Returns to Research and Development in Chinese Industry: Evidence from State-owned Enterprises in Beijing

May 25, 2003

Published in *China Economic Review*, 15,4:2004

Abstract

This paper estimates returns to research and development (R&D) in Chinese industry. Using a firm-level dataset on innovation activity in large- and medium-size industrial enterprises during 1991 to 1997 in the Beijing area, we estimate three equations – an R&D expenditure equation, a production function, and a profit function. Panel data estimation methods are applied to a semi-balanced data set constructed from the raw sample. We find substantial and significant returns to R&D in the cross-section dimension. We also find substantial cross-industry variation in the return to R&D, which declined considerably over the sample period. R&D expenditure increases less than proportionately with firm size but does not seem to be related to cash flow.

JEL Classification: L00, O31, O33, P31

Keywords: Returns to R&D, Productivity, Profitability, Chinese industrial enterprises
Running title: Returns to R&D in Chinese Industry

I. Introduction

Many studies have attempted to assess the technical performance of China's industrial enterprises. Most studies conclude that there has been considerable total factor productivity (TFP) growth in Chinese industry, particularly in non-state enterprises.[1] Much attention has been focused on measures of these efficiency gains, which have been achieved through enterprise reform and economic liberalization. A less often discussed issue is the contribution of research and development (R&D) at the firm level to improving China's industrial performance. In this paper, we investigate the determinants of R&D effort and its contribution to the productivity and profitability of China's industrial enterprises.

There is a large volume of literature that uses a production function framework to estimate the return to R&D in OECD economies, particularly the US. The literature largely grows out of Zvi Griliches's 1979 Bell Journal paper (Griliches, 1979), which laid the intellectual foundation for work in this area. Griliches (1995) later provided a comprehensive survey in which he discussed a wide range of theoretical and econometric issues associated with this genre of research.

A common approach of innovation studies, proposed by Griliches (1979), is to treat R&D within a production function framework as a factor of production, symmetric with physical capital, labor, and other inputs. The R&D input is most appropriately interpreted as a stock of knowledge constructed as the sum of discounted past R&D expenditures, which, as knowledge capital, experience a certain rate of depreciation. Empirical estimates of the output elasticity of the R&D stock provide the basis for inferring returns to R&D.[2] Griliches and Mairesse (1984)

[1] See, for example, Wu Yanrui (1996) and Jefferson, Rawski, Zheng, and Wang (2000). An exception is Woo et al (1994) who found no TFP growth in the state sector.

[2] An alternative approach is to estimate a first difference version of the production function. With this specification, R&D intensity (R&D – sales ratio) rather than R&D stock enters the regression analysis under the assumption that marginal product instead of output elasticity of R&D is constant across firms (see for example, Jaffe, 1988). The results from this approach are usually not very satisfactory partly due to the large amount of cross-section variation being purged out by the differencing procedure. We have therefore chosen not to adopt this approach.

estimate an R&D-augmented production function both in levels and differences using a panel data of 133 large US firms from 1966 to 1977. While they find a strong R&D-productivity link in the cross-section dimension, the relationship collapses in the time series dimension, which they ascribe to problems of simultaneity and measurement error. Estimates of the output elasticity of R&D in the Griliches-Mairesse paper range from 0.05 to 0.3, depending on model specification. Griliches (1986) reports a similar range of R&D output elasticities, from which he computes a marginal product for R&D in U.S. manufacturing as high as 0.62. To assess the impact of knowledge spillovers and technology opportunity on firm performance, Jaffe (1986) estimates a system of three equations: a patent production (knowledge production) function, a profit function, and a market value (Tobin's q) function. In addition to significant effects on firm-level profit of knowledge spillover and technology opportunity, Jaffe finds a return (marginal profit) to R&D of 27 percent. Applying a similar production function framework to French manufacturing, Cuneo and Mairesse (1984) and Hall and Mairesse (1995) find R&D output elasticities that lie in a range similar to those reported by Griliches and Mairesse (1984). These papers also show sharply reduced estimates of R&D elasticities and returns for within OLS estimates as compared with total OLS results.

Studies of the performance of China's industrial enterprises during the reform era are bountiful. Given the transitional nature of China's industrial economy, these studies particularly focus on the impact of institutional reform, such as ownership reform, on the performance of China's industrial enterprises. Groves et al (1994) study the impact of enterprise autonomy and incentives on labor productivity in China's state industrial sector. Using the same state-owned enterprise data, Li (1997) finds considerable growth in both factor productivity and total factor productivity. Jefferson, Rawski,, Zheng, and Wang (2000, Table 7) find that TFP growth in collective-owned enterprises has substantially outpaced that in the state-owned sector. In another related study, Jefferson, Rawski, and Zheng (1999) find that industrial competition between the state sector and the non-state sector contributed to rising innovative activity within Chinese industry, including state industry. The authors also find that, measured in terms of the profitability of innovation, state-owned enterprises occupied higher rungs of the innovation ladder than township village enterprises. Zhang, Zhang, and Zhao (2001) find a higher growth rate of technical efficiency for state-owned enterprises than collective-owned enterprises although the former has the lowest level of efficiency among the various types of ownership.

Our paper is closely related to Hu (2001), who adopts a production function framework to analyze the impact of R&D on productivity using a cross-section of innovative firms from Beijing, China. He finds that private R&D has a strong impact on firm productivity, whereas government R&D has a negligible independent impact on firm productivity, although there is a strong complementary relationship between the two types of R&D. This paper differs from Hu (2001) in using a panel data set, which allows us to control for the firm specific characteristics and to construct an R&D stock, a more carefully constructed measure of R&D input. This study also enables us to compare returns to R&D across industries and over time.

We investigate two questions in this paper: What factors determine R&D effort at the enterprise level, and what is the return to R&D in our sample of Chinese state-owned enterprises? An R&D effort equation examines the determinants of R&D expenditure. The contribution of R&D to productivity is examined using a production function. We use a profit function to estimate the return to R&D. Under the assumption of competitive markets and profit maximizing behavior, any productivity gain should translate into profit, but market power and measurement conventions and errors in Chinese data may cause the two to diverge. The profit equation provides an additional avenue through which we measure the effect of R&D on performance.

The rest of this paper is organized as follows. Section II describes the data and the methods used to construct the sample and various key variables used in the regression analysis. In Section III, we specify the three equations that comprise our empirical model. Section IV reports our empirical findings. Section V concludes with a discussion of results and their implications for further research.

II. Data and Sample

The data used in our study comes from an ongoing annual survey of large- and medium-size enterprises in Beijing, China. The Beijing Municipal Commission on Science and Technology (BMCST) first began the survey in 1991. The current raw sample contains data for all large- and medium-size enterprises (LMEs) filing reports with BMCST from 1991 to 1997. The firms are predominantly state-owned enterprises (SOEs) with a handful of collective ones also included. After excluding nonsensical values, we are left with 1,571 firm-year observations representing 432 firms over a seven-year period. We refer to this trimmed sample as the full (unbalanced) sample. Within the full sample, 106 firms appear in only one year; they account for almost 25 percent of the observations. A fully balanced sample would leave us with only 57 firms representing only 13 percent of the sample.

2.1 Construction of the semi-balanced sample

We wish to establish sufficient continuity in the time series to attempt within sample estimates. However, the 57 firms that comprise a fully balanced sample would leave out too many observations. In an effort to balance our cross-section and time series estimation objectives, we decide to construct a semi-balanced sample. We include in this sample only those firms that report at least five years' data over the seven-year sample time period. Furthermore, in each of these five years we require that the included firms report positive levels of R&D expenditure. This leaves us with 88 firms and 531 firm-year observations. Among the 88 firms in our semi-balanced sample, we find 35 fully balanced firms (reporting positive levels of R&D for all seven years), representing 40 percent of the semi-balanced sample. We will deal with the potential sample selection problem that arises from the sample construction in the next section.

2.2 Construction of knowledge capital stock

Following usual practice in the literature, we use the perpetual inventory investment model to construct measures of the knowledge capital stock. Using Equation (A.1) in the Appendix, we assume an annual depreciation rate of 15 percent for knowledge capital for the firms in our sample. Like previous authors, we find that our results are not sensitive to variation in the depreciation rate.[3] The initial knowledge capital stock is constructed by assuming a constant growth rate of R&D expenditure.

2.3 Industry classification

Although the raw sample does include services and agricultural enterprises, we have only included industrial enterprises in our sample. There is no industrial classification variable in the data set. Using the information on the "*xitong*" (system) to which each firm belongs, we construct a coarse measure of industrial classification. In the Chinese economy, a system consists of all the enterprises and other entities under the supervision of a particular government agency. For example, textile enterprises are in the textile *xitong* and under the supervision of the Textile Bureau. Likewise, electronic product enterprises are under the Electronics Bureau. We use this information to classify firms into different "industries" from which we create the industry dummy variables. Table 1 shows the industry distribution of sample firms. Our conjecture is that among the LMEs in this set of industries, misclassification is unlikely to be a problem.

[Insert Table 1 here]

Not surprisingly most of these innovating firms concentrate in three industries: machinery, electronics, and chemical. Firms from these three industries constitute between 70 and 80 percent of the sample each year. Among the three, electronics is the most extensively

[3] After finding their results robust to different rates of depreciation of knowledge capital, Griliches and Mairesse (1984) and Hall and Mairesse (1995) also assumed a depreciation rate of 15 percent.

represented. The category of “Other” includes all firms that cannot be classified into any of the four principal industries.

We present in Table 2 the sample means of key variables for various samples. The average firm in the semi-balanced sample in an average year employs 2,208 workers and sells about 195 million yuan of products and/or services, yielding a profit of around 14 million yuan. It invests 2 percent of its sales in R&D, or 1.1 million yuan, which helps generate a profit-sales ratio of 5 percent. In the full and unbalanced sample, 76 percent or 1,193 of the firm-year observations report positive R&D expenditures, and 82 percent of the sample observations show profits. These data also show that R&D performing firms are on average larger than non-R&D-performing firms. That they hire in nearly twice as much capital, but only 18 percent more workers, also indicates that R&D performers are more capital intensive than their non-performing counterparts. They also earn nearly twice as much profit as the non-performers. Size and factor intensity differences between profitable and unprofitable firms are much less pronounced than those distinguishing R&D performers and non-performers. Since all the reported differences are between firm-year observations rather than between unique firms, the above comparisons may reflect a higher incidence of switching between profit and loss-making status, compared with a more stable status of R&D performer or non-performer.

[Insert Table 2 here]

III. The Empirical Model

At the core of the empirical model is a production function that relates conventional inputs, capital, labor, and materials, and knowledge capital to a firm’s output in a proportional way. What enters the production process is the new product design or new process, i.e., the output of the innovation process, rather than R&D, which reflects the amount of effort or input the firm commits to innovation. But absent measures of new process and new product innovations, we follow the practice in the literature and construct a knowledge stock using past expenditures.

3.1 The production function

We assume that the following log-linear formulation of a Cobb-Douglas production function characterizes the production activity in Chinese enterprises:

$$gvio_{it} = a + \sigma t + \alpha c_{it} + \beta l_{it} + \gamma m_{it} + \lambda k_{it} + \varepsilon_{it}, \tag{1}$$

where i denotes firms, t represents years, and *gvio* is the gross value of industrial output. The superscript symbols, α, β, γ, and λ are the output elasticities of capital stock (C), labor (L), materials (M), and R&D or knowledge capital (K)[4]. A is the average base level of total factor productivity, which is assumed to grow at the constant rate, σ.

Unfortunately our data set does not include a measure of intermediate inputs, so that we are in fact estimating

$$gvio_{it} = a + \sigma t + \alpha c_{it} + \beta l_{it} + \lambda k_{it} + \varepsilon'_{it}, \tag{2}$$

By doing this, we are incorporating m into the error term, which is now $\varepsilon'_{it} = \varepsilon_{it} + \gamma m_{it}$. If m_{it} is correlated with c, l, and/or k, then we have an omitted variables problem that will bias the output elasticity estimates upward. The source of the bias comes from $cov\ (m_{it}, c_{it})$, $cov\ (m_{it}, l_{it})$, or $cov\ (m_{it}, k_{it})$ being nonzero.

Since OLS estimation of Equation (2) is problematic, we can attempt to address the omitted variables problem by taking advantage of the panel nature of the data. We can write m_{it} as the sum of the within component, M_{it}, and the between component $M_{i\bullet}$. Let x_{it} denote one of the other inputs (c, l, or k). The covariance between m_{it} and x_{it} can then be written as:

$$\mathrm{cov}(m_{it}, x_{it}) = \mathrm{cov}(M_{it}, x_{it}) + \mathrm{cov}(M_{i\bullet}, x_{it}) .$$

[4] We assume that the output and input deflators are the same for all firms in an industry. Therefore the industry and year dummies in the regressions should absorb these deflators. The cost is that the pure industry or time effect is not identifiable.

Since the c and k are fixed factors and l can be considered a quasi-fixed factor[5] in Chinese state-owned enterprises, we should expect the covariance between the inter-temporal component of m_{it} and the x_{it}'s to be zero. In other words, the source of the bias comes from the firm specific effect, i.e., $cov\ (M_{i\bullet}, x_{it})$. Under this assumption, the estimation bias associated with γm_{it} can be purged through a "within" estimator. Then the remaining error, ε_{it}, is assumed to be uncorrelated with the right hand side variables in (2), and the within estimates are unbiased and consistent.

There are two potential problems with this approach. First, for most firm-level panel data, including ours, most of the variation occurs in the cross-section dimension. By purging the firm mean from the variables and eliminating much of the variation, within estimates lose much of their efficiency. Second, when variables are measured with errors, the within estimator is likely to exacerbate the bias introduced by measurement error. Given criticism of the quality of Chinese data, we are concerned with this problem.

Because it is very hard to find instruments for firm specific characteristics subsumed in the error term[6], we report and compare the total and the within results. Since the within estimates exacerbate the measurement error problem, which creates a downward bias to the within coefficient estimates, we take the within estimates to represent a lower bound of the magnitudes of the true underlying coefficients. Given the problematic nature of the within estimation approach, we also take the approach of imposing on the total OLS estimates the constraint of constant returns to scale. While if the technology indeed exhibits increasing returns to scale this may cause an underestimate of the elasticities, the downward bias may not be as severe as that resulting from the within estimates.

3.2 The profit equation

[5] See Oi (1962) for a general interpretation of labor as a quasi-fixed factor.

[6] One of the few studies that has been successful in instrumenting for the firm specific effect is Jaffe (1986), where he used industry variables to identify the impact of R&D stock on a firm's market value and profitability.

Assuming, as we did above, that physical and knowledge capital and labor are predetermined, we use the following variant of the “restricted profit function” (Siu, 1990, and Jaffe, 1986):

$$\pi_{it} = d_0 + \alpha' c_{it} + \gamma' k_{it} + \lambda' l_{it} + \delta S_{it} + \omega_{it} \tag{3}$$

where π_{it} is the log of firm i’s profit in year t. Factor prices and demand and supply shocks are embedded in the error term, ω_{it}. The market share of a firm in the sample, S_{it}, is included as a rough proxy for the market power of the firm. The greater the market power of a firm, the higher the markup the firm can charge, and therefore the more profitable the firm is. The restricted profit function in Equation (3) provides an additional channel to assess the returns to knowledge capital. The potential bias caused by the correlation between unobservable firm specific factors and the three predetermined inputs also applies to the restricted profit equation. We will compare results from the total OLS estimation and the within estimation. Like the within sample production function estimates, applying the within operation to the restricted profit function should minimize the bias associated with firm-specific effects. Also, like the within production function estimates, we will view the within estimates as lower bound estimates of the returns to R&D.

3.3 The R&D effort equation

The question of what drives a firm’s R&D expenditure has engendered long debate. An important feature of innovation is that it is as much an economic process as a technological process. Both economic and technological forces influence a firm’s R&D investment decision. Rosenberg (1974) and Scherer (1965), for example, emphasize the importance of technological opportunity, i.e. the varying degree of ease of innovation across technological fields, in determining R&D expenditure. Recognizing the fixed cost of R&D investment, Schmookler (1966) argues that since the firm can spread the cost of R&D over its total sales the expected market size of a firm’s product should be positively correlated with the incentive to invest in R&D. Contributors to the U.S. literature also recognize that since R&D is high-risk investment, external financing is expensive, and therefore internal cash flow is preferred to external borrowing (Hall 1992). Surveys of Chinese firms also indicate that lack of cash is often cited to explain low levels of R&D expenditure. Without any series on input prices of R&D, we settle on the following model of firm R&D expenditure:

$$r_{it} = e_0 + \theta_1 s_{it-1} + \theta_2 ind_i + \theta_3 c_{it} + \theta_4 \pi_{it-1} + \tau_{it}\ , \tag{4}$$

where the dependent variable is the log of R&D expenditure. The log of last period's sales revenue, s_{it-1}, is used as a proxy for the firm's estimate of the potential market size. Industry dummies, ind_i, are used to represent variation in technology opportunity. Following Bound et al (1984), we also include a firm's capital stock to control for the impact of capital intensity. The availability of internal cash flow is proxied by the log of last period's profit. If the claim that shortage of financing contributes to low R&D expenditure is true, we should expect a positive coefficient on the profit variable.

3.4 Sample selection bias

There are three types of potential sample selection bias that may plague our empirical study. First, not all firms in Beijing file reports with BMCST every year. Entry and exit or mergers and acquisitions alone cannot account for the large number of missing observations in our sample. The extent to which these missing observations represent random non-reporting episodes or non-random selection is unclear. Without any out-of-sample information, there is no way that we can ascertain, let alone correct for, this potential source of sample selection bias. Second, when we construct the semi-balanced regression sample, only one third of the full sample survives, i.e. firms that have been reporting R&D for at least five of seven years. This represents a kind of survival bias. We compare regression results using the semi-balanced sample and the full sample to ascertain the magnitude of this type of selection bias. For us, the third and most interesting potential source of bias is introduced by the fact that in the semi-balanced sample we only include firms reporting positive R&D expenditure. In our full sample, 378 firm-year observations, or 24 percent of the total, either report zero or missing R&D expenditure. Restricting the sample to R&D performers may affect not only the R&D effort equation but also the production function and the restricted profit function.

We attempt to correct for selection bias in the following manner. Suppose that R&D reporting follows the rule below:

$$z_{it}^{*} = f_0 + \rho_1 RSE\_L_{it} + \rho_2 \Pr of_{it} + \rho_3 RORG_i + \mu_{it} \tag{5}$$

$$z_{it} = 1, \text{ if } z_{it}^{*} > 0$$

$$z_{it} = 0, \text{ otherwise}$$

where Z_{it}^{*} is some unobservable threshold level of propensity to report R&D, beyond which we observe positive R&D reporting. We assume that the following factors affect the incidence of reporting R&D: the ratio of the number of research scientists and engineers to the total number of employees (RSE_L_{it}), the presence within the firm of an R&D department ($RORG_{it}$) , and whether a firm is profitable or not ($Prof_{it}$). The latter two are binary variables. When a firm is more R&D intensive in terms of research personnel, it is more likely to report R&D. A separate R&D department should also help make R&D statistical collating and reporting more regular. Firms that are profitable are more likely to report R&D than those that are not. Therefore all three factors increase the likelihood of reporting R&D. To see how this selection rule may affect our estimates, consider equation (2). The expected value of output conditional on the selection is:

$$E(y_{it} \mid Z_{it}^{*} > 0) = BX_{it} + E(\varepsilon_{it}^{'} \mid \mu_{it} > -a) \tag{6}$$

where BX_{it} collects all terms on the right hand side of equation (2) except for the error term and a represents the right hand side of Equation (5) excluding the error. Clearly when the second term on the right hand side of Equation (6) is not zero, or the R&D reporting error and the error in any of our equations are correlated, regression estimates are likely to be biased. The bias can be thought of as a left-out-variable bias and can be corrected by adding a corrective term to the regression equations (Greene 1993). The corrective term, the inverse mills ratio (IMR), takes the form of $\frac{\phi(a)}{\Phi(a)}$, where the numerator is the standard normal density function, the denominator is the cumulative standard normal probability function, and a is defined as above. The regression coefficient of IMR has the interpretation of being the product of the correlation between the two error terms and the standard deviation of ε_{it}'. Assuming that the error terms, ε_{it}' and λ_{it}, follow a bivariate normal distribution, we can estimate equations (6) and (3) jointly by maximum likelihood. Deriving the likelihood function can be elaborate. Instead we adopt the Heckman two-stage procedure (Heckman, 1979), which provides an easy-to-implement method to correct for the selection bias. In the first stage, Equation (5) is estimated by a probit model, from which the predicted values of Z_{it}^* are generated. In the second stage, the IMR is constructed using the predicted values of Z_{it}^* and included in an OLS regression of Equation (2).

In summary, in order to assess the contribution of R&D to firm performance and the determinants of a firm's R&D investment, we have specified a production function, a restricted profit function, and an R&D effort equation. There are three main sources of potential bias that we are concerned about: measurement error, left-out variables, simultaneity, and sample selection[7]. The problem of measurement error can potentially have serious implication for the interpretation of our results. But it is a problem that we do not have very effective tools to deal with. The main source of the left-out variable problem in our model is that the firm specific and time invariant features such as managerial capability, market power, and difference in labor quality across firms are excluded from the equations we estimate. We will compare the results from total and within estimation to gauge the extent of the bias. The main source of the simultaneity problem is that output decision and input choices may respond to the same demand or supply shocks. We try to deal with this issue with the instrumental variable approach. Finally,

[7] The other three problems can also be considered as a form of left-out variable problem.

the Heckman two stage procedure is used to correct for the sample selection bias introduced by only including R&D reporting firms.

IV. Estimation Results and Discussions

4.1. The production function

We first estimate Equation (2). The results are reported in Table 3. The first two columns include estimates of the baseline model using a total OLS estimator. We include the IMR term in column (2) to account for potential selection bias. The IMR is insignificant in column (2) as it is throughout Table 3; sample selection is not a serious problem if the sample selection process we specify is accurate. Moreover, the output elasticity estimates are more or less unchanged between columns (1) and (2).

[Insert Table 3 here]

The coefficient on the R&D variable in column (2) indicates that R&D exerts a substantial impact on productivity. Since material input is omitted from the function, the output elasticities are likely to be biased upward. The extremely large elasticity estimates in column (1), the sum of which well exceeds 1, reinforce this suspicion. In column (6) we impose constant returns to scale (CRS) on the three inputs, capital, labor, and R&D and interpret the production function as a value added function.[8] Relative to the unconstrained total OLS estimates, there is little change in the output elasticity of R&D, which remains highly statistically significant at 0.12. The coefficient of labor is substantially reduced to 0.57 from 0.83, suggesting that it is this factor which captures most of the omitted variables bias, while the capital output elasticity increases slightly to 0.31 from 0.27. The F-statistics and the p-value reported at the bottom of column (6) indicates that the CRS constraint is robustly rejected. In column (8) the CRS constraint is imposed only on capital and labor, and thus allows for some increasing returns to scale (including

[8] Under this interpretation, we should use an estimate of value added and the output elasticities to compute the marginal products of R&D and capital.

R&D input). Under this specification, R&D's output elasticity increases to 0.17. The CRS constraint is now marginally rejected. Overall, columns (1), (2), (6), and (8) imply similar, statistically significant elasticities for R&D and physical capital.

We present results of various within estimators in columns (3), (7), and (9), with and without the CRS restrictions. As before, the unconstrained within estimates of the output elasticities are substantially and implausibly lower than the total OLS estimates, particularly for physical capital and R&D. Only the labor coefficient remains statistically significant. The significant contribution of R&D to productivity disappears in the within dimension. The de-mean operation has seemingly eliminated not only firm-specific effects that correlate with the regressors; they have also significantly dampened useful variation in the regressors. The low R^2 of 0.11 suggests that the model explains very little variation of the log of gross output in the time series dimension.

Another set of total estimates are obtained in column (4) of Table 3, where we replace R&D stock with R&D expenditure lagged one year. This specification implicitly assumes a 100 percent depreciation rate for R&D capital. The coefficient of R&D, which shrinks to 0.07, remains statistically significant. The other coefficients are little changed.

Allowing for the possibility that labor may be endogenous, not predetermined, as we assumed above, we use capital, R&D stock, and labor lagged one period as instruments for labor in estimating Equation (2). The results are reported in column (5) of Table 3. The coefficient of labor slightly rises rather than falls, which indicates that the simultaneity of labor does not seem to be a serious issue. The output elasticity of the R&D stock is still statistically and economically significant at 0.12. In summary, our production function estimates suggest a significant impact of R&D on productivity. The relationship disappears in the within estimations. Sample selection bias does not appear to pose any serious problem.

[Insert Table 4 here]

4.2 The profit equation

The profit equation provides another channel through which the impact of R&D may be identified. Most studies in the US literature have investigated returns to R&D in profitable firms. This may generate an upward selection bias to the returns to R&D estimates. In our full sample, 278 or 18 percent of the observations report losses. In the semi-balanced regression sample, 127 or 31 percent of the observations are loss making. In Table 4, we report results using two different samples: the first is the semi-balanced sample; the second is a subset of the first in which only profitable firms are included. Since our restricted profit function is in log-log form, we face the problem of how to deal with losses in the regression using the first sample. When a profit observation is negative, we convert it to – log(-profit) and use a profitability dummy to control for this treatment in the regression.

Columns (1) to (4) present results from regression using the semi-balanced sample. The total OLS results generally indicate that R&D have economically and statistically significant impact on profits. The profit R&D elasticity in column (2) implies that a 10 percent increase in R&D stock can lead to a 1.5 percent increase in profit (or reduction in loss). The within estimation continues to be disappointing - the return to R&D is not significantly different from zero. The labor coefficient is marginally significant in three out of the four cases again implying that labor is not completely flexible in Chinese SOEs.

Market share has a statistically significant impact on profits. But the impact is not very economically significant. For example, the coefficient on market share in column (2) suggests that if a firm manages to increase its market share, say from 10 percent to 15 percent – a fairly large increase – its profit would only increase by 0.35 percent. As in the case of the production function, controlling for the potential sample selection bias introduced by only including R&D-reporting firms does not noticeably affect the coefficient estimates. The assumption of a 100 percent R&D capital depreciation rate generates an insignificant and much lower R&D elasticity while leaving the other coefficients intact. This may have to do with the fact that R&D expenditure contains more noise than R&D stock, in which measurement error and short term fluctuations tend to smooth out.

Turning to the second set of regression results in columns (5) to (8) in which we restrict the sample to positive values, we can see that the estimates of the profit elasticity of R&D capital are much higher – 90 percent higher for the R&D elasticity when we compare columns (5) and (6) with columns (1) and (2). Clearly, including only profitable firms substantially inflates the profit elasticities of R&D, capital, and labor. In addition to the natural expectation that by restricting the regression to observations with positive profit, an additional potential explanation of these enlarged elasticity estimates is that the factor inputs capture some of the variation in firm size. By comparison, estimates of the market share variable become smaller and statistically insignificant.

As in the case of production function estimation, the potential problem of including only firms reporting positive R&D expenditures does not seem to pose a problem for estimation of the profit function. None of the coefficients of the IMR is statistically significant. Nor does the inclusion of the IMR affect the estimates. A comparison of columns (1) and (2) shows that the results are virtually identical.

[Insert Table 5 here]

4.3. R&D expenditure

The first column of Table 5 shows the results of the first-stage probit estimation of the two-stage Heckman sample bias correction procedure. Both the ratio of research scientists and engineers (RSEs) to total employment and the R&D department dummy are very significant in explaining the likelihood of reporting R&D. Having an R&D department increases the probability of reporting R&D by 0.29[9]. If the ratio of research scientists and engineers to the total labor force increases by 0.1, or 10 percent more of the employees are RSEs, the probability of the firm reporting a positive level of R&D effort increases only by 0.08. All of the industry dummies are highly significant, an indication that inter-industry variation in R&D effort is substantial.

Column (2) reports results from a plain OLS estimation of the R&D effort equation. R&D increases with a firm's last period sales revenue, although less than proportionately – a one percent increase in sales revenue leads to only a little under half a percent increase in R&D expenditure. If last period's sales revenue is a good proxy for the firm's expectation of market demand, then column (2) does lend support to the demand pull hypothesis of R&D spending. In Column (3) we add last period's profit to the R&D equation. If last period's profit is a valid indicator of the availability of funding, our results suggest that Chinese firms' R&D activity is not really constrained by shortage of innovation funds. Columns (3) and (4) show that a neutral one percent increase in firms scale, i.e., an equi-proportionate increase in sales, capital and profit, leads to an increase of approximately 0.6 percent in R&D expenditure. In columns (2), (3), and (4) none of the industry dummies is significant.

Lastly, as we observed in Table 2, R&D performing firms tend to be much bigger than non-R&D-performing firms. We would therefore expect a downward bias of the sale coefficient in column (3); we therefore attempt to correct for possible selection bias by adding the IMR obtained from the first stage Heckman procedure shown in column (1). The results in column (4) show that the addition of the IMR leaves the estimate of the coefficient on sales unchanged – only slightly more efficient. The IMR itself is highly statistically significant and implies that firms that are more likely to report R&D actually conduct less R&D.

[Insert Table 6 here]

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[9] The marginal probability reported here is calculated using the coefficient of R&D department dummy in Table 5 and sample averages of the variables.

4.4. Seemingly Unrelated Regression (SUR) estimation and returns to R&D

Given that the error terms in the equations of our empirical model are likely to be correlated, we should gain more efficient estimates by employing a SUR estimator. Since our main interest is in estimating the returns to R&D, and estimating the R&D effort equation requires us to throw away one year's observations, we estimate two systems separately, one with and one without the R&D effort equation, and report the results in Table 6. The first system consists of the production function and the profit function. This system will be estimated using the same sample that is used to estimate the two equations individually. The second system includes all three equations. We estimate it using a sample in which one year's observations are dropped to accommodate the R&D effort equation.[10]

Estimating the first system yields results in columns (1) and (2) of Table 6. They are very similar to those we obtained in the individual equation estimation. R&D continues to have a strong and positive impact on productivity and profitability. The only exception is the coefficient of the IMR, which has now become marginally significant and negative in both equations. This reinforces our suspicion that the choice of a firm to report R&D be independent of the incentive or the impact of conducting R&D.

Estimating the second system of equations requires us to further restrict the sample. Since our sample is semi-balanced, this restriction favors those firms that have been consistently conducting R&D. Results in columns (3) to (5) show that both the output and profit elasticities of R&D are higher for the three-equation system than for the two-equation system. For example, in column (5) the profit elasticity of R&D is over 60 percent larger than that in column (2). This seems to indicate that restricting the sample, which favors the more innovative firms, introduces an upward bias to the elasticity estimates. For the R&D effort equation, the only substantial

[10] Our calculation of the marginal products/profits of capital and R&D will be based on the two-equation system estimates. Estimating the three-equation system requires us to throw out more than 24% of the observations in order to accommodate the R&D equation, which has a lag term in it. This operation is likely to favor those firms that have been reporting R&D for each of the seven sample years, which are probably the more innovative firms.

change is that the coefficient of capital has gone from marginally statistically significant to insignificant.

At the bottom of Table 6, we report the correlation matrix of the residuals for the two systems. The correlation between the output and profit equations is 0.19 and 0.28 in the two systems respectively. This suggests the potential existence of firm specific effects in the error term, which affect both productivity and profitability. The correlation of these two equations with the R&D equation is negative. When firms over-expend on R&D relative to the levels predicted by the R&D effort equation, the effect may be to depress productivity and profit. The Breusch-Pagan test statistic suggests that the correlation between the equations is materially different from zero.

We discussed earlier that constructing the semi-balanced sample may introduce a survival bias to our estimates. To gauge the extent of this potential bias, we estimate the output and profit equations using the full sample. R&D expenditure replaces R&D stock in the regressions due to the impossibility of constructing R&D stock with the full sample. The results, not reported here to save space, are very similar to those that we obtained earlier, suggesting that constructing the semi-balanced sample has not introduced selection bias in any serious way.

[Insert Table 7 here]

Finally, we compute the return to R&D using the elasticity estimates in the two-equation system in Table 6. We use the semi-balanced sample means of the variables to evaluate the marginal products. In each case, because we use a value added production function to estimate the elasticities, we use average single factor productivities to estimate the marginal products. The average ratio of value added to gross output (gvio) computed with valid observations of the value added series in our sample is 0.3. We compute the marginal product and marginal profitability of R&D and capital for different industries and over the sample years.

There are several interesting features of the results in Table 7. First, although we have not been able to correct all the potential biases in our estimation and the within estimation results are particularly disappointing, the returns to R&D are very large ranging from 18 percent for the electronics industry to 59 percent in the chemical industry. Second, there is substantial cross industry variation in the productivity of and the returns to R&D. The marginal product of R&D is almost three times larger in the chemical industry than in the electronics industry. Third, productivity and returns of R&D have been declining over the years. From 1991 to 1997, the marginal product of R&D decreased from 1.21 to 1.07, a 12 percent decline. Returns to R&D fell from 68 percent at the start of the period to 11 percent in 1997. These declines are consistent with the general observation that across industries, the ownership spectrum, and geography, competition has depressed profitability (Naughton, 1992). Since the majority of our sample firms are SOEs, the drastic decline may be greater than the economy-wide average.

V. Conclusions

Our investigation of technological innovation in China's industrial enterprises focuses on the design and estimation of three equations: a production function, a profit function, and an R&D expenditure equation. To estimate these equations, we have used a semi-balanced sample of 88 R&D-performing Chinese industrial enterprises in Beijing over the period from 1991 to 1997.

Our results indicate that knowledge capital constructed from past R&D expenditures has a strong impact on the productivity and profitability of China's industrial enterprises. While the relationship is robust in the cross-section dimension, as in the U.S. literature, it virtually disappears in the time-series dimension. We try to correct for the potential sample selection bias introduced by admitting only R&D performing firms to our analysis. The equations are also estimated using a system estimator to account for potential cross-equation correlation of the error terms. Our estimates suggest a high and statistically robust return to R&D. Returns to R&D and the productivity of R&D also vary significantly across industries. Over time, the returns to R&D and its productivity have declined.

Estimation of the R&D expenditure related equations shows that R&D expenditure increases less than proportionately with sales revenue, while the availability of retained earnings does not appear to be an obstacle to the conduct of R&D. The likelihood of reporting R&D is substantially enhanced by the number of research scientists and engineers.

Our investigation of the demand for and impact of R&D in Chinese industry provides useful insight into the important role that R&D provides in China's large- and medium- size state-owned enterprise sector. At the same time, the paper underscores some of the limitations of our analysis. These include the small sample size and its relatively narrow ownership and industry scope. We have tried with varying degrees of success to deal with problems of sample selection bias and omitted variables misspecification. While our analysis leads us toward the conclusion that R&D effort in China's SOEs contributes substantially enterprise efficiency and profitability, particularly in the more successful (i.e. profitable) firms, this finding should be reexamined from the perspective of larger data sets, including those that allow for comparisons of R&D's impact across a wider range of ownership types.

Appendix

The construction of R&D stock

To construct the R&D stock variable, we assume a perpetual inventory model for the accumulation of R&D capital, i.e.,

$$K_{it} = (1-\delta)K_{it-1} + R_{it-1}, \tag{A.1}$$

where K_{it} is the R&D stock for firm i in year t; δ is the depreciation rate of R&D capital; and R_{it} is firm i's gross investment in R&D in year t. To implement the model, we first construct the initial R&D stock for each firm. In our data sample, all firms began reporting R&D expenditure from 1991. Assuming that the growth rate of R&D expenditure, R_{it}, is γ, the initial R&D stock can be written as follows:

$$\begin{aligned} K_{i91} &= (1-\delta)K_{i90} + R_{i90} = (1-\delta)^2 K_{i89} + (1-\delta)R_{i89} + R_{i90} \\ &= R_{i90} + R_{i90}\left(\frac{1-\delta}{1+\gamma}\right) + R_{i90}\left(\frac{1-\delta}{1+\gamma}\right)^2 + \ldots + R_{i90}\left(\frac{1-\delta}{1+\gamma}\right)^N + \ldots \end{aligned} \tag{A.2}$$

By assuming that the potential R&D series goes to the infinite past ($N \rightarrow \infty$), we can write the initial R&D stock K_{i92} as: $K_{i91} = R_{i91}/(\delta+\gamma)$. The initial R&D stock and equation (A.1) can then be used to compute the R&D stock.

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Table 1. Industry Distribution of Sample Firms

	1991	1992	1993	1994	1995	1996	1997
Machinery	18	19	15	13	15	18	17
Electronics	25	19	27	26	28	27	23
Pharmaceutical	3	3	3	4	4	4	3
Chemical	13	12	15	15	14	15	14
Other	13	17	19	15	19	18	18
Subtotal	72	70	79	73	80	82	75

Table 2. Sample means of key variables

	Semi-balanced Sample	Full sample		Full sample	
		No R&D	R&D	Unprofitable	Profitable
Gross value of industrial output (GVIO)	169849	95604	127571	72764	130010
Sales	194513	92714	140059	67118	141900
Profit	14386	6356	11530	-7657	14142
Net value of fixed assets (NVFA)	103630	46976	83882	71070	75847
Employment	2208	1507	1772	1559	1740
R&D expenditure	1129		838	434	680
R&D stock	4770				
Capital - labor ratio	41	32	47	43	43
R&D - sales ratio	0.02		0.02	0.01	0.02
Profit - sales ratio	0.05	0.01	0.05	-0.23	0.1
Labor productivity	63	44	60	47	58
Number of observations	531	378	1193	278	1293

Note: All monetary variables are measured in thousand yuan. The unit of Labor is person.

Table 3. Production function estimate

	Unconstrained					CRS imposed on R, K, and L		CRS imposed on K and L	
	Total	Total	Within	Total	IV	Total	Within	Total	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	-0.57	-0.6	3.35*	-1.25	-1.45*	0.95*	-0.31*	-0.12	-0.33*
	(0.40)	(0.43)	(1.20)	(0.45)	(0.47)	(0.26)	(0.08)	(0.30)	(0.08)
Log (capital)	0.27*	0.27*	0.07	0.36*	0.33*	0.31*	0.07**	0.28*	0.08**
	(0.07)	(0.07)	(0.04)	(0.08)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
Log (labor)	0.83*	0.82*	0.62*	0.86*	0.87*	0.57*	0.82*	0.72*	0.92*
	(0.10)	(0.10)	(0.15)	(0.11)	(0.12)	(0.05)	(0.09)	(0.04)	(0.04)
Log (R&D stock)	0.14*	0.14*	-0.01	-	0.12*	0.12*	0.1	0.17*	-0.01
	(0.04)	(0.04)	(0.10)		(0.05)	(0.04)	(0.08)	(0.03)	(0.09)
Log (R&D_1)	-	-	-	0.07**	-	-	-	-	-
				(0.03)					
IMR	-	0.06	-0.07	-0.01	0.03	0.04	-0.02	0.12	-0.03
		(0.30)	(0.33)	(0.33)	(0.32)	(0.36)	(0.16)	(0.35)	(0.16)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	531	531	531	531	404	531	531	531	531
Adjusted R^2	0.71	0.71	0.11	0.76	0.76	-	-	-	-
	-	-	-	-	-	F=22.92	F=4.07	F=2.92	F=5.88
						P=0.00	P=0.04	P=0.09	P=0.02

Note: labor instrumented by labor(-1), capital and R&D capital.

Numbers in parentheses are standard errors. "*", "**", "***" – 1%, 5%, and 10% significance levels respectively.

Table 4. Profits equation estimation

	The semi-balanced sample				The restricted sample (Profit>0)			
	Total	Total	Within	Total	Total	Total	Within	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-9.50*	-9.53*	-7.14*	-11.12*	-1.92***	-2.01***	2.66	-3.67**
	(1.14)	(1.21)	(2.74)	(1.47)	(1.05)	(1.19)	(2.53)	(1.57)
Log (capital)	0.17**	0.18**	0.07	0.23**	0.26**	0.27*	0.07	0.28**
	(0.08)	(0.08)	(0.10)	(0.10)	(0.12)	(0.12)	(0.09)	(0.13)
Log (R&D_1)				0.01				0.11**
				(0.06)				(0.05)
Log (R&D stock)	0.15**	0.15**	-0.2		0.27*	0.27*	-0.05	
	(0.08)	(0.07)	(0.23)		(0.08)	(0.08)	(0.21)	
Log (labor)	0.32***	0.32***	0.36	0.42**	0.73*	0.72*	0.47	0.98*
	(0.17)	(0.17)	(0.34)	(0.21)	(0.17)	(0.17)	(0.29)	(0.18)
Market share	6.31*	6.31*	4.15***	5.14**	2.55	2.53	-1.64	1.05
	(2.42)	(2.43)	(2.19)	(2.53)	(2.23)	(2.24)	(1.66)	(2.28)
Profit dummy	11.31*	11.31*	11.26*	11.52*				
	(0.30)	(0.30)	(0.22)	(0.35)				
IMR		0.05	0.15	0.03		0.15	-0.03	0.3
		(0.48)	(0.75)	(0.52)		(0.52)	(0.61)	(0.58)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Number of obs	531	531	531	531	404	404	404	404
Adjusted R^2	0.9	0.9	0.88	0.9	0.56	0.56	0.02	0.55

Note: numbers in parentheses are standard errors. “*”, “**”, “***” – 1%, 5%, and 10% significance levels respectively.

Table 5. R&D effort equation

	Probit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Constant	-0.49	-1.296	-2.05*	-0.48
	(0.17)		(0.66)	(0.79)
Log (sale_1)		0.47*	0.46*	0.46*
		(0.07)	(0.08)	(0.07)
Log (capital)		0.15**	0.14**	0.12***
		(0.07)	(0.07)	(0.07)
Log (profit_1)			0.01	0.01
			(0.02)	(0.02)
RSE labor ratio	3.05*			
	(0.82)			
R&D organ dummy	0.88*			
	(0.10)			
Profitability dummy	0.02		-0.14	0.17
	(0.10)		(0.22)	(0.22)
IMR				-2.02*
				(0.59)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Highly significant	Yes	Yes	Yes
Number of observations	1571	404	404	404
Adjusted R^2	0.15	0.3	0.3	0.31

Note: numbers in parentheses are standard errors.
"*", "**", "***" – 1%, 5%, and 10% significance levels respectively.

Table 6. SUR estimates

	Two-equation system		Three-equation system		
	Output	Profit	Output	R&D	Profit
	(1)	(2)	(3)	(4)	(5)
Constant	1.80*	-8.58*	1.70*	-1.71*	-9.52*
	(0.14)	(0.83)	(0.19)	(0.65)	(0.94)
Log (capital)	0.32*	0.11	0.41*	0.08	0.26*
	(0.04)	(0.07)	(0.05)	(0.08)	(0.09)
Log (R&D stock)	0.12*	0.10	0.16*		0.19*
	(0.04)	(0.06)	(0.04)		(0.08)
Log (labor)	0.56*	0.34*	0.43*		0.11
	(0.05)	(0.13)	(0.06)		(0.17)
Profitability dummy		11.22*			11.39*
		(0.18)			(0.20)
Market share		7.30*			5.03*
		(1.24)			(1.31)
IMR	-0.88*	-1.18*	-0.91*	-1.34*	-0.35
	(0.24)	(0.45)	(0.29)	(0.49)	(0.55)
Log (sale_1)				0.56*	
				(0.08)	
Log (prof_1)				0.01	
				(0.02)	
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	531	531	404	404	404
Adjusted R^2	0.69	0.90	0.73	0.31	0.91
Correlation matrix:					
	System 1		System 2		
	Output	Profit	Output	Profit	R&D
Output	1		1		
Profit	0.19	1	0.26	1	
R&D			-0.11	-0.08	1
Breusch-Pagan Test	χ^2=18.33		χ^2=33.56		
	P=0.00		P=0.00		

Note: numbers in parentheses are standard errors. CRS imposed in columns (1) and (3).
"*", "**", "***" – 1%, 5%, and 10% significance levels respectively.

Table 7. Marginal productivity (MPD) and profitability (MPF) of R&D

	MPD of R&D	MPF of R&D
Industry		
Machinery	1.91	0.39
Electronics	0.62	0.18
Pharmaceutical	0.9	0.19
Chemical	2.28	0.59
Other	1.91	0.39
Year		
1991	1.21	0.68
1992	1.89	0.53
1993	1.49	0.43
1994	1.62	0.33
1995	1.65	0.27
1996	1.18	0.19
1997	1.07	0.11

Note: the calculation is based on the following elasticity estimates: α=0.28, γ=0.14; and the material's share of gross output=0.7.