R&D and Technology Transfer: Firm-Level Evidence from Chinese Industry[1]

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Abstract

The capacity of developing economies to narrow the gap in living standards with the OECD nations depends critically on their ability to imitate and innovate new technologies. Toward this end, developing economies have access to three avenues of technological advance: technology transfer, domestic R&D, and foreign direct investment. This paper examines the contributions of each of these avenues, as well as their interactions, to productivity and knowledge production within Chinese industry. Based on a large data set for China's large and medium-size enterprises, the estimation results show that technology transfer – whether domestic or foreign – affects productivity only through its interactions with in-house R&D. Foreign direct investment does not appear to facilitate the adoption of market-mediated foreign technology transfer. Firms wishing to produce patentable knowledge do not benefit from technology transfer; patentable knowledge is created exclusively through in-house R&D operations.

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1. Introduction

Economists have documented the inability of large numbers of developing countries to demonstrate progress in narrowing their gaps in living standards with the world's richer countries.[2] At the same time, among countries where evidence of catchup is apparent, the pace with which advancing economies span the huge gaps in living standards is a matter of concern. Along with institutional reform and political stability, technological progress is a critical ingredient for economic growth and catchup.

One group of countries that during the past several decades has exhibited substantial catch up are the economies of East and Southeast Asia. All of these economies have simultaneously exhibited substantial patterns of technology transfer, foreign direct investment, and firm-level research and development activity. In each of these economies, technologically lagging firms have learned to innovate by first imitating technologies created in developed economies. Imitation may occur through different channels, including market-mediated purchases of technology, technology transfer from multinational corporations to local subsidiaries or joint ventures, or the reverse engineering or products and capital goods. The relative contribution of these channels to technological advance has varied from country to country. While the Philippines and Thailand have been relatively open to foreign direct investment (FDI), Korea has tended to limit FDI but has relied on foreign technology transfer and indigenous R&D.[3]

[2] Jones (1997), for example, finds that about one-half of all developing countries, albeit many with small populations, exhibited negative economic growth between 1980 and 1993.
[3] See, for example, Jefferson and Zhong (forthcoming), Tables 12 and 13.

Overtime, with the establishment of formal R&D operations, many firms are making the transition from imitation to innovation, including the creation of patentable knowledge.[4]

For countries in which few firms have well-established R&D operations, tapping into the existing world technology stock would seem to be a natural way of bridging the technology gap, and arguably more efficient than trying to advance the domestic technology frontier through indigenous R&D effort alone. However, imperfections in the technology transfer markets that compromise the ability to appropriate returns, say through licensing, reduce the volume and sophistication of technologies that can be transacted on such markets (Caves, 1992). Foreign direct investment may provide a partial solution. With more control through direct equity participation, the parent company is likely to be more willing to part with more advanced technologies. One well-established motivation for FDI is to capture rents of proprietary assets that are difficult to appropriate through market transactions.

If R&D and technology transfer have independent and similar effects on a firm's knowledge base and productivity, we should expect to find the two types of innovative activity relating as substitutes. That is, technology transfer would substitute for the firm's internal R&D effort. This belief in the crowding-out effect of foreign technology on indigenous R&D effort motivated earlier efforts by the Indian government to restrict the purchase of foreign technology (Deolalikar and Evenson, 1989). However, technology transfer and R&D can also share a complementary relationship. Cohen and Levinthal (1989) argue that R&D not only involves innovation but also learning. A by-product of R&D is therefore to enhance a firm's absorptive capacity, which in turn boosts the

[4] Many researchers have documented the experience of Korea and Taiwan in making the leap from imitator to innovator. See for example, Kim (1997) and Kim and Nelson (2000).

efficacy of technology transfer. Drawing on the recent experience of East Asian economies, Kim and Nelson (2000) suggested that imitation through the adoption of existing technologies serves as an effective learning experience that paves the way for indigenous technological innovation.

A number of empirical studies have been concerned with Indian firms. These studies (Deolalikar and Evenson, 1989; Basant and Fikkert, 1996; and Katrak, 1997) generally find significant returns to technology transfer and R&D, which relate as complements, rather than substitutes, as avenues of technology acquisition.[5] Outside India, Braga and Willmore (1991) find robust complementarity between technology imports and firm technology effort in Brazilian industry. Various authors have also examined whether foreign ownership facilitates technology transfer. Ramachandran (1993) reports that technology transfer is more intensive in Indian subsidiaries of foreign multinational corporations than in indigenous Indian firms. This finding is echoed by Vishwasrao and Bosshardt (2001).

Over the past two decades, China has become an important venue for technology transfer, foreign direct investment, and indigenous R&D.[6] Using an extremely rich firm-level data set of Chinese manufacturing firms, this paper investigates three questions regarding R&D, foreign and domestic technology transfer, and FDI. These are: Do R&D and technology transfer contribute to productivity; do they relate as complements or substitutes? Does FDI facilitate the purchase and adoption of foreign technologies? Do R&D and technology transfer contribute to knowledge creation? In our study, we are

[5] An exception is Ferrantino (1992), who does not find robust returns to R&D or technology transfer in Indian firms.

able to assess the complementarity between R&D and technology transfer not only in the usual production function framework but also in the production of new knowledge. By including data on domestic technology transactions, our data set also allows us to examine the role of domestic technology transfer. Many issues that have been raised in the literature concerning international technology transfer also relate to domestic technology transfer, particularly in a country as large and technologically heterogeneous as China. Moreover, as with international technology transfer, understanding the avenues through which domestic technology transfer operates is important to evaluating the government's options in designing a national innovation policy.

The remainder of the paper consists of four sections. Section 2 describes the data used in this paper and discusses issues related to the construction of the sample and variables. In Section 3, we estimate the returns to R&D and technology transfer. By estimating a patent production function, Section 4 examines the roles of R&D and technology transfer in knowledge production. Section 5 concludes with further observations and policy implications.

2. Data

The data for this research are drawn from the Survey of Large and Medium Size Enterprises that China's National Bureau of Statistical (NBS) conducts each year. Jefferson, Hu, Guan, and Yu (2001) provide a comprehensive description of this rich data

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[6] China's 2000 S&T census (NBS, 2001) reports that in that year, China's R&D spending as a share of GDP reached one percent, about one half that of the OECD average and a substantial increase relative to the level of 0.6 percent reported in 1995.

set.[7] Our sample spans a period of five years from 1995 to 1999 and includes data for 29 two-digit manufacturing industries and over 400 four-digit industries.

Continuity of the data at the firm level, as provided by the panel, is important to our research strategy for two reasons. First, innovation and learning are path-dependent processes. A firm's past experience in innovating and imitating directly affects its future performance. Second, such continuity of the data at the firm level provides us with a tool to deal with the unobservable or un-measurable firm-specific characteristics in our econometric analysis. However, in our sample the data for all firms are not continuous. Due to ownership restructuring, which often entails a change in identifiers, and the entry and exit of firms, many of the firms in the data set cannot be tracked over the full five-year period. By including all firms that report data for at least four of the five years, we create a semi-balanced sample of approximately 10,000 firms a year over the five-year period.

[Insert Figure 1 here]

Foreign (domestic) technology transfer is measured by a firm's expenditure on technology purchased from a foreign (domestic) provider. Figure 1 charts the intensity of R&D, foreign technology transfer, and domestic technology transfer for 29 two-digit manufacturing industries. Intensity is calculated as the average ratio of the relevant expenditure to sales revenue; in constructing Figure 1, which compares intensities across industries, we weight each firm's intensity by the firm's share of total industry sales.

[7] To define large and medium-size enterprises, China's NBS uses either of two industry specific criteria: production capacity or original value of fixed assets. For example, an iron and steel firm must meet or exceed a production capacity of 600,000 tons to qualify as a "large" enterprise. For semiconductor manufacturing firms, the original value of fixed assets of a large enterprise must exceed 50 million yuan. For further elaboration of the criteria used to classify firm size, see the web site of the China's NBS (www.stats.gov.cn).

Figure 1 shows that foreign technology transfer tends to be relatively more intensive in the technologically less advanced industries, i.e. tobacco, textile, apparel, leather, furniture, paper, printing, and rubber, in which firms spend equal or greater amounts on foreign technology transfer than on R&D. The industries usually thought to be more technologically sophisticated, such as pharmaceutical, electric, electronics, and instruments, invest far more in R&D than in technology transfer. In sharp contrast to their foreign counterparts, domestic suppliers seem to be an insignificant source of technology transfer.

Following the methods of Griliches (1979), we construct stock measures for each of the three technology variables – R&D, foreign purchased technology, and domestic purchased technology – to examine their roles in shaping productivity and patenting. Knowledge accumulated through these three activities in the past generates benefits in the present and the future thereby making technological innovation an inherent path-dependent process. However, knowledge becomes obsolete and therefore depreciates due to the passage of time and the emergence of new knowledge taking its place. Thus the stocks of R&D, foreign technology transfer, and domestic technology transfer are constructed as the discounted sum of past expenditures on the respective activity. The perpetual inventory model used to construct these variables is outlined in the appendix. The stock measures of the three technology variables are based on the assumption of a discount rate of 15 percent.[8]

[Insert Table 1 here]

[8] This seems to be the rate that most, if not all, R&D researchers use. As in many studies, our estimation results are not sensitive to the assumption of the discount rate.

Table 1 provides additional information about the sample, including the means and standard deviations for key variables for each of the sample years and the whole sample. The statistics show interesting changes that have been taking place in China's large and medium size enterprise sector. First, during the latter half of the 1990s, these Chinese firms were shedding employees and becoming more capital intensive. The average number of workers per firm decreased from 1,528 in 1995 to 1,292 four years later. During the same period, the average capital-labor ratio nearly doubled from 44 thousand yuan per worker to 84 thousand yuan. Second, labor productivity as measured by value-added per worker rose significantly, if not steadily, while profits were relatively stable, implying that, whether measured by sales or assets, profitability fell during this period. These two seemingly contradictory observations – rising labor productivity and declining profitability – can be partially explained by increasing competition in China's industrial sector, which has squeezed profit margins across all Chinese enterprises. State-owned enterprises, which dominate our sample, have been particularly hard hit, losing monopoly power in an increasing number of industries and having to meet competition from all corners of the economy, particularly from the private sector and foreign invested enterprises. Lastly, the patent statistics show that the number of patent applications by and grants to China's large and medium-size enterprises have been rising steadily, although they remain concentrated in a handful of star performers as indicated by the high variance. During 1995 to 1999, the average number of patents granted to each firm increased from 0.11 counts to 0.25 counts.

3. R&D, technology transfer, and productivity

We examine the potentially different impacts of R&D and technology transfer on a firm's economic and technological performance by estimating both a conventional production function and a knowledge production function. R&D expenditure and the two measures of technology transfer serve as inputs to both production processes. By examining the channels – direct and interactive – through which R&D and technology transfer affect physical and knowledge production, we compare and contrast the avenues through which these different sources of innovation operate.

3.1 The production function and estimation issues.

We first specify and estimate a value-added Cobb-Douglas production function:

$$Y_{it} = A_{it} C_{it}^{\alpha} L_{it}^{\beta}, \tag{1}$$

where α and β are the output elasticities of capital and labor. A is the total factor productivity parameter, which is driven by R&D, technology transfer, and industry and ownership characteristics. We characterize the evolution of productivity by:

$$A_{it} = e^{f(K_{it}^{F}, K_{it}^{D}, K_{it}^{R}) + rt + \sum_{j} \gamma_j I_j + \sum_{h} \delta_h W_h} \tag{2}$$

where r is the economy-wide rate of autonomous technical progress. Inputs to the firm's knowledge production consists of three stocks: foreign technology transfer (K^F), domestic technology transfer (K^D), and R&D (K^R). The industry dummies (I_j) represent differences in technological opportunity across industries; the ownership dummies (W_h) account for differences in incentive structures and policy regimes that vary systematically across ownership classifications. Absent clear theoretical guidance for the specific function form of *f( )*, we assume a relatively flexible specification that includes the log of the three stock measures and three pair-wise interactive terms. Substituting (2) into (1) and taking logarithms, we obtain the following value-added production function:

$$y_{it} = \alpha_0 + \alpha_1 c_{it} + \alpha_2 l_{it} + \sum_M \beta_M k_{it}^M + \sum_M \sum_N \beta_{MN} k_{it}^M k_{it}^N + \sum_j \gamma_j I_j + \sum_h \delta_h W_h + \varepsilon_{it} \qquad (3)$$

where lower case letters denote logs, *M, N* = foreign (*F*)*,* domestic (*D*)*,* and R&D (*R*) and $M \neq N$. Industries and ownership groups are indexed by *j* and *h* respectively. Equation (3) allows us to estimate the returns to R&D and technology purchase and to ascertain the relationship between R&D and technology purchase through the interaction terms.[9]

In estimating equation (3), we face a possible econometric problem concerning the potential correlation between the independent variables and firm specific characteristics, such as heterogeneous managerial capabilities. It is quite likely that these firm specific characteristics are correlated with the production inputs on the right hand side of equation (3). The ordinary least square (OLS) estimates would then be subject to omitted-variable misspecification and bias.

Various possibilities exist to correct for the bias. With panel data, an easy solution would be to “de-mean” the variables with a within or first-difference type of estimator. This procedure would rid equation (3) of the time invariant firm specific characteristics and allow for unbiased estimates of the output elasticities. But this easy-to-implement procedure comes with a cost. For most panel data, particularly short panels such as this, most of the variation of the data is in the cross-section dimension. Applying a within estimator to the data not only eliminates the invisible firm specific characteristics but also wipes out useful inter-firm variation, which may account for most of the total variation. Another problem is that, by reducing the amount of useful information in the variable, the within estimator is likely to exacerbate the bias introduced by measurement errors. This effect will bias the estimated coefficients toward zero. A stylized finding in the R&D literature (Griliches, 1984) is that studies using the production function framework usually find significant returns to R&D in the cross-section dimension. In the time-series dimension, the causal relationship between R&D and productivity is less robust. Our data and estimation results share this feature.

Another method – that which we use – is the instrumental variable (IV) approach. The ideal instruments should be correlated with the firm's input choices but be independent of firm specific effects. Such instruments are hard to find. But Jaffe (1986) showed that proper industry variables could potentially become effective instruments to correct for firm specific effects. These variables define the environment in which the firms operate and yet are independent of a firm's specific characteristics. Therefore by using the industry variables as instruments we are implicitly assuming that these industry variables are independent from the firm specific characteristics. In the IV estimation, we use the four-digit industry average of all the variables in equation (3) and the ownership, year, and industry dummies as instruments for all the input variables. Because the industry variables may not be entirely independent of firm characteristics that exhibit a distinct industry-specific bias, such as technological opportunity or managerial capability,

[9] Not shown in equation (3) are time dummies, which we use to proxy time-dependent shifts associated with trend and cyclical changes in productivity and inflation.

which may differ systematically say between the pharmaceutical and textile industries, we rely on the 4-digit industry dummies to capture these industry specific effects.

[Insert Table 2 here]

3.2 Results and discussion

We report four sets of results in Table 2: the OLS estimates, IV estimates, IV estimates for the group of scientific industries and the non-scientific group. The full sample estimates include two variants – one with and one without the interactive terms involving the three technology variables. To save space, we do not report the estimated coefficients for the industry and year dummy variables; neither do we report the coefficients of capital and labor, which across all sets of estimates are highly statistically significant and within normal ranges.

3.2.1 The overall picture.

In Table 2, a common result across the regressions that omit the interactive terms, i.e., columns (1) and (3), is that the estimates on both R&D and foreign technology transfer are positive and quite significant, whereas those on domestic technology transfer are negative and generally significant. By including interaction terms for the three technology inputs, column (4) provides strong evidence of complementary relationships between R&D and the two technology transfer variables. With the interactive terms, the coefficient of R&D remains significant and largely unchanged in magnitude, whereas the coefficient for direct foreign technology transfer declines from a highly significant positive value to an insignificant level. The coefficient on direct domestic technology transfer, a negative estimate, becomes more robust. In the same regression, the interaction between R&D and foreign technology transfer exhibits a positive and statistically significant impact on productivity. The estimate of the interaction between R&D and domestic technology transfer is also robust. While affirming the direct contribution of R&D to productivity, these results also indicate that technology transfer only becomes productive when the firm is also engaged in internal R&D. This result applies to technology purchased from both foreign and domestic suppliers.[10]

As well as corroborating the hypothesis that R&D enhances the firm's absorptive capacity and therefore makes the adoption of new technology more effective, the complementarity results also have important policy implications. In using its R&D policy instruments – direct grants (*shangji bokuan*) and tax incentives (*jianmian shui*) – to promote technology transfer, China's government should direct these policy instruments toward those industries that exhibit robust complementarities with purchased technology. In the next section, we take an initial look at differences in technology transfer across industries.

3.2.2 Scientific vs. non-scientific and ownership differences

Due to the considerable heterogeneity of technological sophistication of the firms in our sample, we divide the full sample into two groups – scientific and non-scientific – and estimate equation (3) separately. We adopt the classification of previous authors (e.g., Griliches, 1984) with slight modification in view of the patterns of R&D intensity in Chinese industry as shown in Figure 1. The scientific group includes chemical,

[10] Using the "all" R&D stock figure in Table 1, out estimate for the total elasticity of value added (i.e. productivity) with respect to domestic technology transfer is 0.022, a positive estimate.

pharmaceutical, chemical fiber, ordinary machinery, special equipment, electric, electronics, and instruments.

Overall, the results we obtain with the full sample largely carry through for scientific firms. In column (5), the R&D-productivity link is even stronger than in the full-sample regressions. While the direct impact of stand-alone R&D is magnified in the scientific group, the complementarity between R&D and technology transfer, both foreign and domestic, is substantially unchanged. In the non-scientific group, the direct R&D-productivity link disappears, although indirectly R&D effectively complements foreign technology transfer. For the non-scientific group, the complementarity of domestic technology transfer with internal R&D disappears, even though the direct impact of domestic technology purchases remains negative. In the scientific group, we find three sources of productivity advance – direct R&D and the interactions of R&D with both purchased foreign and domestic technology. By comparison, in the non-scientific group we find only one effective innovation channel, which is the interaction between R&D and foreign technology.

In Table 2, each of the regressions includes ownership dummy variables to control for ownership specific effects. The eight ownership groups are state-owned enterprises (SOE), collective-owned enterprises (COE), private enterprises (PRE), limited liability companies (LTE), jointly operated enterprises (JOE), stock-incorporated enterprises (SKE), foreign invested enterprises (FIE), and Hong Kong-Taiwan-Macao invested enterprises (HMT). The productivity ranking, which starts with FIEs at the top, is followed by HMTs and concludes with SOEs at the bottom. The pattern is consistent across all regressions and is compatible with earlier studies (e.g., Jefferson, Rawski, Zheng, and Li , 2000).

3.2.3 Does foreign ownership lead to more efficient technology transfer and adoption?

Earlier, we introduced the hypothesis that foreign ownership might have an impact on the efficacy of foreign technology transfer. We should expect this if a foreign invested firm is more likely to transfer more advanced and appropriate technology from the firm's foreign parent, i.e. the multinational corporation, since the latter may be more willing to part with proprietary technology given its equity stake in the firm. In Table 2, we find support for this proposition, since the productivity levels for FIE and HMT firms lie significantly above the productivity of all forms of domestic ownership.[11]

But how does foreign equity participation affect the propensity to engage in successful arms-length market-mediated technology transfer? One possibility is that, with its expertise in the field, the foreign party in the firm may be able to help the firm identify appropriate international technologies to license that would be obtained from other international sources. Moreover, the legal connection of the foreign subsidiary to a foreign-based parent firm may ensure greater compliance with intellectual property rights law so as to reassure potential suppliers that restrictions on the use of transferred technology. An alternative conjecture is that the creation of the subsidiary foreign firm as a conduit for technology within the expanded boundaries of the firm serves as a substitute for market-mediated technology transfers. To test these contending conjectures,

[11] In a survey of Chinese firms engaged in foreign technology transfer, Wang (1999) cites this foreign ownership effect as an important determinant of successful technology transfer. The high productivity levels for FOR and HKT forms shown in Table 2 may also result from the transfer of embodied technologies, such as imported equipment.

we repeat the production function estimates for four ownership groups and report the results in Table 3.

[Insert Table 3 here]

Table 3 combines the non-SOE domestic ownership groups into one group – non-SOE domestic. We also carry out the exercise separately for FIEs and HMTs, as various studies (e.g., Pomfret, 1991, and Hu and Jefferson, 2002) have commented on the relative technological sophistication of OECD-based FIEs in comparison with overseas HKT firms. For all four groups, we find reductions in the robustness of the direct impact of R&D on firm productivity. While all of the direct estimates remain positive, only that for the FIEs is statistically significant at the 10 percent level or better. The interactive results remain robust, but the results for the domestic firms and foreign firms show distinct differences. On the domestic side, the interactive terms for R&D and both sources of technology transfer – domestic and foreign – remain statistically significant at the one percent level. For the foreign firms, however, the interaction of R&D and domestic technology transfer become insignificance. The interaction of R&D and foreign technology transfer remain significant, but the robustness of these estimates is less than it is for the domestic groupings. Our results show that foreign equity participation weakens the tendency of Chinese firms to absorb market-mediated technology; foreign firms appear to be less integrated with foreign technology markets and are not at all linked to the domestic technology market. On balance, we find some support for the proposition that foreign direct investment tends to substitute for market-mediated technology transfer. Rather than interfacing more efficiently with technology markets, FDI firms appear to be achieving their foreign technological advantage through informal channels that become available to MNCs by expanding the boundaries of the firm abroad.

4. R&D, technology purchase, and patenting

The innovation process in a Chinese firm may be thought of as occurring in stages, i.e.,

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                 Stage I                        Stage II
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     R&D                   imitation/
       and/or      →       knowledge          →      economic performance
     technology              production                 (productivity and
     transfer      →     →     →     →        →         profitability)
                             (reduced form)
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In equation (3) we have embedded the knowledge production process and estimated the returns to R&D and technology transfer in a production function framework. With this substitution, we have implicitly estimated a kind of "reduced-form," which omits the knowledge production stage of the innovation process[12]. Within this staged model of the innovation process, technology transfer may function differently in producing knowledge and in enhancing the firm's economic performance. We posit three hypotheses regarding the respective roles of R&D and technology transfer in the process of knowledge creation.

Our first hypothesis is that knowledge production, particularly patenting, entails the creation of "generic" technologies that are not immediately useful for enhancing the economic performance of innovating firms. Patent production may result from an act of insight that involves the novel use or slight modification of a technology that is already on the shelf or available through the market. In this case, the role of R&D interactions is relatively incidental to knowledge production; technology transfer largely operates through its direct impact on patent production.

Our second hypothesis is that technology transfer relates to the creation of knowledge in a similar way that it relates to economic performance – and for similar reasons. The firm's knowledge creation needs and capabilities are far more specific to the firm than are the technologies that are available on the market. Technology transfer is useful to knowledge creation, but only insofar as it interacts with in-house R&D in order to create knowledge that is relevant to the production mission of the firm and patentable. The implication is that, as with economic performance, we should expect that technology transfer contributes to the creation of knowledge principally through its interaction with R&D. Direct effects are likely to be incidental.

Our third hypothesis is that we should not expect to find any patentable information in the market. Patentable knowledge grows out of the specific problems of firms that develop patents. These specific problems are largely addressed by in-house R&D operations. Under this hypothesis, we expect to find in our knowledge production function estimates that the direct impact of R&D is significant, while the interactive effects between R&D and both forms of technology transfer are insignificant. Market-mediated technology transfer is irrelevant, or at least incidental, to the creation of patents.

To test these alternative hypotheses, we estimate a knowledge production function with inputs of R&D and the two measures of technology transfer. We compare the

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[12] See Jefferson, Bai, Guan, and Yu (forthcoming), who derive "reduced form" R&D performance equations in a similar manner.

results with those shown in Table 2 that focus on the relationship of R&D and technology transfer to physical production.

4.1 The knowledge production function and estimation issues

To measure the output of knowledge production, we use patent counts, i.e. the number of patents granted to a firm. A detailed discussion of the pros and cons of using patent counts to measure knowledge production lies beyond the scope of this paper. Griliches (1990) provides a comprehensive survey and discussion on patent statistics. Our empirical work that follows builds on the premise that although imperfect, patent counts provide a useful measure of the amount of knowledge generated by a firm.

Following earlier authors (Hausman, Hall, and Griliches 1984, Henderson and Cockburn 1996), we assume the following patent generation process:

$$\begin{aligned} P_{it} &= \exp(\gamma_0 + \gamma_1 c_{it} + \sum_M \beta'_M k_{it}^M + \sum_M \sum_N \beta'_{MN} k_{it}^M k_{it}^N) + \varepsilon'_{it} \\ &= \exp(B'X) + \varepsilon'_{it} \end{aligned} \qquad (4)$$

where in addition to the R&D and technology transfer variables, we also include the log of capital stock to control for differences in firm size. For simplicity of notation in the following discussions, we will write the exponential terms in (4) as $B'X$, where B is the coefficient vector and X includes all the independent variables and a constant.

In estimating the knowledge production function in (4), we are concerned with two econometric issues. The first of these is the distribution of the dependent variable, patent counts; the second issue concerns fixed effects whereby firm-specific characteristics, such as the differential quality of R&D personnel or the tendency for R&D intensive firms to use a larger portion of R&D for patent research, may be simultaneously associated with high patent counts and high R&D intensity.

A unique feature of patent counts is that they tend to have highly skewed distributions – many firms acquire no patents in a given year while others acquire disproportionately large numbers. This skewed distribution is in part due to the nature of the innovation process – there are usually only a handful of lucky winners – and calls for a non-linear estimator to estimate the knowledge production function.

The Negative Binomial model provides a partial solution to the problem of a skewed distribution by assuming a gamma distribution for the conditional mean of the dependent count variable and therefore allows the conditional mean and variance to vary. Gourieroux, Monfort, and Trognon (1984) propose an alternative approach – a distribution-free *quasi-generalized pseudo-maximum likelihood estimator* (QGLPML). This approach also allows the conditional mean and variance to differ, but is distinguished from the Negative Bionomial model by not making the restrictive assumption of the conditional mean following a gamma distribution. In Table 4, we report results from estimating both of these models.

The problem that we encountered earlier in estimating the production function, i.e., the potential correlation between production inputs and unmeasurable firm specific characteristics, also relates to the knowledge production function. The unobservable firm specific effect can enter equation (4) in one of two ways. First, if equation (4) is additively separable in the firm specific term, i.e., $\varepsilon'_{it} = \mu'_i + \upsilon'_{it}$, then the error structure is similar to that in the production function. Our Negative Binomial and QCPML estimators include ownership and industry dummies, which we expect capture some portion of the fixed effects, but these estimators will not correct for variations in firm-specific effects that persist within our ownership and industry categories. Amemiya

(1974) shows that nonlinear instrumental-variable estimators are consistent in such situations. The draw back of this approach is the implicit assumption that the unobservable firm specific characteristics affect knowledge production in a way that differs from the impacts of R&D and technology transfer on knowledge production.[13] Alternatively, we employ a fixed effects Negative Binomial estimator. Under this approach, μ_i', the firm-specific effect, enters the exponential part of equation (4) and transforms it into:

$$P_{it} = \exp(B'X + \mu_i') + \upsilon_{it}' \qquad (5)$$

Hausman, Hall, and Griliches (1984) derived a fixed-effect Negative Binomial estimator for equation (5), which is conditional on the total number of patents a firm is granted ($\sum_t P_{it}$). This estimator allows for both over-dispersion and firm-specific effects. We will use this estimator to deal with the issue of potential correlation between the inputs of knowledge production and the firm specific characteristics.

[Insert Table 4 here]

4.2 Results and discussion

The coefficients of the technology variables in the estimation of the knowledge production function reported in Table 4 provide revealing comparisons with those in the production function in Table 2. The major contrast, shown in Tables 2, 3, and 4, is the disappearance in Table 4 of the interactive effects for knowledge production that had

[13] **It is not desirable to assume, for example, a nonlinear relationship between innovation output and measured innovation input (R&D), while at the same time assuming a linear association between innovation output and unmeasured firm innovative capability.**

been important for overall firm productivity. Table 4 shows that the only consistently positive and significant determinant of patent counts is in-house R&D.

The difference between the Negative Binomial-fixed effect estimates and the Negative Binomial (without fixed effects) and the *QGPML* estimates indicates that R&D and technology transfer are not independent of firm specific characteristics. While shifting from the QGPML estimator to the Negative Binomial fixed effects estimator increases the estimated elasticity for foreign technology transfer by about one-third, the standard error increases nearly three-fold, thereby reducing the statistical significant to below the 20 percent level. The coefficient on in-house R&D, on the other hand, is extremely robust even after controlling for correlation between the unobservable firm effects and R&D expenditures.

The complementary relationship between R&D and technology transfer, which we observed in the production function estimations, largely disappears in the knowledge production process. Our results support the last of our three hypotheses; that is, whether directly or interactively through in-house R&D, market-mediated technology transfer embodies little information that is directly useful for patent development. Most patentable knowledge, at least in Chinese industry, evolves from the application of in house R&D to problems that are specific to the firm.

The ownership dummies in Table 4 reveal how the propensity to patent varies across firms of different ownership categories. FIEs and HMTs understandably patent less in China, as the headquarters are responsible for most of the patents granted to foreign multinational corporations.[14] An interesting result is that privately owned enterprises exhibit the highest propensity to patent, followed by stock-incorporated enterprises and collective-owned enterprises. State-owned enterprises are among the least active in patenting. This pattern of the propensity to patent among different domestic ownership groups arguably results from the interaction of corporate governance and technological innovation and is consistent with the finding of Jefferson, Bai, Guan, and Yu (forthcoming) that state-owned enterprises are relatively inefficient in knowledge production.[15]

5. Conclusions and policy implications

With the goal of examining complementarities between in-house R&D and technology transfer, we use a panel of China's large and medium-size enterprises to test the avenues through which these different forms of innovation expenditure affect productivity and knowledge production. Given the relatively generic nature of market-based technology transactions, we anticipate that the effective transfer of purchased technologies is likely to require applications through a process of in-house R&D. We also investigate whether foreign direct investment facilitates technology purchase. From one perspective, if FDI is motivated as a solution to imperfections in the technology licensing market, we might expect to observe fewer market transaction between foreign-invested firms and foreign technology suppliers. On the other hand, given the relative technological sophistication of FDI firms and familiarity with the international technology market, we might expect to observe a greater volume of technology transactions involving foreign invested firms.

A central finding of our research is strong returns to both R&D and technology transfer in Chinese firms. Against this background, we have identified four additional

[14] Mowery (1998) showed that American corporations conducted over 90 percent of its R&D at home.
[15] This paper, however, focuses on new products, not patent counts, as the measure of knowledge production. This result is consistent with the finding of Amsden (2001) that foreign companies in

findings. Although we examine innovation expenditure in different contexts, in no case do we find that domestic or foreign technology transfer exhibits a direct impact on either firm productivity or knowledge production.

Our second finding relates to the impact of innovation on productivity. Innovation affects firm productivity most consistently through the direct impact of in-house R&D, particularly for firms associated with scientific industries, and through interactions between in-house R&D and technology transfer – both domestic and foreign. This finding reinforces empirical work for other developing economies that confirms the role of in-house R&D as a precondition for absorbing externally-acquired technologies.

Our findings indicate that foreign equity participation is not associated with a greater role for market-mediated technology transfer. Domestic technology transfer, which interacts with in-house R&D in domestic firms, is not important for the foreign sector. Foreign-invested firms are largely isolated from domestic technology transfer. However, the complementary relationship between foreign technology transfer and in-house R&D, shown in the domestic firm sector, does operate in the foreign sector, although not so robustly as in the domestic. While FDI may create a channel that reduces the transaction costs of technology transfer within the firm, the presence of foreign investment and foreign expertise does not enhance arms-length market-mediated foreign technology transfer.

Finally, our last final finding is that for knowledge production we find very different channels of innovation than those relating to overall firm productivity. Contrary to the findings regarding the importance of complementarities between R&D and

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Singapore primarily engaged in production-related R&D; they expend few resources on knowledge creation.

technology transfer in motivating productivity gains, in-house R&D expenditures are the sole channel for the creation of patentable knowledge. Market-mediated techology transfer is incidental to knowledge production.

Developing country governments sometimes find themselves in the position of promoting indigenous R&D for fear that purchasing off-the-shelf technologies from developed economies may crowd out domestically-sponsored R&D. Our analysis shows that R&D and technology transfer are not substitutes. Both R&D and foreign technology transfer exhibit positive returns but their roles in boosting firm performance are quite different. When combined with R&D, foreign technology transfer generates measurable productivity gains; the addition of technology transfer- both foreign and domestic – raises the returns to indigenous R&D. For China, our results show the importance of in-house R&D both for the more technologically advanced coastal firms that seek to innovate and create new knowledge and also for interior firms wishing to imitate foreign technology and the achievements of their coastal counterparts.

Appendix: The construction of the technology stock variables

To construct the stocks of R&D, foreign and domestic technology purchase, we assume a perpetual inventory model for the accumulation of the respective technology capital, i.e.,

$$K_{i,t}^{M} = (1-\delta)K_{i,t-1}^{M} + I_{i,t-1}^{M}, \qquad M = F, D, R$$

where $K_{i,t}^{M}$ is the stock of R&D or technology purchase for firm i in year t; δ is the depreciation rate of the respective technology capital; and $I_{i,t}^{M}$ is firm i's gross investment in R&D or technology purchase in year t. To implement the model, we first construct the initial technology stock for each firm, i.e., $K_{i,95}^{M}$. Assuming that the growth rate of $I_{i,t}^{M}$ is γ, the initial R&D stock can be written as follows:

$$K_{i,95}^{M} = \frac{I_{i,95}^{M}}{\delta + \gamma}$$

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Figure 1. Industry R&D and Technology Transfer Intensities

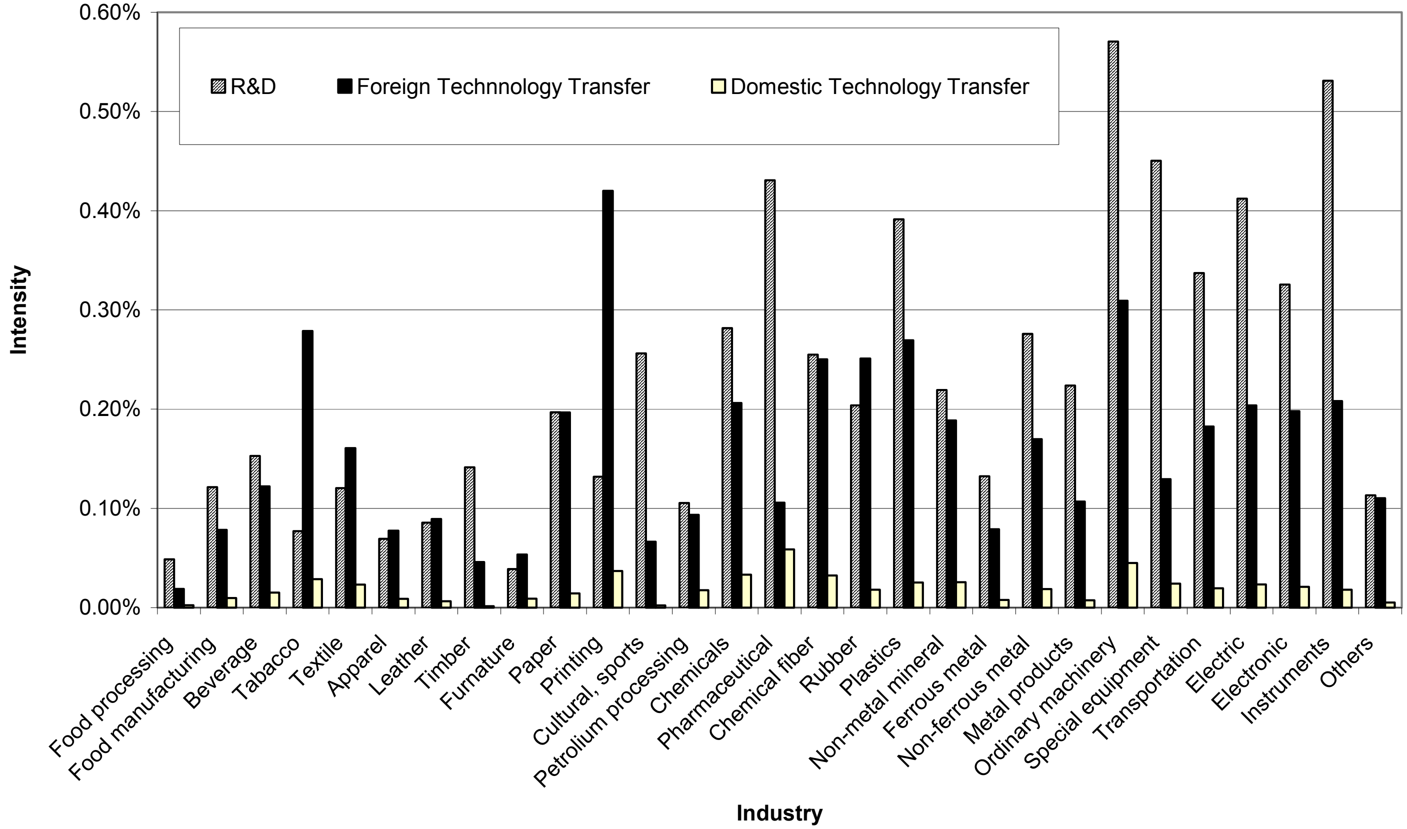

Table 1. Sample statistics

	1995	1996	1997	1998	1999	All
Number of firms	9556	11615	11650	11282	9940	54043
Employment	1528	1457	1427	1351	1292	1411
	(3082)	(3180)	(3008)	(2879)	(2786)	(2994)
Capital labor ratio	44	58	65	74	84	65
	(70)	(86)	(102)	(109)	(125)	(101)
Labor productivity	28	34	35	35	40	35
	(61)	(67)	(81)	(71)	(84)	(74)
Profits	21706	18788	19298	17950	20184	19496
	(82373)	(62775)	(67013)	(62889)	(76020)	(70033)
R&D stock	2933	2712	2863	3129	3400	2997
	(8796)	(8358)	(8833)	(9623)	(10423)	(9213)
Foreign technology	1961	1760	1948	2251	2447	2065
transfer stock	(11809)	(11068)	(11966)	(13820)	(15376)	(12858)
Domestic	258	267	278	278	286	274
technology	(1480)	(1637)	(1704)	(1643)	(1704)	(1639)
transfer stock						
Patent grants	0.11	0.13	0.12	0.15	0.25	0.15
	(0.92)	(1.34)	(1.49)	(1.18)	(3.53)	(1.90)
Patent applications	0.16	0.21	0.22	0.20	0.30	0.22
	(1.37)	(2.17)	(2.97)	(1.47)	(2.57)	(2.22)

Note: The unit of monetary variables is thousand yuan. The exchange rate between yuan and U.S. dollar during the sample period fluctuates in a narrow range between 8.27 to 8.35 yuan per dollar (NSB, 2001).

Table 2. The Production Function

	OLS		IV		Scientific	Non-scientific
	(1)	(2)	(3)	(4)	(5)	(6)
Log K^R	0.007*	0.005*	0.029*	0.027**	0.058*	0.003
	(0.001)	(0.001)	(0.011)	(0.01)	(0.017)	(0.016)
Log K^F	0.005*	-0.003***	0.032*	-0.007	-0.005	-0.005
	(0.001)	(0.001)	(0.005)	(0.004)	(0.007)	(0.006)
Log K^D	-0.007*	-0.12*	-0.011**	-0.018*	-0.019*	-0.012**
	(0.002)	(0.002)	(0.005)	(0.001)	(0.005)	(0.006)
Log K^F*Log K^R	-	0.002*	-	0.01*	0.009*	0.011*
		(0.0003)		(0.001)	(0.002)	(0.002)
Log K^D*Log K^R	-	0.001*	-	0.005*	0.006*	0.002
		(0.000)		(0.001)	(0.002)	(0.002)
Log K^D*Log K^F	-	0.002*	-	-0.001	-0.001	-0.001
		(0.000)		(0.001)	(0.002)	(0.002)
COE	0.55*	0.54*	0.54*	0.52*	0.61*	0.48*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
PRE	0.57*	0.57*	0.55*	0.54*	0.31*	0.64*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)	(0.09)
LTE	0.36*	0.36*	0.35*	0.33*	0.32*	0.34*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
JOE	0.40*	0.40*	0.38*	0.38*	0.29*	0.43*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)
SKE	0.49*	0.48*	0.47*	0.46*	0.49*	0.43*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
FIE	1.03*	1.03*	0.94*	0.95*	1.13*	0.80*
	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)	(0.04)
HMT	0.88*	0.88*	0.81*	0.81*	0.74*	0.82*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)
Industry dummies	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes
Number of obs.	54043	54043	54043	54043	21768	32275
Adjusted R^2	0.54	0.54	0.53	0.52	0.45	0.56

*Statistically significant at the 1% level; **statistically significant at the 5% level; ***statistically significant at the 10% level.

Table 3. The Production Function by Ownership Type

	SOEs (1)	Non-SOE domestic (2)	FIE (3)	HMT (4)
Log K^R	0.02	0.038	0.09***	0.05
	(0.01)	(0.027)	(0.04)	(0.05)
Log K^F	-0.007	-0.001	-0.022	-0.052**
	(0.005)	(0.010)	(0.018)	(0.024)
Log K^D	-0.015*	-0.019**	-0.037	-0.009
	(0.002)	(0.009)	(0.025)	(0.024)
Log K^F*Log K^R	0.011*	0.009*	0.008***	0.014**
	(0.001)	(0.003)	(0.004)	(0.006)
Log K^D*Log K^R	0.005*	0.012*	-0.014	-0.013
	(0.002)	(0.003)	(0.013)	(0.011)
Log K^D*Log K^F	0.001	-0.007**	0.005	0.009
	(0.002)	(0.003)	(0.008)	(0.009)
Industry dummies	yes	yes	yes	yes
Time	yes	yes	yes	yes
Number of obs.	32261	15458	3263	3061
Adjusted R^2	0.54	0.48	0.49	0.55

*Statistically significant at the 1% level; **statistically significant at the 5% level; ***statistically significant at the 10% level.

Table 4. The Knowledge Production Function

	neg. binomial		QGPML		fixed effect neg. binomial	
	(1)	(2)	(3)	(4)	(5)	(6)
Log NVFA	0.659*	0.645*	0.657*	0.643*	0.226*	0.23*
	(0.026)	(0.026)	(0.035)	(0.035)	(0.032)	(0.03)
Log K^R	0.062*	0.063*	0.062*	0.063*	0.058*	0.067*
	(0.007)	(0.007)	(0.009)	(0.009)	(0.016)	(0.020)
Log K^F	0.037*	0.027*	0.037**	0.028**	-0.025***	0.037
	(0.008)	(0.010)	(0.011)	(0.013)	(0.013)	(0.038)
Log K^D	-0.008	-0.020***	-0.007	-0.021	0.028***	-0.049
	(0.009)	(0.010)	(0.013)	(0.014)	(0.016)	(0.050)
Log K^F*Log K^R	-	-0.0004	-	-0.001	-	-0.008**
		(0.002)		(0.002)		(0.004)
Log K^D*Log K^R	-	0.0001	-	0.0002	-	0.008
		(0.002)		(0.002)		(0.006)
Log K^D*Log K^F	-	0.012*	-	0.012*	-	0.003
		(0.002)		(0.003)		(0.004)
COE	0.455*	0.453*	0.460*	0.459*	-	-
	(0.078)	(0.078)	(0.108)	(0.104)		
PRE	1.235*	1.205*	1.220**	1.192**	-	-
	(0.461)	(0.457)	(0.629)	(0.605)		
LTE	0.607*	0.627*	0.601*	0.624*	-	-
	(0.145)	(0.144)	(0.198)	(0.191)		
JOE	0.378***	0.364	0.374	0.363	-	-
	(0.229)	(0.229)	(0.317)	(0.306)		
SKE	0.886*	0.840*	0.879*	0.836*	-	-
	(0.097)	(0.097)	(0.132)	(0.128)		
FIE	-0.052	-0.030	-0.054	-0.033	-	-
	(0.115)	(0.114)	(0.157)	(0.152)		
HMT	0.158	0.159	0.146	0.150	-	-
	(0.119)	(0.119)	(0.164)	(0.158)		
Industry dummies	yes	yes	yes	yes	no	no
Time dummies	yes	yes	yes	yes	no	no
Log likelihood	-14082	-14059	-14124	-14097	-5330	-5327
Pseudo R^2	0.58	0.59	0.91	0.91	0.08	0.08

*Statistically significant at the 1% level; **statistically significant at the 5% level; ***statistically significant at the 10% level.