R and D Performance in China's Large and Medium-Size Enterprise Sector[1]

Gary H. Jefferson
Graduate School of International Economics and Finance
Brandeis University, Waltham, MA
Jefferson@brandeis.edu

Bai Huamao
Graduate School of International Economics and Finance
Brandeis University, Waltham, MA

Guan Xiaojing
Department of Population, Social, and Technology Statistics
National Bureau of Statistics
Beijing, China

Yu Xiaoyun
Department of Industrial and Transportation Statistics
National Bureau of Statistics
Beijing, China

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ABSTRACT

Using an unusually rich set of data for China's large and medium-size manufacturing enterprises that span seven ownership types, this paper investigates three fundamental questions that shape the R&D literature. These questions - the determinants of firm-level R&D intensity, the process of knowledge production, and the impact of innovation on firm performance - are investigated in a recursive three-equation system. Several results stand out. Overall, our findings are surprisingly robust. These include the important roles of firm size, market concentration, and profitability in shaping R&D intensity. Also, large firms that specialize in non-labor R&D expenditures capture most of their returns to R&D through new products and patents; medium-size firms that specialize in R&D personnel secure a smaller fraction of their returns through these channels.

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1. Introduction

During the last two decades of the 20th century China's economic reforms spurred impressive rates of economic growth. Much of this growth, however, arose from gains in allocative efficiency that resulted from the initial stages of market and ownership reform. In order to sustain these rates of growth into the 21st century and enable China to enter the ranks of the world's advanced economies, its manufacturing sector must learn how to deploy and utilize R&D resources effectively. Over the long-term, China's economic performance will depend on its ability to innovate, acquire new technologies, and eventually to become a leading contributor to the world's stock of industrial knowledge.

This paper uses an extraordinary set of firm-level data to investigate three questions relating to research and development in China's manufacturing sector. These are also the three classic questions that frame the considerable research on firm-level R&D in the advanced industrial countries: (i) what determines variations in R&D effort across enterprises?; (ii) how does R&D effort translate into R&D output, i.e. can we identify knowledge production functions at the firm level?; and (iii) how do levels of R&D activity, measured in terms of R&D inputs and outputs, affect firm-level productivity and profitability?

To investigate these questions, we use a panel of firm-level data that spans China's approximately 20,000 large and medium-size manufacturing enterprises that are grouped according to seven different ownership types. While measures are not yet available for the R&D effort of China's small-size enterprise sector, we anticipate that like the U.S., China's larger enterprises, which account for approximately one-third of total manufacturing sales, sponsor the vast majority of that country's manufacturing R&D activity.[2]

2. Modeling R&D

Economists in the U.S. have developed an extensive literature that investigates the impact of R&D on firm performance. While this literature as a whole focuses on the three questions posed above, none, with which we are familiar, has examined all three of these issues simultaneously within an integrated model of R&D.

We construct and estimate a model which consists of the following three equations:

$$\text{R\&D intensity: } RDin(t-1) = f_1[W(t-1),X(t-2)]\varepsilon_1, \tag{1a}$$

$$\text{R\&D output: } RDout(t) = f_2[RDin(t-1), Y(t)]\varepsilon_2, \tag{1b}$$

$$\text{Performance: } PERF(t) = f_3[RDout(t),Z(t)]\varepsilon_3. \tag{1c}$$

In this 3-equation model, R&D intensity is a function of contemporaneous conditions, including sales and market concentration, summarized by the vector W, and prior period variables including profitability, summarized by the vector X. In estimating the contribution of these factors to R&D intensity, we control for the separate effects of ownership status and industry affiliation. We use two measures of R&D intensity - the

[2] According to Hay and Morris (1991), in the U.S.A. in 1970 the largest 100 employers accounted for 79 percent of total manufacturing R&D expenditure.

ratio of R&D expenditure to sales and the ratio of R&D personnel to sales – and therefore estimate two R&D intensity equations.

R&D output, measured as the ratios of R&D expenditure and R&D personnel to sales, is driven by historic R&D intensity, i.e. RDI(t-1), as well as current factors, including size and age, summarized by the vector Y. Again, we investigate the independent effect of ownership and industry type on the efficiency of knowledge production. With two measures of R&D output, we estimate two knowledge production functions: a new product function and a patent function.

Finally, firm performance, measured by productivity and profitability, is hypothesized to be driven by available R&D outputs, which serve as inputs to the production process, and by the usual factor inputs, summarized by the vector Z. We again include ownership classification and industry type to investigate their independent effects on firm performance. Using measures of output and profit, we estimate a productivity function and a profitability function.

The model is consistent with the behavior of a profit-maximizing firm manager. Research and development provides the bridge between the set of technical possibilities that the agent observes in the wider world and the realized technologies that she can put to use within the firm in the future. While innovation outside the firm will gradually enlarge the set of product and process possibilities that are embodied in purchased equipment and hired-in labor, work by Mowrey (1983) and Basant and Fikkert (1996) demonstrate that the firm’s own investment in R&D will accelerated these spillover effects. With the promise of higher future returns from new products and process technologies, the manager solves a first-order condition, which equates the expected stream of marginal benefits from R&D effort to the marginal cost of R&D. Specifically, the agent chooses an optimal stock of R&D and the net adjustment to that stock in each period. These choices are based on his familiarity with the technologies implicit in the stochastic knowledge production function summarized in equation (1b) and the performance equation summarized in equation (1c), as well as the reduced form equation, which captures the total direct effect of R&D effort on performance.

Estimates from this three-equation model will enable us to calculate and compare the returns to R&D resources across firm size and ownership classifications. Using the results from equations (1a) – (1c), we can estimate the combined impact of R&D activity on enterprise performance as it operates through new product sales and patent applications, i.e. $[dPERF/dRDin]_M = (\partial PERF/\partial NP)(\partial NP/\partial RDin) + (\partial PERF/\partial PAT)(\partial PAT/\partial RDin)$. In addition, by substituting equation (1b) into (1c), we estimate a reduced form equation, which examines directly the total impact of R&D inputs on performance, i.e.$[dPERF/dRDin]_T$. Because R&D can be expected to operate through multiple channels that may not be fully captured by new product sales and patent applications, such as process innovation, we anticipate that the total impact (T) of R&D will equal or exceed the combined impact of only the measured channels (M), i.e. $[dPERF/dRDin]_T \geq [dPERF/dRDin]_M$.

3. China's R&D Performers

During the three years covered by the panel data that we use for this analysis, approximately one-half of the total population of large and medium-size manufacturing enterprises reports using R&D resources or producing R&D outputs. We omit from the regression sample enterprises for which R&D expenditure, R&D personnel, new products, and patent applications are either ALL zero or are unreported. When a firm does not report a positive value for any of these variables, we characterize it as a "non-performer."

Table 2 presents the results based on 1999 data of a probit estimate of the effects of certain firm characteristics on the likelihood of a firm with those characteristics being an R&D performer (designated "1") or an R&D non-performer (designated "0"). The reference intercept in the regression is the sub-sample of small-size, state-owned enterprise, in industry 31, i.e. non-metal mineral products. The likelihood of a firm in this reference group being an R&D performer is 51.9 percent. The results show that scale, measured in terms of sales, capital intensity, and designation as a "large-size" enterprise all significantly increase the probability of being an R&D performer and hence being included in the regression sample. Furthermore, controlling for these factors and industry affiliation, R&D performers are concentrated among state owned and shareholder owned enterprises. The foreign and overseas (HKT) sectors include a low incidence of R&D performers. Finally, high concentrations of R&D activity are found in the instrument (42), special purpose equipment (36), ordinary machinery (35), and medical and pharmaceutical products sectors. The lowest concentrations of R&D activity are reported in the printing (23), garment (18), and furniture manufacturing (20) sectors.

While the presence of R&D non-performers reduces our regression sample by about one half, another substantial proportion of enterprises drops out of the sample as a result of our balancing the sample over the years 1997, 1998, and 1999. Among the

5,740 performing enterprises, just 289 enterprises, or 5 percent of the sample, are loss-making. Because these represent a small portion of the sample and because their inclusion would complicate the use of log-linear analysis, which we use here, we drop the loss-making enterprises from the sample. The resulting sample is 5,451 enterprises. Table 3 shows the distribution by size and ownership of both the total number of enterprises in the 1999 population of LMEs and the composition of the regression sample by size and ownership.

4. R&D Effort

R&D effort is the outcome of the interaction of factors that condition the demand for and supply of R&D resources. Within the context of the model outlined in Section 2, a manager is assumed in period t-2 (i.e. 1997) to be setting next period's R&D intensity, conditional on his expectations of sales (SALES) and the firm's market power (CR2) in period t-1. His choice of R&D effort is shaped by profitability in t-2, since retained assets are an important source of innovation finance, as well as by the set of technological opportunities that are intrinsic in his industry (IND). The manager's demand for R&D resources is also conditioned by his incentive structure and the regulatory environment, which are influenced by the firm's ownership structure (OWN). The supply curve is determined partially by firm-level profitability; where R&D depends on outside financing, the firm's financial condition, ownership structure, and industry affiliation will also bear on the supply of bank finance or government funding.

We summarize a reduced form for R&D effort as:

$$\ln(\text{RDin/SALES})(t\text{-}1) = \alpha_0 + \alpha_1 \ln\text{SALES}(t\text{-}1) + \alpha_2 \ln(\text{PROF/SALES})(t\text{-}2) + \alpha_3 \ln\text{CR2}(t\text{-}1)$$
$$+ \alpha_4[(\ln\text{CR2})(t\text{-}1)]^2 + \alpha_5[\ln(\text{RDI/SALES})(t\text{-}2)] + \Sigma\alpha_j\text{IND} + \Sigma\alpha_i\text{OWN} + \varepsilon_1. \quad (2)$$

R&D effort may also be conditioned by the level of R&D in the last period. The firm's ability to utilize R&D resource effectively, even in the presence of favorable movements in sales, profits and other drivers of R&D effort, may be limited by its established R&D capabilities. The robustness of the coefficient on lagged R&D effort measures the persistence of R&D intensity; as such it is a useful measure of R&D flow as a proxy for R&D stock, the preferred measure of R&D effort. We estimate equation (2) with and without a lag in R&D intensity.

The concentration ratio (CR2) is the ratio, constructed from the data set for each of China's 552 four-digit industries, of the combined output of the largest two firms to total sales of large and medium enterprises. We use this variable to test the competing perspectives of Schumpeter (1943), who emphasizes the virtues of monopoly power, and Arrow (1962), who demonstrates the advantages of competitive markets to innovation.

In the U.S. economy, R&D is generally financed through retained earnings. In China, where enterprises face particularly severe liquidity constraints, the importance of retained earnings may be quite pronounced. On the other hand, as competition and the legal system evolve in China, poor profit performance may motivate R&D effort, including R&D subsidies from the state, to avoid chronic losses and bankruptcy.

The demand for R&D resources will vary across industries depending on the degree of technological opportunities intrinsic to the industry. Comanor and Scherer

(1969), for example, argue that a pharmaceutical innovation is relatively easy to patent; it is much harder for an invention like a ballpoint pen to be patented in a way that will exclude competition. New product innovation will also be limited in industries that produce relatively homogeneous goods, such as petroleum and natural gas production, mineral mining, and tobacco processing.

Finally, ownership structure may matter in multiple ways. The entrepreneur's incentive structure and time horizon will be affected by the system of ownership. Also, ownership may influence the availability of R&D resources, such as government subsidies that are more readily available to the state sector. Finally, the opportunity for R&D decision-makers to capture the returns to innovation may vary due to differences in tax systems and enforcement of intellectual property rights.

China's large and medium-size enterprises report a variety of measures of R&D effort. We use two measures of R&D intensity: the ratios of R&D expenditure to sales and R&D personnel to sales. While labor compensation for R&D personnel is a component of R&D expenditure, the association between these variables is not as great as it has been shown to be in the U.S., where labor personnel accounts for a substantial majority of R&D expenditure. In our population of LMEs, labor compensation accounts for less than one-third of total expenditure. This proportionately small share of labor compensation in total R&D expenditure arises in part from differences in relative prices of R&D inputs. Within China, compensation for scientists and engineers is low relative to the high cost of sophisticated equipment, licensed technology, and other inputs from outside the firm, which serve as complements to labor in the innovation process.

5. Knowledge Production Functions

In recent decades, the knowledge production function has emerged as an economic concept that links R&D outputs to R&D inputs.[3] For reasons explained later, we represent the relationship between R&D inputs and R&D outputs in intensive form, i.e. as RDin/SALES and RDout/SALES.

We use the following functional form.

$$\ln(\mathrm{RDout/SALES}) = \alpha_0 + \alpha_1 \ln(\mathrm{RDI/SALES})_{-1} + \alpha_2[\ln(\mathrm{RDI/SALES})_* \ln\mathrm{SALES}]_{-1} + \alpha_3 \ln\mathrm{AGE} + \Sigma\alpha_j \mathrm{IND} + \Sigma\alpha_i \mathrm{OWN} + \varepsilon_2 \qquad (3)$$

A central issue in the estimation of knowledge production functions is the role that firm size plays in determining the efficiency of knowledge production. We explicitly test this scale hypothesis through the inclusion of a cross-product, $\ln(\mathrm{RDI/SALES})_* \ln\mathrm{SALES}]$, in the estimation equation. The marginal product of R&D inputs with respect to R&D output is measured as:

$$\partial\mathrm{RDout}/\partial(\mathrm{RDin}_{-1}) \cong [\alpha_1 + \alpha_2(\ln\mathrm{SALES})_{-1}](\mathrm{RDin}_{-1}/\mathrm{RDout})^4 \qquad (4)$$

Values of $\alpha_2 \neq 0$ imply non-neutral scale effects. Positive scale effects may arise from internal economies of scope, say as between production, marketing, and R&D, or they may capture external marketing capabilities that make it easier to launch new

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[3] The only application of the knowledge production function to Chinese industry with which we are

products or enhance returns to new patents. Alternatively, negative scale effects may reflect problems of coordination or disincentive effects associated with scale.

We include in our knowledge production function a test for the role of experience (AGE), which may serve to enhance, through learning effects, or impair, say through organizational sclerosis, a firm's R&D capabilities. Finally, different ownership forms may imply different incentive structures that impact on R&D efficiency. Also, within different industries, the degree of difficulty is likely to vary in terms of the requisite volume of R&D inputs that are needed to produce comparable measures of new products or patents.

We use two common measures of R&D output: the ratios of new product sales to total sales and patent applications to sales. To allow for a broader measure of the impact of R&D on firm performance, such as process innovations that are not embodied in patents, Section 9 derives and estimates a reduced form version of Equations 1(b) and 1(c). Even if new product sales and patent applications turn out be incidental aspects of the innovation process, i.e. they are statistically insignificant in equations 1(b) and 1(c), we may still find in the reduced form estimates that R&D effort exerts a significant impact on firm performance.

6. Performance

We investigate the impact of R&D on two performance measures: productivity and profitability. In principle, in a perfectly competitive setting, with uniform price-

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familiar is Hu (1998).

[4] This expression is derived using the approximation SALES(-1) $\cong$ SALES.

taking behavior, a firm's relative productivity and profitability should perfectly correspond. In practice, they may not for various reasons. Both within and across industries, the markup of price over marginal cost will vary with market concentration and ease of entry in both input and product markets. A second reason why we do not expect productivity and profitability to correlate perfectly is the presence of measurement error. Differences in productivity, which we estimate from available input and output data, will not correlate fully with differences in profitability reported by the individual enterprises. For these reasons, we investigate the impact of R&D on both productivity and profitability.

Productivity. We model production as a Cobb-Douglas technology that allows for neutral shifts in the isoquants to represent efficiency differences across industries.

$$\ln Q = a + \alpha_K \ln K + \alpha_L \ln L + \alpha_M \ln M + \Sigma\alpha_j IND + \varepsilon_3 \qquad (5)$$

Productivity differences arise from differences in R&D performance and ownership:

$$a = a_0 + \theta \ln(RDout/SALES) + \Sigma\alpha_i OWN + \varepsilon_{4.} \qquad (6)$$

Substituting Equation (6) into Equation (5), the third estimation equation in the model becomes:

$$\ln Q = a_0 + \theta \ln(RDout/SALES) + \alpha_K \ln K + \alpha_L \ln L + \alpha_M \ln M$$

$$+ \Sigma\alpha_j IND + \Sigma\alpha_i OWN + \varepsilon_5, \qquad (7)$$

where $\varepsilon_5 = \varepsilon_3 + \varepsilon_4$.

The R&D variable enters in intensive form for the following reason. R&D can be measured as either an output or as an input. In the latter case, we may use either R&D expenditure or R&D personnel. The former includes expenditures on labor, capital, and intermediate inputs; the latter is simply the total of R&D personnel. In either case, the R&D input variable represents inputs to the R&D production process that are already included in the firm's reported use of fixed capital, labor, and intermediate inputs. While double counting is not a problem for the measures of R&D output used in Equation (7) above, it will prove to be a problem in estimating the reduced form in Section 9, in which performance is driven by R&D inputs. To avoid double counting in the reduced form, which is derived by substituting Equation (3), the R&D output equation, into Equation (7), the productivity equation, we construct the variable RDout/SALES to represent the R&D intensity of the {K,L,M} vector of inputs

Profitability: To investigate the impact of R&D on profitability, we start with the function:

$$PROF_i = \rho Q \nu_i, \qquad (8)$$

Equation (8) characterizes profit as a stochastic function of output and other factors, summarized by ρ, an average competitive, long-run rate of return, and ν, a stochastic variable that captures differences in efficiency, inventory accumulation, and pricing practices across firms. Substituting (7) into (8), dividing through by SALES, setting SALES = $Q\mu$, and rearranging gives:

$$\ln(\text{PROF/SALES}) = a + \theta\ln(\text{RDout/SALES}) + \alpha_K\ln(K/Q) + \alpha_L\ln(L/Q) + \alpha_M\ln(M/Q) + \gamma\ln Q + \Sigma\alpha_j\text{IND} + \Sigma\alpha_i\text{OWN} + \varepsilon_5, \qquad (9)$$

where $\varepsilon_5 = \varepsilon_4 + \ln(\nu - \mu)$.

Equation (9) requires some interpretation. First, the terms (K/Q), (L/Q), and (M/Q) are measures of factor intensity. Since Equation (9) controls for output, Q, any increase in factor intensity, raising K, L, or M, without a corresponding increase in Q will likely depress profitability. We therefore expect the coefficients on the factor intensities to be negative. Second, note that in the case of constant returns to scale i.e. $\alpha_K+\alpha_L+\alpha_M = 1$, the coefficient on output, i.e. γ, is just zero.

7. The Data

Our data set covers the years 1995-1999. In principle, we should use all the data, or a balanced set of data, to estimate our model. Using five years of panel data, we can (i) construct a stock of R&D capital and/or (ii) incorporate time series analysis into our estimation. In this paper, we use only the recent three years of the data: i.e. 1997, 1998 and 1999. We do this for two reasons. These are:

- The number of enterprises for which we would be able to construct a meaningful stock of R&D capital over a five-year period is severely limited by the large number enterprises for which observations are missing in one or more years.
- The further back we go in time, the more homogeneous the ownership structure of the data set. Due to exit and entry and ownership conversions, which involves the assignment of new enterprise IDs, just 46 percent of the firms reporting in1999 can be found in the data set in 1994.[5]

Once we account for these conditions, even limiting our panel to three years – 1997, 1998 and 1999 – our balanced sample is reduced to 5,451.

A second issue that arises in relating our data to the estimation equations is the role of prices. Since we are using a single cross section, we are generally able to avoid the problem of constant versus current prices. In estimating the production function, we use a current price measure of gross output.

The capital stock is a composite price. To approximate a fixed unit price measure of capital, we adjust the net capital stock by a vintage index, which we construct as the ratio of net value of fixed assets (NVFA) to original value of fixed assets (OVFA). Hence, we define the capital stock as:

$$K = NVFA(NVFA/OVFA)^{\alpha_v}. \qquad (10)$$

[5] Relative to 1994, the proportions of shareholding and private enterprises that survived until 1999 with the same IDs were just 12 and zero percent respectively. Less than 30 percent of the overseas and foreign enterprises survived through 1999.

The index NVFA/OVFA falls within the range 0 to 1, where values close to one represent a relatively newly-installed capital stock and those closer to zero represent an older, depreciated stock of capital. Estimates of $\alpha_V > 0$ imply that for a given net stock of capital, the newer vintages are relatively more productive per yuan of investment; alternatively $\alpha_V < 0$ implies that older vintages tend to be more price efficient than newer vintages.

Our data include 23 ownership classifications. For purposes of estimation, we combine these into seven classifications, which correspond to the more commonly-used set of ownership classifications. These are: state-owned enterprises (SOE), collective-owned enterprises (COE), foreign-invested enterprises (FOE), H.K. and Taiwan-owned enterprises (HKT or overseas), shareholding enterprises (STK), privately-owned enterprises (PRI), and other (OTH) forms of domestic ownership. While each enterprise is classified according to one of 552 four-digit enterprises; we aggregate these into the 29 two-digit industries shown in Annex I.

In the regression analysis that follows, the reference intercepts are represented by nonmetal mineral products (31) and by state-owned enterprises. Coefficients on dummy variables that are statistically significant are significantly different – larger or smaller – than these reference categories.

7. Estimation Results

We estimate the R&D intensity equation (2), the knowledge production function (3), the productivity equation (7), and the profitability equation (9). The key results are outlined below.

R&D intensity. The coefficient on SALES measures the responsiveness of R&D intensity to firm size; $\alpha_1 = 0$ implies scale neutrality. Estimates for equation (1), shown in Table 4, indicate an elasticity of R&D expenditure intensity with respect to sales of 0.060, whereas for R&D personnel intensity the elasticity is –0.401. One possible reconciliation of these seemingly inconsistent results is that larger firms spend larger proportions of their R&D expenditure on non-labor inputs, i.e. equipment, intermediate inputs, and technology purchases. This interpretation implies that R&D personnel in large-size firms operate with more complements than their counterparts in medium-size firms. We therefore expect that the marginal products of R&D personnel in large-size enterprises should exhibit a greater advantage over those of medium-size enterprises than the comparable advantage of marginal products for R&D expenditure. The marginal products shown in Table 12 indicate that this is indeed the case. For example, the ratio of dNP/dRDper98 for large to medium size enterprises is 19,745/12,709 = 1.554, which is substantially larger than the ratio of productivities for R&D expenditure (dNP/dRDexp98) for large and medium size enterprises, i.e. 0.389/0.400 = 0.973.

Estimates of the R&D intensity equations also yield the following results:

- Consistent with Schumpeter's hypothesis, we find that increasing market concentration elevates R&D intensity measured in terms of expenditure. At the same time, market concentration has no apparent effect on the intensity of R&D personnel. This result seems to suggest that complements to R&D personnel – R&D equipment and technology and material inputs to the innovation process purchased from outside the firm – are in greater demand among firms operating in industries with high concentration ratios.

- Profitability lagged one year significantly affects R&D effort. Given the generally risky nature of the R&D operation and the difficulty of monitoring R&D activity externally, this finding is not surprising. Grabowski (1968), for example, found in U.S. manufacturing data that profits lagged by one year were a significant determinant of R&D expenditure at the firm level. This pattern in Chinese industry is particularly pronounced for R&D expenditures; a 10 percent increase in profitability results in a 2.65 percent increase in the intensity of R&D expenditures.
- R&D effort, lagged one period, enters robustly. These high levels of statistical significance suggest a high degree of persistence of R&D effort. We expect, therefore, that recent R&D resource flows provide a reasonable proxy for R&D stock, the more appropriate measure of R&D input.
- Levin et al (1985) identified key characteristics of industries that exhibit high levels of R&D intensity. These include: (i) dependence on basic science, (ii) dependence on technology supplied by upstream suppliers, and (iii) effectiveness of mechanisms to prevent imitation. Controlling for sales, profit, exports, and ownership, our results show that within Chinese industry, the industry that most consistently registers the highest R&D intensity is electronic and telecommunications equipment (41); transport equipment (37) is near the top of the personnel equation. Curiously, while

the pharmaceuticals industry (27) registers high for R&D expenditures, it's intensity of R&D personnel is among the lowest. We surmise that pharmaceuticals is an industry in which R&D labs, financed by non-labor expenditures, play a major role.

- After controlling for the determinants of R&D effort, we find that among the key ownership classifications, overseas (HKT) enterprises register high levels of R&D expenditure intensity. Controlling for sales, profitability, and market concentration, state-owned enterprise is more intensive in R&D personnel than virtually all other ownership types.

Knowledge production function. The estimation results for new product sales production and patent applications are shown in Tables 5a and 5b respectively.

Including the cross-product of ln(RDin/SALES) and ln(SALES) allows for a test of scale neutrality. The results in Table 5a show the elasticity of new product sales with respect to R&D inputs declining with firm size. Table 5b shows the opposite result: the elasticity of patent production with respect to R&D inputs rises with firm size. In Table 12a, we see that the relative marginal products are distinguished by a combination of firm size and R&D inputs. Because medium-size enterprises are intensive in personnel, their knowledge returns to personnel are relatively low. Since large-size enterprises are intensive in expenditures, they exhibit relatively low returns to R&D expenditures. Differences in the intensities of knowledge production may also explain the results shown in Table 12a. As shown in Table 3, medium-size firms are comparatively specialized in new product innovation, whereas large-size firms produce comparatively more patents. These comparative intensities in knowledge production serve to depress the returns to patent production for large firms relative to medium firms. In the performance equations, we see that even though large firms are comparatively focused on patents, their patenting activity enjoys higher marginal returns than that of medium-size enterprises.

In addition, our findings include the following:

- AGE, as a proxy for experience, is consistently insignificant.
- In the creation of new product sales, the equipment and machinery industries (i.e. 41, 40, 35, 36, 37, 42) enjoy a significant edge. Steel (32) and tobacco products (16) show low contributions to new product development. Both R&D spending and personnel make their largest contributions to patent production in cultural, educational, and sporting goods industry (24).
- Across ownership classifications, R&D inputs make their largest contributions to new product sales in the foreign sector; in the production of patents, R&D resources make their largest contributions in the collective sector. Measured in terms of R&D personnel, Table 12a shows that in FOR enterprises, the marginal product of R&D personnel in producing new products is five times that of the average LME and more than times that of the SOE group. Measured in terms of R&D expenditure, this advantage declines to a factor of two.

. ***Productivity***. Table 6 shows the estimation results for the third equation in the model – the productivity equation. Controlling for inputs of capital, including the vintage effect (i.e. the ratio of net to gross value of fixed assets, labor, and materials, we find that both new product sales and patent applications are associated with higher productivity. Both exhibit output elasticities in the range of 0.35-0.37. Table 12a indicates that a one dollar increase in new product sales yields only a seven cent increase in output, while a new patent application is associated with 15,765,000 yuan of additional sales. One possible explanation of this seemingly small effect on output of new product sales is that the introduction of new products may result in the retirement of old products.

In addition, our results show that:

- While medium-size enterprises enjoy a small advantage in the marginal productivity of new products, large-size firms exhibit a substantial advantage in productivity gains associated with new patent applications – more than twice that of medium-size firms. Whether this advantage derives from the ability of large-size firms to create higher quality patents or their greater ability to capture the returns to innovation is unclear. Having found that market concentration promotes R&D expenditure, we surmise that market concentration is one factor that enables large-size firms to capture higher returns to patenting activity.
- We find a high correspondence among industries in which productivity gains result from both new products and from patents (i.e. the industry dummies in the new product and patent equations are both positive and significant). These include tobacco (16), beverages (15), pharmaceuticals (27), and electronic equipment and machinery (38).
- Table 12a shows that the marginal productivies of new products and patents are comparatively high in the state-owned sector. This finding suggests that while SOEs appear to be inefficient in knowledge production, once they secure new knowledge, in the form of new products and patents, they are able to use it to achieve productivity gains.

Profitability. The estimates reported in Table 7 show that both new product sales and patenting activity contribute to profitablity. Contributions to profitability of both new products and patents in the foreign and pharmaceutical sectors stand out. Measures of marginal profitability, shown in Table 12a, show comparatively uniform patterns of returns across both firm size and ownership types. Our estimates show rates of return on new products in the range of 17.7 percent. The average return on a patent application falls in the range of 5.7 million yuan.

8. SUR estimates

The three-equation model that we estimate above with OLS represents a system of equations. To obtain the most efficient set of estimates and to explore any insights that we can gain from an examination of the covariance of the residuals, we re-estimate the model using a seemingly unrelated (SUR) estimator. We implement the SUR estimator for both the R&D expenditure and personnel versions of the new product model. The results are shown in Table 8. Throughout the results are very similar to the OLS estimates with a pattern of slightly larger t-statistics and adjusted R^2.

We wish to examine the covariance of the residual matrices to gauge the nature of the error structure in the model. A pattern of positive correlations would indicate the presence of firm effects, such as differences in managerial quality, that are not captured by the model. A firm whose high quality is not captured by the model, might be expected to have higher than predicted returns to new products, high returns to R&D inputs, and mount a higher than expected R&D effort. Alternatively, a pattern of negative correlations may be interpreted as a sign of measurement error or optimizing error.

The correlations, shown in Table 8b, do not exhibit a uniform pattern. While most of the signs on the correlation matrix are negative, only one of the correlations exceeds an absolute value of 0.02. The negative correlation between the R&D personnel intensity equation and the associated productivity equation equation indicates that, on average, firms for which R&D intensity is higher than expected, create new products whose productivity is lower than expected. While we might interpret this negative association between effort and returns as the logical result of optimizing error, since the association between the R&D intensity and profitability residuals is virtually zero, this interpretation does not seem appropriate.

9. Reduced Form Estimation

In order to test directly the impact of R&D effort on performance, we substitute the knowledge production functions, summarized by equation (3), into the productivity and profitability equations, Equations (7) and (9). To address the possibility of simultaneity bias arising from reverse causality from the dependent variables – GVIO and profit/sales – to the sales variables on the RHS of the equations, we estimate the reduced forms using instrumental (IV) estimates as well as OLS. The instruments that we use for sales are five categories used by the NBS to distinguish firm size, as well as the ownership and industry dummies. The results discussed below are based on the IV estimates.

Productivity. In the U.S., there is a well-established practice of investigating these reduced form functions. Griliches (1986) has examined the effect of R&D

expenditure on productivity in approximately 1,000 of the largest U.S. manufacturing firms in the period 1957-77. He found very higher returns, including in 1977 gross rates of return of 33 percent.

Estimates for the reduced form productivity equation are shown in Table 9. We estimate the R&D expenditure and R&D personnel equations with and without the SALES cross product, but we report here only the results that include the cross-product that allows for scale non-neutrality.

- Allowing for scale non-neutrality, the results in Table 9 show that the elasticity of output with respect to R&D – both R&D expenditure and R&D personnel – declines with firm size. Our estimates of marginal productivities, reported in Table 12b, show that with respect to R&D expenditures medium-size firms enjoy a considerable productivity advantage, but for R&D personnel, this advantage nearly disappears.
- As shown in Table 12b, measured in terms of R&D personnel, foreign and overseas-owned enterprises exhibit the highest marginal productivities, while SOEs exhibit the lowest. The pattern for R&D expenditure is nearly reversed. The likely explanation of these disparities in the marginal efficiencies of personnel and expenditures is that overseas and foreign-owned enterprises direct a large proportion of their expenditures to non-labor inputs, including equipment, intermediate inputs, and other technology purchases, which raise the productivity of their R&D personnel.

Profitability. Branch (1974) examined the relationships between R&D expenditure and profits for 111 large U.S. firms in seven R&D intensive sectors in the period 1950-65. He found a strong link between profits and previous R&D activity in all seven sectors. Jaffe (1986) investigated the effects of R&D spending on profit in a sample of 432 U.S. manufacturing firms for 1973 and 1979. His estimates suggest a gross return to R&D expenditure of 27 percent, compared with just 15 percent for physical capital.

Estimates for the reduced form profitability equation are shown in Table 10. We include the SALES cross product for the R&D personnel equation, however since the interactive term is statistically insignificant for the R&D expenditure equation, we do not include it.

- Table 12b shows that returns to R&D expenditure tend to be higher in medium-size enterprises than in the larger enterprises that are more intensive in R&D expenditures. The opposite result holds for R&D personnel, for which returns are higher in large-size firms.
- The tendency for foreign and overseas-owned firms to specialize in R&D expenditures creates a huge advantage in the profitabiliy of R&D personnel in this sector. Notwithstanding their relative emphasis on R&D expenditure, however, returns to expenditure in the foreign and overseas sector are comparable to those of Chinese industry overall. Apart from returns to R&D expenditure in the "other" sector, the returns to both R&D personnel and R&D expenditure are lowest in the state-owned sector

Our analysis throughout has been conducted in intensive form, involving the use of functional forms that are somewhat different than those found in some of the R&D literature. In order to make more direct comparisons with other estimates of R&D performance available in the literature, we estimate a restricted profit function of the form:

$$\ln\pi = \alpha_0 + \alpha_1 \ln LAB + \alpha_2 \ln NVFA + \alpha_3 \ln RDE(-1) + \Sigma\alpha_j IND + \Sigma\alpha_i OWN + \varepsilon. \quad (10)$$

Equation (10) is estimated using two measures of RDE – R&D expenditure and R&D personnel, both for 1998. The estimation results are shown in Table 12c. The marginal profitabilities of RDexp98 and RDper98 reported in Table 12c are similar to those reported for the reduced form estimates shown in Table 12b. The average return to R&D derived from the profitability equation is 20.5 percent; that in the restricted profit equation is 17.0 percent. These estimates both exceed our estimate of the measured return to physical capital of 12.1 percent. For R&D personnel, the estimated return in the profitability equation is 36,548 yuan per person as compared with an estimate of 31,296 in the restricted profit function. This compares with a return of 8,866 yuan per production worker. These results suggest approximately a 40 percent advantage to R&D capital over physical capital and a nearly four-fold advantage of R&D personnel over production personnel.

9. The channels of innovation

The three-equation model used in this paper is based on the assumption that innovation operates through one or a combination of two channels – new product innovation and/or the development of patented innovations. In fact, innovation may be broadly construed to span a much wider variety of activities than new products and patents. Other forms of innovation include improvements in product design and quality;

innovation also includes many aspects of process innovation that do not entail patenting, including the installation of new equipment and quality control methods. In a developing economy, such as China's, we might indeed anticipate that much of R&D is unrelated to the development of new products and patents.

In order to identify the proportion of returns to R&D effort that can be attributed to new products and patents, we compute the individual contributions of R&D that operate through new product sales and patenting activity and compare these with the total returns to R&D that we estimate from the reduced form equations. The results, shown in Table 13, indicate that the combined return to R&D expenditure in the production of new products and patents is 17.3 percent, approximately 84 percent of the total 20.5 percent return. For R&D personnel, the combined return through the two innovation channels that we examine in this paper is just 6,727 yuan per R&D personnel, less than 20 percent of the total return to R&D personnel. This contrast in the composition of returns to R&D expenditure and R&D personnel is consistent with previously reported results. We see a pattern in which R&D expenditures are specialized in large-size firms that use comparatively large quantities of R&D equipment and other purchased technology inputs to create new products and patents. By comparison, firms that organize their innovation programs around R&D personnel – principally medium-size firms – appear to capture a substantially smaller share of their innovation returns from new products and patents. A substantial proportion - even the majority - of such resources may be used for more routine work that is broadly construed as R&D.

10. Conclusions

Using a panel of China's large and medium-size enterprises, we investigate patterns of R&D activity and its impact on firm-level performance. A key result of our analysis is that we find statistically significant relationships for all of the essential R&D relationships within the model. Among our findings are:

- R&D performers are more concentrated among capital-intensive firms with large sales volumes, particularly those classified by the NBS as "large size". The highest incidence of R&D performers is located in equipment and machine manufacturing and in the pharmaceutical industry; the lowest concentrations are located in printing, garments, and timber. Across ownership types, controlling for size, capital intensity, and industry, R&D performers are more concentrated among SOEs and shareholding companies and least concentrated among foreign and overseas enterprises.
- The ratio of R&D expenditures to R&D personnel rises substantially as firm size increases; the implication is that larger firms purchase more complements to R&D personnel, which appear to provide for the construction and operation of laboratory facilities. This tendency for medium-size enterprises to specialize in the use of R&D personnel in the innovation process and for large-size firms to specialize in non-labor inputs to R&D is a defining feature of R&D activity in Chinese industry.
- While R&D expenditures are significantly responsive to market power, the intensity of R&D personnel is not. Where firms enjoy market power, they seem to invest more in capital-intensive R&D operations, although it may also be the case that

sophisticated R&D operations reinforce market concentration. The pharmaceutical industry seems to fit this description.

- In most of the estimated relationships, large-size firms enjoy a substantial efficiency with respect to the use of R&D personnel; medium-size firms enjoy efficiency advantages in their use of R&D expenditures. Because large-size firms are comparatively specialized in the production of patents, relative to medium-size firms that are comparatively specialized in new products, large-firms exhibit comparatively low returns in knowledge patent production.
- State-owned enterprises exhibit the lowest levels of efficiency in knowledge production. However, once they acquire new knowledge, SOEs appear to be able to use the innovations as effectively, or sometimes more so, than enterprises of other ownership forms. Using the reduced forms to examine the overall impact of R&D effort, we find that foreign and overseas enterprises most efficiently use R&D personnel in the innovation process, probably because of large quantities of complementary expenditures that they employ in the R&D process.
- The profitability of knowledge capital and R&D personnel in Chinese industry exceed counterpart returns to production capital and production workers.
- Firms whose R&D operations are intensive in R&D expenditure capture the majority of their returns through new product sales and patenting. Firms with few R&D complements for their R&D personnel focus principally on innovation processes apart from the creation of new products and patents.

Table 1
Basic Statistics

Variable	All LMEs[1]				Regression sample[2]
	All		Omit all 0s		
year	1995	1999	1995	1999	1999
RDexpenditure/ SALES	0.004	0.008	0.021	0.028	0.013
RDperson/total employment	0.034	0.073	0.054	0.143	0.080
NP/SALE	0.088	0.118	0.194	0.325	0.159
PATAP	0.175	0.362	2.86	5.38	0.664
No. of enterprises	20,781	19,943	14,169	9,204	5,451

[1] Manufacturing industries only. (Two digit non-manufacturing industries, #09,…are omitted.
[2] Omits observations for which RDexp = RDper = NP (new products) = PATAP (patent applications) = 0 and profit < 0.

Table 2
Probit estimates of marginal probabilities of R&D performance*

Variable/enterprise type	Marginal probability of inclusion[1]	Variable/enterprise type	Marginal probability of inclusion[1]
Large	0.098*	30	0.148*
Sales	0.110*	34	0.138*
NVFA/GVIO	0.010*	26	0.137*
COE	-0.114*	33	0.060*
FOR	-0.368*	28	0.055
HKT	-0.240*	15	0.050*
STK	-0.009	17	0.025
PRI	-0.220*	14	0.020
OTH	-0.117*	43	0.012
By industry:	-	19	0.006
42	0.393*	16	0.002
36	0.348*	25	-0.012
35	0.344*	32	-0.022
27	0.339*	22	-0.026
41	0.290*	20	-0.075
40	0.283*	18	-0.115*
37	0.253*	23	-0.199*
29	0.231*	pred. P (at x-bar)	0.519
24	0.202*	Pseudo R^2	0.178
21	0.183*	No. of obs.	19,165

[1] Reference = small, SOE, industry 31.

Table 3
Distribution of R&D Performers

	Full sample	med	large	SOE	COE	FOR	HKT	STK	PRI	OTH
Full sample distribution	19,943	13,097	6,846	9,354	3,350	1,937	1,517	3,283	313	189
(1) RDexp>0	3,052	1,424	1,628	1,833	356	170	150	321	192	30
(2) RDper>0	4,957	2,519	2,438	2,958	660	250	233	222	585	49
(3) NPsales>0	3,710	1,783	1,923	2,188	487	208	182	373	228	44
(4) PATapp>0	761	279	482	429	96	38	38	106	51	3
(5) Profit ≥ 0	17,515	11,387	6,028	8,003	3,044	1,642	1,264	2,994	291	177
Trim sample distribution*	5,451	2,881	2,570	3,148	803	279	262	643	261	55

*At least one of (1) to (4) and (5).

Table 4
Determinants of R&D Intensity [(RDE/SALES)(98)]

Variable	RD expend	RD expend.	RD personnel	RD personnel
Constant	-9.007 (12.272)	-5.778 (8.245)	-2.281 (8.391)	-0.376 (1.590)
lnSALE(98)	0.060 (2.299)	0.022 (0.898)	-0.401 (41.663)	-0.309 (36.336)
ln[(PROF/ SALES)(97)]	0.265 (5.375)	0.158 (3.398)	0.155 (8.498)	0.068 (4.345)
lnCR2(98)	1.023 (2.537)	0.653 (1.720)	-0.031 (0.207)	-0.111 (0.871)
[ln(CR2(98)] *sq	-0.139 (2.213)	-0.083 (1.412)	0.008 (0.354)	0.019 (0.945)
ln[RDE/ SALES(97)]	n.a.	0.330 (26.629)	n.a.	0.397 (44.624)
IND[1]	(+) 41,27,37, 42,,40 (-) 17,18,23,16, 18,13	(+) 41,27 (-)17,23,18,	(+) 41,37,36,35, 42,40,32 (-) 13,16,15,26, 23,14,22,17, 22,20,27	(+) 37,41,35,36, 32,42,25 (-) 16,15,27,26, 14,13
OWN[1]	(+) HKT	(+) HKT	(-) COE, FOR, HKT, SKT, OTH	
Adj R^2	0.049	0. 159	0.433	0.586
Obs.	5451	5451	5451	5451

[1] Estimates of reported ownership and industry classifications are significant at the 95-100% level of statistical significance. Ownership and industries are ordered from the most to the least statistically significant.

Table 5a
Knowledge Production Function
(new product sales/sales)

Variables	R&D expenditure		R&D personnel	
Constant	-2.007 (18.749)	-2.013 (18.809)	-1.685 (10.859)	-1.224 (7.286)
Dln(NP/ sales)[1]	-6.887 (185.230)	-6.870 (182.375)	-6.893 (185.838)	-6.835 (180.456)
lnAGE	-0.018 (1.072)	-0.016 (0.962)	-0.024 (1.430)	-0.023 (1.362)
lnRDexp/ SALE(98)	0.034 (4.622)	0.094 (4.049)	n.a.	n.a.
ln(RDexp/SALE) *lnSALE(98)	n.a.	-0.005 (2.711)	n.a.	n.a.
lnRDper/ SALE(98)	n.a.	n.a.	0.079 (4.525)	0.321 (8.261)
ln[RDper/SALE) *lnSALE(98)]	n.a.	n.a.	n.a.	-0.016 (-6.967)
Industry[2]	(+) 41,40,36,37,42 (-) 32,16,15,25,26,27,14			
Ownership[2]	(+) FOR		(+) FOR	+
Adj. R2	0.877	0.877	0.877	0.878
Obs.	5451	5451	5451	5451

[1]Values of NP/SALES = 0 have been converted to 0.0001

[2] Estimates of reported ownership and industry classifications are significant at ≥ the 95% level of statistical significance. Ownership and industries are ordered from the most to the least statistically significant.

Table 5b
Knowledge Production Function
(patent applications/sales)

Variables	R&D expenditures		R&D personnel	
Constant	-11.237 (216.647)	-11.161 (222.843)	-10.621 (144.749)	-11.187 (151.093)
Dln(PAT/ sales)[1]	-7.153 (309.300)	-7.251 (318.429)	-7.160 (314.059)	-7.301 (323.627)
lnAGE	-0.003 (0.438)	-0.009 (1.216)	-0.009 (1.152)	-0.010 (1.360)
ln[RDexp/ SALE(98)]	-0.002 (0.600)	-0.204 (19.755)	n.a.	n.a.
ln[RDexp/SALE) *lnSALE(98)]	n.a.	0.018 (20.624)	n.a.	n.a.
ln[RDper/ SALE(98)]	n.a.	n.a	0.083 (10.629)	-0.269 (15.958)
ln[RDper/SALE)* lnSALE(98)]	n.a.	n.a	n.a.	0.023 (23.324)
Industry[2]	(+) 24 (-) 32,37,25	(+) 24,15	(+) 24 (-) 32,37,25	(+) 24,16
Ownership[2]	(+) COE		(+) COE	(+) COE
Adj. R2	0.948	0.952	0.949	0.954
Obs.	5451	5451	5451	5451

[1]Values of PAT/sales = 0 have been converted to 10.0 x 10^{-9}, i.e. less than the smallest of the observations for which PAT > 0.

[2] Estimates of reported ownership and industry classifications are significant at ≥ the 95% level of statistical significance. Ownership and industries are ordered from the most to the least statistically significant.

Table 6
Impact of R&D output on productivity (ln GVIO)

Variable	New products	Patents
Constant	0.737 (19.382)	-0.447 (6.575)
lnK (capital)	0.143 (31.266)	0.139 (30.206)
ln(NVFA/OVFA) Vintage effect	-0.124 (10.809)	-0.122 (10.613)
lnL (labor)	0.098 (17.461)	0.092 (16.538)
lnM (materials)	0.749 (n.a.)	0.749 (n.a.)
ln(NP/sales)	0.013 (4.952)	n.a.
Dln(NP/sales)	0.037 (1.956)	n.a.
ln(PAT/sales)	n.a.	0.035 (5.885)
Dln(PAT/ sales)	n.a.	-0.331 (7.524)
IND	(+) 16,15,27,38,13,12,25,32,36,37,…	
OWN	(+) FOR, COE, HKT,STK	
Adj R2	0.970	0.970
Obs.	5451	5451

Table 7
Impact of R&D output on profitability*
(dependent variable = ln(profit/sales)

Variable	New product sales	Patent applications
Constant	-2.337 (18.933)	-1.971 (0.030)
ln(L/Q) labor/output	-0.024 (1.359)	-0.029 (1.667)
ln(K/Q) capital/output	0.091 (5.499)	0.092 (5.512)
ln(NVFA/OVFA) vintage capital	-0.198 (5.333)	-0.202 (5.416)
ln(M/Q) materials/output	-0.648 (13.914)	-0.650 (13.928)
lnQ (output)	0.011 (1.035)	0.023 (2.007)
ln(NP/sales)	0.024 (2.951)	n.a.
Dln(NP/sales)	0.043 (0.710)	n.a.
ln(PAT/sales)	n.a.	0.052 (2.739)
Dln(PAT/sales)	n.a.	0.317 (2.229)
IND	(+) 27 (-) 13,16,32,17,28,25,14,….	
OWN	FOR	
Adj. R-square	0.118	0.114
Observations	5451	5451

Table 8
SUR estimates of the new product models

Equation/variable	R&D expenditure	R&D personnel	Equation/variable	R&D expenditure	R&D personnel
R&D intensity equation (A1,A2)			**Productivity equation (C1,C2)**		
Constant	-5.805 (8.315)	-0.724 (3.090)	Constant	0.587 (12.737)	0.563 (12.640)
lnSALE(98)	0.023 (0.951)	-0.291 (34.513)	lnK (capital)	0.143 (31.371)	0.143 (31.543)
ln[(PROF/ SALES)(97)]	0.164 (3.543)	0.080 (5.123)	ln(NVFA/OVFA) Vintage effect	-0.124 (10.844)	-0.124 (10.848)
lnCR2(98)	0.669 (1.768)	-0.109 (0.862)	lnL (labor)	0.098 (17.518)	0.102 (18.374)
[ln(CR2(98)]*sq	-0.085 (1.448)	0.019 (0.950)	lnM (materials)	0.749 (n.a.)	0.749 (n.a.)
ln[RDE/ SALES(97)]	0.330 (26.782)	0.388 (44.083)	ln(NP/sales)	0.015 (5.820)	0.014 (5.460)
-	-	-	Dln(NP/sales)	0.253 (4.809)	0.230 (4.394)
R^2	0.165	0.587	R^2	0.970	0.970
Knowledge production function (B1,B2)			**Profitability equation (D1,D2)**		
Constant	11.866 (109.382)	8.445 (21.671)	Constant	-2.664 (18.048)	-2.715 (18.917)
Dln(NP/ sales)	-20.672 (541.412)	-20.636 (535.252)	ln(L/Q) labor/output	-0.023 (1.328)	-0.021 (1.222)
lnAGE	-0.017 (1.011)	-0.025 (1.489)	ln(K/Q) capital/output	0.093 (5.638)	0.093 (5.652)
ln[Rdexp/ SALE(98)]	0.111 (4.687)	-	ln(NVFA/OVFA) vintage capital	-0.200 (5.402)	-0.199 (5.376)
ln[Rdexp/SALE)* lnSALE(98)]	-0.006 (2.974)	-	ln(M/Q) materials/output	-0.638 (13.764)	-0.643 (13.860)
ln[Rdper/ SALE(98)]	-	0.262 (8.216)	lnQ (output)	0.011 0.998	0.011 (1.037)
ln[Rdper/SALE)* lnSALE(98)]	-	-0.016 (6.792)	ln(NP/sales)	0.024 (3.029)	0.026 (3.259)
-	-	-	Dln(NP/sales)	0.379 (2.262)	0.416 (2.483)
R^2	0.984	0.984	R^2	0.124	0.124

Table 8b: Correlation matrix of residuals

	A1	B1	C1	D1		A2	B2	C2	D2
A1	1.000				A2	1.000			
B1	-0.018	1.000			B2	-0.001	1.000		
C1	-0.000	-0.013	1.000		C2	-0.108	-0.012	1.000	
D1	-0.004	-0.001	0.004	1.000	D2	-0.008	-0.003	0.004	1.000

Table 9
Reduced Form: Effect of R&D effort on productivity
Dependent variable = ln(Output), OLS

Variable	R&D expenditure		R&D personnel	
	OLS	IV*	OLS	IV*
Constant	2.072 (44..412)	0.735 (16.406)	2.615 (43.332)	1.006 (15.038)
lnK (capital)	0.059 (13.302)	0.141 (29.153)	0.021 (4.609)	0.132 (25.006)
ln(NVFA/OVFA) Vintage effect	-0.048 (4.792)	-0.123 (10.481)	-0.014 (1.466)	-0.113 (9.496)
lnL (labor)	0.045 (9.035)	0.097 (17.187)	0.029 (6.051)	0.088 (15.028)
lnM (materials)	0.749 (n.a.)	0.749 (n.a.)	0.749 (n.a.)	0.749 (n.a.)
ln[RDexp/ SALE(98)]	0.238 (42.707)	0.010 (2.575)	n.a.	n.a.
ln[RDexp/SALE) *lnSALE(98)]	-0.021 (43.601)	-0.001 (2.101)	n.a.	n.a.
ln[RDper/ SALE(98)]	n.a.	n.a.	0.304 (34.612)	0.071 (6.386)
ln[RDper/SALE) *lnSALE(98)]	n.a.	n.a.	-0.027 (45.306)	-0.005 (5.822)
IND	(+)16,42,15,27,13,39,25,23 37,38,22,18,20,26,33,17		(+)16,42,15,27,13,23,39, 25,18,37,38,20,26	
OWN	(+) FOR, COE, HKT,STK			
Adj. R2	0.978	0.970	0.980	0.970
Obs.	5451	5451	5451	5451

*The instrumental variables are size [i.e. Large (2 discrete sizes) or Medium (3 discrete sizes)], ownership (OWN), and industry classification (IND).

Table 10
Reduced Form: Effect of R&D effort on profitability
Dependent variable = ln(Profit/sales)

Variable	R&D expenditure		R&D personnel	
	OLS	IV[1]	OLS	IV[1]
Constant	2.427 (19.496)	2.506 (20.493)	4.218 (13.022)	-1.873 (9.178)
ln(L/Q) labor/output	-0.029 (1.579)	-0.029 (1.647)	-0.038 (2.111)	-0.044 (2.467)
ln(K/Q) capital/output	0.085 (5.120)	0.088 (5.288)	0.108 (6.356)	0.078 (4.374)
ln(NVFA/OVFA) vintage capital	-0.195 (5.234)	-0.199 (5.315)	-0.227 (6.072)	-0.188 (4.917)
ln(M/Q) materials/output	-0.646 (13.821)	-0.651 (13.938)	-0.624 (13.413)	-0.644 (13.804)
lnQ output	0.017 (1.633)	0.017 (1.557)	0.196 (7.146)	-0.017 (1.071)
ln[RDexp/ SALE(98)]	0.015 (3.348)	0.002 (1.700)	n.a.	n.a.
ln[RDexp/SALE) *lnSALE(98)]	n.a.	n.a.	n.a.	n.a.
ln[RDper/ SALE(98)]	n.a.	n.a.	-0.207 (4.592)	0.127 (3.744)
ln[RDper/SALE) *lnSALE(98)]	n.a.[2]	n.a.[2]	0.023 (6.389)	-0.007 (2.824)
OWN	-	(+) COE	-	-
IND				
Adj. R2	0.114	0.112	0.124	0.115
Obs.	5451	5451	5451	5451

[1]The instrumental variables are size [i.e. Large (2 discrete sizes) or Medium (3 discrete sizes)], ownership (OWN), and industry classification (IND).
[2]Including this variable caused estimates of both itself and ln[RDper/SALE(98)] to be statistically insignificant.

Table 11
Restricted profit function

variable	R&D expenditure	R&D personnel
constant	-0.608 (3.412)	-0.471 (2.631)
labor	0.459 (17.253)	0.406 (14.490)
capital	0.577 (27.481)	(0.562) (26.579)
R&D expenditure98	0.008 (3.460)	n.a.
R&D personnel98	n.a.	0.104 (6.196)
OWN	FOR,HKT, COE, STK,PRI	FOR,HKT, COE,STK,PRI
IND	27,16,25,	27,16,25
Obs.	5451	5451
R^2	0.486	0.489

Table 12a: Calculated marginal products*

Marginal products	Elasticities: Full Sample	Full Sample	Medium -size	Large-size	SOE	COE	FOR	HKT	STK	PRI	OTHER
Knowledge production equations											
dNP/ dRDexp98*	0.033	0.394	0.400	0.389	0.327	0.588	0.730	0.486	0.487	0.583	0.187
dNP/ dRDper98* ($x10^{3}$)	0.144	15.680	12.709	19.745	11.861	22.670	74.501	44.043	18.282	20.279	16.649
dPATAP/ dRDexp* ($x10^{-8}$)	0.002	1.798	2.101	1.528	1.552	2.999	1.918	1.748	2.244	2.586	0.750
dPATAP/ dRDper98* (10^{-4})	0.010	6.918	6.455	7.499	5.441	11.177	18.921	15.311	8.319	8.703	6.445
Performance equations											
dGVIO/ dNPsale**	0.013	0.067	0.070	0.066	0.090	0.089	0.031	0.030	0.061	0.055	0.109
dGVIO/ dPATENT**($x10^{6}$)	0.035	15.765	8.160	18.951	20.234	8.996	23.733	15.800	9.926	9.392	19.352
dPROF/ dNP*	0.024	0.177	0.200	0.157	0.188	0.189	0.107	0.137	0.186	0.174	0.160
dPROF/ dPATENT*($x10^{6}$)	0.052	5.712	5.608	5.877	5.838	5.451	6.006	5.606	5.799	5.765	5.870

*Computed from Table 5a, 5b, 6, and 7.

Table 12b: Reduced Form Marginal Products (with IVs)*

Marginal products	Elasticities: Full Sample	Full Sample	Medium -size	Large-size	SOE	COE	FOR	HKT	STK	PRI	OTHER
dGVIO/ dRDexp98[2]	0.002	0.315	0.305	0.317	0.375	0.449	0.247	0.150	0.278	0.283	0.483
dGVIO/ dRDper98 $(x10^3)$[2]	0.016	36.487	26.083	39.316	30.147	56.965	89.318	87.510	38.056	41.621	37.816
dPROF/ dRDexp98[1,3]	0.002	0.205	0.237	0.178	0.181	0.328	0.228	0.196	0.260	0.297	0.088
dPROF/ dRDper98 $(x10^3)$[1,4]	0.046	36.548	37.064	35.865	29.667	58.124	94.316	74.501	43.650	44.252	36.122

*The instrumental variables are size [i.e. Large (2 discrete sizes) or Medium (3 discrete sizes)], ownership (OWN), and industry classification (IND).
[1]derived under the assumption SALES99 $\cong$ SALES98; [2]estimated with regressions in which the levels of R&D are used as RHS variables in lieu of intensities (ratios to sales); [3]derived from Table 9 and 10, [4]derived from Table 10 with the interactive term.

Table 12c
Marginal productivities based on the restricted profit function

Marginal profit	Elasticities: Full sample	Full Sample (yuan)	Marginal profit	Elasticities: Full sample	Full Sample (yuan)
dPROF/dLAB	0.459	10,007	dPROF/dLAB	0.406	8,866
dPROF/dNVFA	0.577	0.121	dPROF/dNVFA	0.562	0.118
dPROF/dRDE98	0.008	0.170	dPROF/dRDper98	0.104	31,296

*derived from Table 11

Table 13
Channels of R&D impact*

	dPROFIT/ dRDexp =	∂PROFIT/ ∂NPsales x ∂NPsales/ ∂RDexp + ∂PROFIT/ ∂PATapp x ∂PATapp/ ∂RDexp	SUM
RDexpenditure		(0.117 x 0.394) + ($5.712 \times 10^{6} \times 1.798 \times 10^{-8}$)	
	0.205	0.070 + 0.103	= 0.173
RDpersonnel		($0.117 \times 15.680 \times 10^{3}$) + ($5.712 \times 10^{6} \times 6.918 \times 10^{-4}$)	
	36,548	2,775 + 3,952	= 6,727

* derived from Tables 12a and b.

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Annex 1
Industry Code

13 Food processing
14 Food production
15 Beverage production
16 Tobacco processing
17 Textile industry
18 Garments and other fiber products
19 Leather, furs, down and related products
20 Timber, bamboo, cane, palm fiber and straw products
21 Furniture manufacturing
22 Papermaking and paper products
23 Printing and record medium reproduction
24 Cultural, educational and sports goods
25 Petroleum processing and coking
26 Raw chemical materials and chemical products
27 Medical and pharmaceutical products
28 Chemical fiber
29 Rubber products
30 Plastic products
31 Nonmetal mineral products
32 Smelting and pressing of ferrous metals
33 Smelting and pressing of nonferrous metals
34 Metal products
35 Ordinary machinery manufacturing
36 Special purpose equipment manufacturing
37 Transport equipment manufacturing
40 Electric equipment and machinery
41 Electronic and telecommunications equipment
42 Instruments, meters, cultural and office machinery
43 Other manufacturing