of efficiency improvement

	All	High tech	Medium-high	Medium-low	Low tech
Firm R&D Intensity	1.388***	0.666*	1.229**	2.694***	3.404*
	(0.33)	(0.38)	(0.61)	(0.79)	(1.81)
Industry SOE R&D %	-0.0006	-0.0055	-0.0001	-0.0036**	0.0025
	(0.001)	(0.0042)	(0.0025)	(0.0016)	(0.0016)
Industry POE R&D%	-0.0105***	-0.0159**	-0.0122***	-0.0098***	-0.0073***
	(0.0016)	(0.0064)	(0.0033)	(0.0029)	(0.0027)
Industry Collective R&D %	-0.0024***	-0.0092***	-0.0044**	0.0031*	-0.0109***
	(0.0009)	(0.0035)	(0.0021)	(0.0018)	(0.0014)
Industry Ethnic R&D %	-0.0005	0.0002	-0.0082***	-0.0032**	0.0033
	(0.0010)	(0.0054)	(0.0018)	(0.0015)	(0.0022)
Industry Foreign R&D %	0.0023**	0.0171***	-0.0030	0.0096***	-0.0136***
	(0.0011)	(0.0056)	(0.0026)	(0.0018)	(0.002)
Industry SHC R&D%	0.0066***	-0.0076	0.0080**	0.0062**	0.0123***
	(0.0016)	(0.0073)	(0.0034)	(0.003)	(0.0026)
Int'l R&D * Firm openness	-0.0160*	0.0002	-0.0287	-0.0468*	-0.0103
	(0.0094)	(0.012)	(0.022)	(0.028)	(0.019)
Int'l R&D * Industry openness	0.0083***	-0.0005	0.0453***	-0.0236***	0.0585***
	(0.0027)	(0.0075)	(0.0042)	(0.0051)	(0.0077)
Initial Technical Efficiency	-0.483***	-0.373***	-0.243***	-0.652***	-0.501***
	(0.011)	(0.035)	(0.02)	(0.019)	(0.018)
Age	0.0035	0.0004	-0.0048	0.0053	0.0128***
	(0.0027)	(0.0087)	(0.0047)	(0.0049)	(0.0045)
Employment	0.0006	-0.0148**	-0.0081***	0.0151***	-0.0031
	(0.0019)	(0.007)	(0.0034)	(0.0036)	(0.0033)
Market Size	-0.0574	-0.528	0.262*	-0.452***	-0.774***
	(0.097)	(0.47)	(0.15)	(0.17)	(0.23)
Intangible Asset	0.0001	0.0095**	-0.0038*	0.0021	-0.0018
	(0.0014)	(0.0039)	(0.0023)	(0.0025)	(0.0025)
Training Expenditure	0.0531***	0.0949***	0.0737***	0.0336	0.0317
	(0.012)	(0.028)	(0.021)	(0.021)	(0.022)
Export Intensity	0.0011**	-0.0001	0.0027***	0.0014	-0.0007
	(0.0006)	(0.0017)	(0.001)	(0.0011)	(0.0009)
Foreign Share	0.447	0.0234	1.143	1.273	0.275
	(0.29)	(0.44)	(0.88)	(0.84)	(0.5)
Ethnic Share	0.0214	0.3	0.674	-0.186	0.0775
	(0.091)	(0.2)	(0.71)	(0.18)	(0.14)
Constant	2.294***	1.737***	0.622***	1.959***	1.837***
	(0.032)	(0.12)	(0.051)	(0.058)	(0.074)
Observations	155,885	9,610	37,377	56,227	51,997
Exogenous test	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J test	0.4743	0.1312	0.2395	0.4646	0.8785

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