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The Impact of Imported and Domestic Technologies on Productivity: Evidence from Indian Manufacturing Firms

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ABSTRACT

Proponents of trade liberalization in developing countries often argue that one of its most important benefits is that it enables firms in developing countries to access the international knowledge base by importing technology in both disembodied form (i.e., as technological know-how) as well as embodied form (i.e., embodied in imported capital goods). Opponents of trade liberalization argue otherwise. In addition to doubting that there are significant gains to be had from utilizing foreign technologies in developing country contexts, they believe that imports of technology dampen local efforts at developing new technology with negative consequences for local capabilities and long-run growth prospects.

This paper utilizes panel data on a sample of Indian manufacturing firms for the years 1977-87 to examine these views. Production function estimates reveal that imported technologies, especially those of disembodied nature and obtained through contractual arrangements with foreign firms, impact productivity positively and significantly. Firms' own R&D efforts, on the other hand, are not very productive. Finally, while domestically produced capital goods impact productivity positively and significantly, their impact appears to stem from the technological know-how imported by domestic producers of capital goods.

Although these findings support the optimism of liberalizers that foreign technologies represent an important opportunity for productivity enhancement for developing country firms, the estimates of this paper also lend support to the notion that a liberal import policy will dampen local efforts at developing new technologies. More specifically, the estimates reveal that firms do not need to undertake significant R&D efforts to utilize imported technologies effectively. Thus, taken together the results suggest that while firms in India's recently liberalized economic environment will be able to raise their productivity by importing greater amounts of foreign technologies, they will also have less incentives to carry out their own R&D. To the extent that local efforts at R&D are a "good" to be encouraged, the challenge for public policy will be to devise policy tools that are able to encourage local R&D, but not through a trade policy which blocks an important and direct channel by which firms can raise productivity.

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1. Introduction

There has been a resurgence of interest in the role of international trade in promoting economic growth and productivity in recent times. In particular, the emphasis of new growth theories on the growth and productivity enhancing role of investments in technical knowledge by profit seeking firms has led a number of researchers to contemplate how trade may influence these investment decisions. At one level, trade is believed to affect firms' incentives to invest in technology via its impact on market structure and competition.[1] At another, it is believed to influence the pace of technological change by transforming the set of knowledge available to a country and its firms. Indeed, as Grossman and Helpman (1991) write, "perhaps the most important benefit to a country from participating in the international economy might be the access that such integration affords to the knowledge base in existence in the world at large" (pg. 238).

There are a number of ways in which a country may access the international knowledge base. Perhaps the most direct and important of these are the import of physical inputs which embody new and/or superior foreign technology (particularly capital goods) and the import of designs, blueprints, technical assistance, and training from foreign firms. The latter represent imports of disembodied technology as they primarily involve the transfer of technical knowledge and skills.[2]

Unfortunately not too much is known about the effects of these technology/knowledge imports on firms' productivity and their interactions with domestic efforts at understanding and generating technology. In fact, in contrast to the optimistic picture painted by the statement of Grossman and Helpman above, there are doubts in the minds of economists and policy makers in some less developed countries (LDCs), particularly India, about the benefits of foreign technology for the growth prospects of LDCs. A commonly held view has been that the import of disembodied technology takes place at the behest of foreign firms looking for quick profits and that the technology transferred does not represent any significant gain in performance or productivity for the Indian firms.[3]

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[1] It may be noted that contrary to popular perceptions, the new framework does not provide an unambiguous theoretical underpinning to the notion that opening to trade increases the incentives of less developed country (LDC) firms to invest in innovations (see for example, Rodrik 1992, Young 1991).

[2] There are a number of other channels as well. For example, case study evidence suggests that export activities by firms in LDCs lead to improvements in their technical efficiency as international buyers transmit technical assistance and knowledge to them. While a number of econometric studies purport to show the same, see Clerides, Lach, and Tybout (1996) for a critique of these studies. Spillovers of international knowledge represent yet another mechanism of drawing upon the international knowledge base. In principle, such spillovers do not have to be related to trade. In practice, however, even these are likely to depend on trade (Coe and Helpman, 1995).

[3] For example, case studies by Scott-Kemmis and Bell (1988) and Desai (1988) examining the contractual purchase of foreign technology by Indian firms suggest that the importing Indian firms do not get enough technological know-how through the contracts. Although this evidence has been interpreted differently by various researchers, many have taken the case study evidence to be indicative of low returns from the import of technology. Indeed, even Arora (1996) who clearly believes technology transfer to be a potentially important source of technology and focuses on policies that would improve the efficiency of technology transfer is prompted to write that the "ability of Indian firms [engaged in arm's length import of technology] to assimilate, utilize, and improve

Another view holds that even if the imports of technology (embodied or disembodied) are productivity improving, they lead to a dampening of domestic R&D activity as local firms purchase technology (embodied or disembodied) from foreign ones. If there are significant externalities from domestic R&D efforts, then a liberal technology import policy could be detrimental for an LDC's long-term growth prospects (Kumar 1990). However, whether imports of technology substitute for local efforts at technology generation or not is the subject of much debate. Indeed, some economists have argued that imports of technology spur domestic R&D activity because of the need to adapt and utilize effectively imported technology (see Katrak 1997 for a recent review of the debate).

This paper uses panel data from 1976-77 to 1986-87 for a sample of Indian manufacturing firms to determine the extent to which the productivity of Indian firms has been affected by their investments in imported and domestic sources of technology and the nature of these technology inputs' interactions in production, thus shedding some light on the views above. Production functions augmented with various technology inputs are estimated using a variety of econometric specifications. In particular, the technology inputs include not only firms' stocks of R&D, but also their stocks of imported disembodied technology following Basant and Fikkert (1996), Raut (1995), and Ferrantino (1992). However, because new technologies are widely believed to be embodied in the capital goods used by firms, this paper also includes measures of embodied technical change as additional determinants of firms' productivity.

The inclusion of technology embodied in capital goods as a possible source of technological change is an important one. For instance, one interpretation of cross-country growth regressions that find investments in capital goods, particularly of the imported variety, to have a strong and robust impact on economic growth (De Long and Summers 1991, 1993; Lee 1995), is that new capital goods embody superior technology. Unfortunately, the results of cross-country growth regressions, are not easy to interpret as they tend to be prey to a number of econometric problems and aggregation biases which may be alleviated by using micro-level panel data. By using data on the sample firms' investments in domestic and imported capital goods this paper attempts to provide direct, micro-based evidence on the impact of technology embodied in capital goods on productivity.

The paper is organized as follows. Section 2 discusses the conceptual framework and estimation strategy used in this paper. Section 3 presents a description of the data set and the variables used in estimation. Section 4 details the results from the empirical analysis and compares these with the earlier literature. Finally, section 5 concludes.

2. Conceptual Framework and Estimation Issues

2.1 Conceptual Framework

A firm is assumed to produce output Q using capital K, labor L, and materials M, subject

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the technology is limited."

to a state of technology S, in accordance with a production function:

$$Q = F(K, L, M, S). \tag{1}$$

A firm's state of technology is assumed to depend not only on the technical knowledge possessed by it but also the technology embodied in the capital goods it uses. Improvements in a firm's state of technology represent increases in its productivity or technical efficiency.

Most studies in this strand of the literature have been conducted for developed countries and have generally focused on firms' own R&D as the sole determinant of technical knowledge.[4] While this may be realistic in the case of developed countries, it is not likely to be a good one in the context of an LDC like India. This is because in addition to conducting their own R&D, Indian firms' routinely acquire technical knowledge through the import of disembodied technology from foreign firms. These imports take place through technology transfer agreements with foreign firms which supply designs, blueprints, and technical assistance to the contracting domestic firm. Thus the framework adopted in this paper considers there to be two distinct sources of technical knowledge: own R&D and the purchase of disembodied technology from foreign firms.

As far as technology embodied in capital goods is concerned it is quite difficult, if not impossible, to measure how much technology is embodied in a particular piece of equipment. A simplification made by many researchers is to assume that recently purchased capital goods embody newer, more productive vintages of technology than older capital goods (for example, Bahk and Gort 1993; Baily, Hulten, and Campbell 1992; Bregman, Fuss, and Regev 1991).[5] In this paper, these embodiment effects are captured by using the shares of the total capital stock made up of recent investments in imported capital goods and recent investments in domestic capital goods, an approach which minimizes multicollinearity problems in estimation and is along the lines of

[4] Some studies also incorporate a measure of the R&D preformed by other firms belonging to the same industry in order to capture the importance of R&D spillovers. Two recent studies have examined similar issues for India. See Basant and Fikkert (1996) and Raut (1995).

[5] A couple of factors would seem to suggest that in the Indian context, this assumption is more likely to hold for recently imported capital goods than recently produced domestic capital goods. First, India's trade and industrial policies restricted the imports of capital goods on account of a desire to protect India's capital goods producing industries and to conserve foreign exchange (Ahluwalia 1994). A complex licensing procedure ensured that the import of a capital good was allowed only if it could be demonstrated that a domestic substitute did not exist. As a result, the capital goods actually imported would tend to embody newer technologies than those produced domestically. Second, it is doubtful that Indian capital goods producers could undertake the kind of R&D effort that goes into the manufacture of foreign capital goods and thus produce capital goods that embody significantly new technologies (Lall 1987). However, it has to be factored in that Indian capital goods producers would be able to tap into the superior technical knowledge required to produce technologically advanced capital goods by entering into technology transfer agreements with foreign capital goods producers. Thus, domestically produced capital goods could well embody productivity improving technological advances from abroad.

Bregman, Fuss, and Regev (1991) and Berndt and Morrison (1995).[6]

In summary, Indian firms' state of technology is assumed to depend on their R&D, their purchases of disembodied technology from foreign firms, and the shares of their capital that are composed of recent investments in imported and domestic capital goods:

$$S = f(R, T, RI^M/K, RI^D/K), \tag{2}$$

where R and T represent the stocks of technical knowledge generated by a firm's own R&D expenditures and purchases of disembodied technology from foreigners, respectively, and RI^M/K and RI^D/K represent firms' shares of new imported and domestic capital. Firms with higher levels of R and T and, therefore, a higher state of technology, should then be the more productive ones. Similarly, if new capital goods embody advances in technology and these advances improve productivity, then the shares of capital that are of recent vintage should impact output positively in a production function.

In order to estimate the four-input production function in equation (1), two functional forms are used: the Cobb-Douglas and Translog, which can be viewed as first and second order approximations to any production function, respectively. The Cobb-Douglas takes the form:

$$\ln Q_{it} = A_t + \sum_{j=1}^{4} \gamma_j \log S_{jit} + \sum_{k=1}^{3} \beta_k \log X_{kit} + \varepsilon_{it}, \tag{3}$$

where Q is as previously defined, $S=(S_1, S_2, S_3, S_4)=(R, T, RI^M/K, RI^D/K)$, $X=(X_1, X_2, X_3)=(K, L, M)$, A represents a time-specific intercept term that captures exogenous, economy-wide shifts in productivity, ε denotes an error term, and i and t index firm and time, respectively.

Similarly, the Translog takes the form:

$$\ln Q_{it} = A_t + \sum_{j=1}^{4} \gamma_j \log S_{jit} + \sum_{k=1}^{3} \beta_k \log X_{kit} + (1/2)\cdot\sum_{k=1}^{3} \beta_{kk} \log X_{kit}^2 + \sum_{k<l} \beta_{kl} \log X_{kit}\cdot\log X_{lit} + \varepsilon_{it}, \tag{4}$$

where all of the variables are as previously defined. Note that while a firm's state of technology is

[6] One alternative to the share approach is to measure the embodiment effect by including the actual levels of recently purchased capital goods, imported and domestic (RI^M and RI^D). This, however, would exacerbate multicollinearity problems in estimation on account of the inclusion of total K in the production function. K includes all investments in fixed assets and would thus include recent investments in capital goods, domestic and imported. This double counting is likely to cause problems of multi-collinearity in the regressions. Indeed, the partial correlations between K and RI^D and K and RI^M (taking into account firm effects) are 0.67 and 0.57, respectively. These are substantially larger than the corresponding partial correlations between K and RI^D/K and K and RI^M/K, 0.25 and 0.33, respectively, suggesting that the usage of the shares suffer less from multi-collinearity problems.

assumed to be additively separable throughout, in some of the empirical analysis below the various technology inputs are allowed to interact with one another, thereby allowing the inputs to be substitutes or complements for one another in production in the sense that two inputs are substitutes (complements) for one another if an increase in the usage of one leads to a decline (increase) in the output elasticity of the other. Finally, because the various technology inputs can take zero values across observations, a 1 has been added to each of the technology inputs as in Raut (1995) in order to avoid the problem of having to take a log over a zero.

2.2 Estimation Issues

Estimation of the production functions above requires that some assumptions be made about the error term. In view of the panel nature of the data, the error term is assumed to be composed of two terms:

$$\varepsilon_{it} = u_i + v_{it}. \tag{5}$$

The first term, u_i, corresponds to firms' unobserved time-invariant technical efficiency and the second term, v_{it}, captures the residual variation in output. If u_i is not correlated with the regressors, then OLS is consistent. However, it is not efficient as it does not take into account the fact that part of the error term is constant for each firm over time. A gain in efficiency may be made by using the random effects estimator.

The assumption that u_i is not correlated with the regressors is a rather strong one. In particular, while a firm's level of time-invariant technical efficiency may be unobservable to the econometrician it is very likely to be known to the firm. If this is the case, then firms may be expected to make input choices on the basis of their technical efficiency. In other words, u_i will be correlated with the regressors and treating it as part of the error term, as is done in the random effects model, will introduce an omitted variable bias. One way to deal with this is to transform the data in order to sweep away the u_i. This may be done by expressing each variable in terms deviations around its firm-specific (within-group) mean value (for example, $x_{it} - \sum x_{it}/T$), as in the so-called fixed effects model.[7] Alternatively, it is possible to express each variable in differenced form (for example, $x_{it}-x_{it-1}$) and thereby rid the regression equation of the u_i. Which particular procedure is used usually depends on whether the other component of the error term, v_{it}, is assumed to be endogenous or not. In particular, if v_{it} is assumed to be correlated with the regressors then an instrumental variables estimator can yield consistent estimates of the regressors. In many applications, finding valid instruments is easier for the first differenced estimator as compared to the within-group estimator. This is because, typically, the only valid instruments available for panel data on micro-level variables are lagged values of the regressors themselves. Since the error term of the within-group or fixed effects model contains shocks from every period in the panel ($\varepsilon_{it} - \sum \varepsilon_{it}/T = v_{it} - \sum v_{it}/T$), it will be correlated with lagged values of the regressors under the assumption

[7] A Hausman specification test can be used to determine whether the fixed effects or random effects model is appropriate.

of endogenous v_{it}, rendering these invalid as instruments. This is not a problem with the first differenced transformation, however. Since the error term for that model is $(\varepsilon_{it}-\varepsilon_{it-1})=(v_{it}-v_{it-1})$, a lagged regressor, say x_{it-2}, will not be correlated with either v_{it} or v_{it-1} as long as the v_{it}'s themselves are not autocorrelated.[8]

3. Data and Variable Construction

The data set used in this paper consists of the annual reports of 286 public limited firms, defined as private corporations with more than 50 shareholders, covering the years 1975-76 to 1986-87.[9] The firms may be placed into 8 manufacturing industries at the approximately two-digit level, spanning the broad range of the manufacturing sector: 5 percent of the firms belong to food processing; 17 percent to textiles; 11 percent to light manufacturing (which is taken here to include firms producing paper, cement and rubber and plastic goods); 8 percent to metal products; 20 percent to chemicals and 8 percent to pharmaceuticals; 9 percent to transportation equipment; 12 percent from electrical machinery; and 10 percent from non-electrical machinery.

The variables required for the estimation of the production functions in equations (3) and (4) are firm-level measures of output, capital stock, labor, material inputs, stocks of R&D and imported technology, and measures of technology embodied in imported and domestic capital goods. These are described below.

Output (Q): Each firm's value of production for any given year was deflated to constant 1985-86 rupees using the wholesale output price deflators for the firm's industry.[10] These deflators were obtained from the Index Numbers of Wholesale Prices of India contained in Chandhok and the Policy Group (1991).

Labor (L): Labor units were derived by dividing each firm's total payments for wages and salaries by industry-specific wages for each year. The industry-specific wage data was computed by dividing each industry's "total emoluments to employees" by the "total number of labor hours worked" using the industry-level data reported in the Annual Survey of Industries of India.

Materials (M): Each firm's expenditures on materials and intermediate inputs were deflated by an industry-specific materials price deflator. India's input-output matrix was used to weight output price indices in order to construct an industry-specific, materials price deflator. The source of the output price indices was once again the Index Numbers of Wholesale Prices of India contained in

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[8] Even if the v_{it}'s were autocorrelated following, for example, an AR1 process, a suitable transformation of the original model along with a sufficiently lagged regressor can still serve as a valid instrument as is shown in Appendix 2 below.

[9] I am extremely grateful to the Institute for Studies in Industrial Development of New Delhi, India for allowing me to use the firm-level data utilized in this study.

[10] The industry-wide deflators are based on the lowest level of aggregation possible. For most variables this is the three-digit level (the firms can be assigned to roughly 29 industries at the three-digit level).

Chandhok and the Policy Group.

Capital (K): Firms' capital stocks were constructed using the perpetual inventory method:

$$K_{it} = I_{it} + K_{it-1} \cdot [1 - \delta], \tag{6}$$

where I_t denotes real investment, calculated as the difference in firms' total gross fixed assets deflated by the wholesale price index for investment goods, P_{kt}, and δ denoted the rate of depreciation, assumed to be six percent. Details of the procedure, including the construction of starting values of the capital stock are given in Appendix 1.

(R) R&D Capital: Firms' expenditures on R&D activities were converted into stocks of R&D by using the perpetual inventory method to aggregate firms' annual real investments in R&D.[11] Following previous research, R&D was assumed to affect output with a one year lag and decay at the rate of 15 percent per annum..[12] The evolution of the stock of R&D may be expressed as:

$$R_{it} = RD_{it-1} + R_{it-1} \cdot [1 - \delta], \tag{7}$$

where R is the stock of R&D generated knowledge and RD are the annual, real expenditures on R&D activities.

Several steps had to be undertaken before the above equation could be applied to the data. First, the annual expenditures on R&D activities had to be converted into real values. For the annual expenditures on R&D, this was accomplished by using the average of the wage and capital goods deflators as the R&D deflator. Using these deflators, the real expenditures, RD, were obtained.

The next step was to come up with starting values for R. If a firm had incurred no expenditures on R&D in the first year for data, then it was assumed that the firm did not conduct R&D in any of the previous years. This assumption is not as strong as it may seem; most firms in India did not conduct R&D prior to 1975-76, the first year for which the firm-level R&D data is

[11] A cross-checking of the R&D numbers from the firms' annual reports with those contained in the Compendium on In-House R&D Centers (Department of Science and Technology) revealed that a number of firms failed to itemize their R&D expenditures in their annual reports. For such firms, the R&D expenditures reported to the Department of Science and Technology were used as in Fikkert (1994).

[12] Experimentation with alternative assumptions about the lag with which R&D (and imports of disembodied technology) impacts productivity and depreciation rates did not alter results very much. In particular, while a one year lag and depreciation rate of 15 percent may be appropriate for data from developed countries, it is possible that in a more protected and less competitive market such as India's, technical knowledge becomes obsolete at a lower rate, thereby implying a lower depreciation rate. Similarly, the lower skills of the labor force may mean that it takes longer for investments in technical knowledge to impact output. However, experimentation with lower depreciation rates (for example, 6 percent) and longer impact lags (for example, two years) yielded parameter estimates very similar to those based on a 15 percent rate of depreciation and impact lag of one year.

available. For firms conducting R&D in 1975-76, it was necessary to determine the number of years for which firms had been doing R&D prior to 1975-76 and also the growth in real R&D expenditures over the period. The Department of Science and Technology's Research and Development Statistics can be used to estimate these. Computations reveal that among the Indian firms which had been recognized by the Department of Science and Technology in 1975-76 as operating R&D units, the average age of the R&D unit was about 5 years and that real R&D expenditures per firm had grown by about 5 percent per annum.

Assuming a rate of deprecation of 15 percent and a one period lag in the impact of R&D expenditures on output, the stock of R&D in such firms in 1975-76 is:

$$R_{i76} = RD_{i75} + (1-\delta) \cdot RD_{i74} + \ldots + (1-\delta)^{4} \cdot RD_{i71}, \tag{8}$$

where, the year 1975-76 is written as 76 for notational convenience, etc. Further, since real R&D expenditures per firm had grown by about 5 percent per annum, the above may be rewritten as:

$$R_{i76} = \frac{RD_{i76}}{1+0.05} \cdot \sum_{s=0}^{4} \left(\frac{1-0.15}{1+0.05} \right)^{s}. \tag{9}$$

For all subsequent years, equation (8) was applied.

(T) Imported Disembodied Technology Capital: Stocks of imported disembodied technology were constructed by applying the perpetual inventory method to firms' annual real imports of disembodied technology obtained through technology transfer agreements with foreign firms. As in the case of R&D stocks, the import of disembodied technology (TP) was assumed to impact output with a one year lag and decay at the rate of 15 percent per annum. The stock of imported disembodied technology T is assumed to evolve as:

$$T_{it} = TP_{it-1} + T_{it-1} \cdot [1-\delta]. \tag{10}$$

The annual expenditures on disembodied technology imports include payments to foreigners for technical assistance and consulting plus lump sum and royalty payments for the purchase of technology through licensing agreements between Indian and foreign companies. In order to deflate these technology import expenditures the procedure used was to adjust the R&D deflator for U.S. manufacturing industry for changes in the Dollar-Rupee exchange rate. The R&D deflator for U.S. industry was considered appropriate since U.S. firms constitute the largest source of transfers of technology to Indian firms.

To compute the starting values for T for each firm it is necessary to obtain information on firms' histories of disembodied technology import. The Directory of Foreign Collaborations in India lists the years in which Indian firms entered into technology based licensing agreements with foreign firms. This publication was used to determine the years in which the sample firms entered into such licensing agreements from 1965-75 and the flows of technology based on these licensing agreements were assumed to last for four years on the basis of Kapur (1983). To derive numbers that would represent the payments for these technology flows for the identified years, the initial year's sales of the firms with the pre-sample technology imports were multiplied with the average three-digit disembodied technology import to sales ratio for the initial year. Finally, all the expenditures on disembodied technology import, including the pre-sample expenditures just described above, were deflated and used in equation (11) to get the stocks of imported disembodied technology, T.

(RI^M/K) Technology Embodied in Imported Capital Goods: The annual reports of firms also detail investments in imported capital goods and the book values of plant and equipment. The expenditures on imported capital goods were deflated by the unit value index of imported capital goods available in the Statistical Abstract of India to arrive at real investments in imported capital goods (I^M). Real total investments in plant and equipment (I^P) were derived by differencing the book values of plant and equipment and then deflating the resulting figures by the wholesale price index of capital goods.[13]

The stock of recent investments in imported capital goods, RI^M, may be expressed as:

$$RI_{it}^{M} = \sum_{s=0}^{T} I_{it-s}^{M} \cdot (1-\delta)^{s}. \qquad (11)$$

The past flows were discounted using depreciation rates of six percent and a value of T=4 was chosen as in Bregman, Fuss, and Regev.[14] The share of total capital stock made up of recent investments in imported capital goods is then RI^M/K.

(RI^D/K) Technology Embodied in Domestic Capital Goods: The stock of recent investments in domestic capital goods can be constructed as:

$$RI_{it}^{D} = \sum_{s=0}^{T} I_{it-s}^{P} \cdot (1-\delta)^{s} - RI_{it}^{M}, \qquad \mathbf{(12)}$$

where RI^M is as defined in equation (12) and I^P, representing total investment in plant and equipment, is composed of investments in domestic and imported capital goods in that period. The share of total capital stock made up of recent investments in domestic capital goods is then RI^D/K.

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[13] Recall that (total) capital, K, is made up of investments in fixed assets. Fixed assets can be sub-divided into either (i) land and buildings, or (ii) plant and equipment. It is the latter which may be either imported or domestically produced.

[14] The results were not sensitive to an alternative rate of fifteen percent for depreciation. The results were also not sensitive to a choice of T=5 or T=3.

In order to use as many years of data as possible it is necessary to estimate pre-sample investments in imported capital goods and total plant and equipment. First, the average investments in imported capital goods and total plant and equipment from 1976-77 to 1979-80 were computed for each firm.[15] An average was taken instead of the first year's investments since it is likely to be a more representative indicator of a firm's pattern of investments. Next, using the national accounts statistics presented in Chandhok and the Policy Group (1990) and Statistical Abstract of India, the aggregate growth rates of real investments in total plant and equipment and imported capital goods were computed for the 1972-73 to 1977-78 period.[16] These were found to be 6.4 percent and 1.2 percent per annum on average, respectively. Finally, these aggregate growth rates were used to compute firms' pre-sample investment levels of imported capital goods and total plant and equipment using each firms' average investments in imported capital goods and total plant and equipment (computed in the first step) as a base.

Table 1a-c describes various statistics relating to the variables used in estimation by two-digit industry. As can be seen from examining the columns relating to the technology inputs, the various industries can vary significantly in terms of the propensity with which firms use these, especially technical knowledge. Thus, while only 35 percent of firms in textiles conducted any R&D, 88 percent of firms did so in electrical machinery (Table 1b). Similarly, while only 13 percent of the firms in the food processing industry imported disembodied technology 93 percent of firms did so in non-electrical machinery. These numbers, along with those on the intensity of various technology stocks with respect to output (and detailed in Table 1c) suggest that technology opportunities vary by industry (and that even within an industry firms will vary in the extent to which they are willing to exploit these opportunities) and that it is important that production functions be estimated over firms belonging to technologically homogenous groupings.

While the two digit industry level presents itself as a basis to group firms over, the relatively small number of firms in many of the two digit industries can leave econometric estimates susceptible to small sample biases. Thus, in what follows, estimation is performed over firms which are pooled over more aggregated groupings that are likely to be technologically homogeneous. In particular, following Cueno and Mairesse (1984), Griliches and Mairesse (1984), and Basant and Fikkert (1996), the sample firms are divided into either a scientific group - consisting of 113 firms belonging to the electrical, chemical, and pharmaceutical industries - or a non-scientific group - consisting of 173 firms belonging to the remaining industries. Although such a grouping of firms may be appropriate for developed countries where technological opportunities appear greatest in the electrical, chemical, and pharmaceutical industries its validity for the less sophisticated Indian context is unclear. For example, on the basis of the intensities of the technical knowledge stocks presented in Table 1c, it would appear that in addition to the electrical and chemical and pharmaceutical industries, firms in transportation and non-electrical machinery also invest

[15] Recall that because domestic investments are derived by differencing the book values of plant and machinery, the first year for which domestic investment is available is 1976-77.

[16] This includes not only the four pre-sample years (T=4) but also the first two sample years ending in 1977-78 - roughly the middle of the 1976-77 to 1979-80 period used to compute firms' average investments in the first step.

considerable amounts in accumulating technical knowledge. Thus, this paper also considers an additional grouping consisting of firms in these four "technology intensive" industries. To check whether and to what extent the results are driven by pooling across two-digit industries, separate estimates by two-digit industry are also presented.

4. Empirical Findings

Tables 2a and 2b detail estimates from the standard fixed and random effects models for both the Cobb-Douglas and the Translog production functions for various firm groupings. There are several significant features of the estimates. First, in every set of estimates the Hausman statistic rejects the random effects specification, suggesting that unobserved time-invariant firm heterogeneity does influence the input choices of firms. Second, the estimated coefficients pertaining to the conventional inputs, capital, labor, and materials lie in ranges conforming with those found by virtually every study which utilizes firm-level data to estimate production relationships while controlling for firm specific heterogeneity.[17] Additionally, the estimated returns to scale in terms of these inputs are reasonable. For the Cobb-Douglas production function, returns to scale range from 0.95 to 1.02 for the various estimates. In the case of the Translog production function where output elasticities are not constant over the estimated equation but vary with individual observations, average returns to scale lie in a similar range.[18] Taken together these findings suggest that the estimated relationships are fairly sensible. Finally, a focus on the fixed effects estimates reveals that the estimates of the various technology related variables are fairly similar across the Cobb-Douglas and Translog functional forms. In fact, the estimates for all firms and scientific firms are virtually identical: exactly the same set of variables are statistically significant and for these variables even the sizes of the estimated parameters are very similar.

The various sets of estimates reveal a positive and generally statistically significant impact of new capital goods on productivity. More specifically, the parameter estimates indicate that a doubling of the share of new domestic capital leads to a 1% to 0.3% increase in output. While the impact of a doubling of the share of new imported capital goods is less - it ranges from 0.3% to 0.1% - new imported capital goods are a much smaller share of total capital to begin with, typically about one-fourth of new domestic capital goods on average. In other words, the real impact of new imported and domestic capital goods on productivity is actually quite similar. By contrast,

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[17] See, for example, Tybout and Westbrook (1996) for a survey on the econometric evidence on the structure of production based on firm-level data from developing countries. In addition, see Basant and Fikkert (1996) and Raut (1995) for studies using firm-level data from India. While the latter estimates a value-added production function, the implied elasticities of capital based on value-added here are very similar to those of Raut (1995). Moreover, in the production functions estimated here the total impact of capital on output is spread across the capital stock variable and the variables measuring the new technology embodied in recently purchased capital goods.

[18] The Translog estimates of output elasticities for capital, labor, and materials are obtained by evaluating the estimated production function at the mean values of those variables. T-statistics were obtained using the delta method. For all four industry groupings, the estimated production functions display generally good curvature properties. For example, returns to scale from the preferred fixed effects model decline with output as theory would suggest and lie within conventionally reported ranges.

investments in technical knowledge only have a positive and statistically significant impact on productivity if they are foreign in origin. Firms' own R&D never shows up with a positive and statistically significant sign in any of the fixed effects estimates although they do so in some of the random effects estimates.

4.1 Autocorrelated Errors

The coefficients from the fixed effects model (and random effects model) above are estimated assuming that the idiosyncratic component of the error term, v_{it}, is independent across firms and over time. While the assumption of independence of this error term across firms is fairly innocuous, the same cannot be said about the assumption of its independence over time. In other words, v_{it} may be autocorrelated. Autocrorrelated errors can arise for several reasons. For instance, an important independent variable that itself is autocorrelated may be omitted. Alternatively, random shocks that impact firms' output and productivity, such as a strike, may have effects that persist over time. As is well known, ignoring the autocorrelation of the error term when it is present renders estimates inefficient. It is thus important to test for autocorrelated errors and, if they are present, correct for them.

Assuming first order autocorrelated (AR1) errors, i.e., $v_{it} = \rho v_{it-1} + \eta_{it}$ where ρ is the autocorrelation coefficient and η_{it} is an i.i.d. error, it is possible to utilize the procedure of Bhargava, Franzini, and Narendranathan (1982) to test for autocorrelation in the fixed effects model.[19] In every case, the Bhargava et al procedure leads to a rejection of the null of no autocorrelation making it necessary to correct for AR1 errors. This is done following the standard two step procedure whereby, first, a consistent estimate for ρ is obtained by estimating the model ignoring the autocorrelation, and second, efficient estimates are obtained for the production function using Cochrane-Orcutt transformed data (for example, $x_{it}^* = x_{it} - \rho' x_{it-1}$, where ρ' is the estimated

[19] Using the Durbin-Watson statistic generalized to panel data, $D_p=(\Sigma_{i=1}\Sigma_{t=2}(v_{it} - v_{it-1})^2/\Sigma_i\Sigma_t v_{it}^2)$ where i runs from 1 to N and t runs from 2 to T and 1 to T in the numerator and denominator, respectively, Bhargava, Franzini, and Narendranathan (1982) develop lower (D_{pl}) and upper bounds (D_{pu}) on D_p that vary only with the number of panels and time-periods. Analogous to the standard Durbin-Watson test, the null hypothesis of no (positive) autocorrelation is rejected if the sample criterion D_p is less than D_{pl}. It is accepted if D_p is greater than D_{pu}. The test is inconclusive if $D_{pl}<D_p<D_{pu}$.

autocorrelation coefficient).[20, 21]

Tables 3a and 3b detail the fixed effects estimates corrected for AR1 errors for both the Cobb-Douglas and Translog production functions.[22] The output elasticities of the various inputs are once again broadly similar across the two production functions. However, the greater flexibility afforded by the Translog appears to come at the expense of precision as evidenced by statistically insignificant estimates on some of the technology inputs that were statistically significant before. Additionally, the estimated Translog production function for the non-scientific firms is not as well behaved as before: estimated returns to scale in terms of the conventional inputs increase with size. Focusing then on the more sensible Cobb-Douglas estimates, it can be seen that the only technology variable that does not change much in either its estimate or statistical significance is the share of new domestic capital. By contrast, the share of new imported capital retains its statistical significance only in the case of the high technology group of firms. As for the imports of disembodied technology, these remain statistically significant in the scientific and technology intensive groupings and when all firms are pooled together.

In broad terms, the pattern that emerges is one where improvements in technology embodied in new domestic capital goods are most easily translatable into improvements in productivity while it is only firms in more technologically oriented industries that are able to utilize their imports of disembodied technology and new capital goods towards improving productivity significantly. While this pattern is a reasonable one - it is entirely plausible that India would lag behind developed countries to a greater degree in the more technologically oriented industries and/or that the transferability of technology would be greatest in these industries - the fact that the broad-based impact of new capital goods stems on account of domestically purchased capital goods is a little puzzling. However, it has to be acknowledged that new domestic capital goods could also embody

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[20] The estimated autocorrelation coefficient is obtained as:

$$\rho' = \frac{[\sum_{i=1}^{N}\sum_{t=2}^{T} \hat{v}_{it} \cdot \hat{v}_{it-1}]/N \cdot (T-1)]}{[\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{v}_{it}^{2}]/[N \cdot (T-1) - K]}$$

where a hat (^) over the v_{it}'s represents estimated values of the error term from the original model ignoring autocorrelation.

[21] If simultaneity between output and inputs is also a concern, then the estimate of ρ so obtained will not be consistent. In practice, addressing simultaneity is very difficult in view of the lack of suitable instruments. See Appendix 2, however, for an attempt to address issues of simultaneity in the presence of autocorrelated errors using GMM-IV techniques applied to panel data.

[22] Random effects models corrected for AR1 errors were also estimated. Of course, these would still be susceptible to an omitted variable bias on account of time-invariant firm effects and to simplify the exposition, are not reported.

superior foreign technologies. In fact, they are very likely to do so as Tables 1a-c show: Indian capital goods producers, i.e. firms in the electrical and non-electrical machinery and transportation producing industries, import a considerable amount of disembodied technology and tend to do so most intensively. To the extent that these imports translate into domestically produced capital goods of higher quality, the latter would be very likely to improve productivity in user industries. Support for this possibility is found from the production function estimates obtained by pooling firms into more disaggregated groupings.

Table 4a presents the estimates from Cobb-Douglas production functions obtained by pooling firms into 8 approximately two-digit industries.[23] Unfortunately, in two of the industries, the estimated coefficients on capital are negative suggesting strongly that while choosing more disaggregated industry groupings limits the possibility of biases from pooling over potentially heterogenous industries, the inevitably smaller size of the sub-samples increases the potential for small sample biases. More sensible estimates are instead obtained by constraining the conventional inputs, capital, labor and materials, to have the same relationship to output across more aggregated industrial groupings while allowing the impact of the technology related variables to vary across the more disaggregated two-digit industries. Table 4b presents such estimates.

It is encouraging to find that there are many similarities in the estimates pertaining to the technology inputs across Tables 4a and 4b. For example, out of a total of 32 estimates for the technology inputs (8 industries with four technology inputs each), only four have different signs across the two sets of estimates. More importantly, the main effect of constraining the estimates of K, L, and M to have the same coefficients across two-digit industry groups seems to be to lower standard errors thereby improving the statistical significance of various estimates (there are only three exceptions to this - two in chemicals and one in non-electrical machinery).

Focusing, then on the estimates of Table 4b, it can be seen that whenever the share of new capital goods is statistically significant it is positive. Additionally, while the positive and significant impact of new domestic capital goods is found in a range of industries - those deemed scientific, non-scientific, or technology intensive - they have a larger impact on productivity in the industries that may be classified as scientific and/or technology intensive, just as the estimates of Table 3a indicated. Similarly, while new imported capital goods impact productivity positively and significantly in only two industries, transportation and non-electrical machinery (and chemicals if the estimate of Table 4a are considered), both (and all three if Table 4a were considered) are industries which may be classified as scientific and/or technology intensive.

A similar pattern of relative importance in productivity improvements across industries is evident for imports of disembodied technology. These have a positive impact on productivity in the electrical and non-electrical machinery industries (and nearly so in chemicals if the estimates of Table 4a are considered), once again industries which may be classified as scientific and/or

[23] Translog production functions were also estimated for each of these eight industries. The estimated elasticities for the various inputs were again quite similar to those from the Cobb-Douglas production functions. However, the curvature properties were not very good in several cases.

technology intensive.[24] Moreover, Table 4b (or even Table 4a) also shows why the non-scientific industries of Table 3a show a statistically insignificant impact of disembodied imported technology on productivity: while these have a positive and significant impact in the textile industry, they have a negative and significant impact in the metal producing industries (although this latter impact is statistically insignificant in the estimates of Table 4a). Similarly, Table 4b (or even Table 4a) also shows why R&D fails to show up with a positive and statistically significant impact in any of the industrial groupings of Table 3a: the individual two-digit industries do not reveal much of a positive and significant impact of R&D stocks on productivity.

What is responsible for the broad-based lack of a positive and statistically significant impact of R&D on productivity? Investments in disembodied technology can entail a fair degree of uncertainty and risk. Thus a firm which conducts R&D in order to streamline its production process, for example, may simply fail to do so. In the best case scenario it would still be able to revert to its previously standardized process and produce as much output given its other inputs. The lack of any statistical relationship between its R&D and output would be consistent with such a scenario. In the worst case scenario the new, failed production process may not be easily reversed to the previous process and the actual production may fall short of what was previously possible given the same inputs. In this case there would appear to be a negative relationship between R&D and output.

Although R&D efforts may fail a significant number of times, it still must be explored whether there are other reasons for the lack of a connection between these and productivity. One possibility that needs to be explored is whether there are important complementarities between the various technology inputs. Thus while an Indian firm conducting R&D in isolation may end up with what in effect turns out to be a misdirected effort, it is still possible that R&D conducted in the context of imports of disembodied technology may lead to productivity gains. This possibility is examined next.

4.2 Interactions between Technology Variables

As mentioned in the introduction, one issue of long-standing interest among economists and policymakers in developing economies is whether significant investments in developing local technological capability - as acquired through formal R&D activities, for example - are required for utilizing imported technology effectively. Various researchers have argued in the affirmative and even claimed that foreign technologies are often the seed for the development of local technological capability.[25] Others have instead argued that no significant local capabilities are required in using imported technology effectively and that imports of technology may even dampen local efforts. While one way to examine these views is by modeling and estimating firms' choices regarding investments in technology using a factor demand framework as in Fikkert (1996) and Raut (1988),

[24] Note also that both of these industries form the backbone of the capital goods manufacturing industries thereby lending support to the hypothesis above that domestic capital goods may well incorporate productivity enhancing foreign technologies.

[25] See, for example, Katrak (1989) and Siddharthan (1992).

another is to estimate the relationship between domestic and imported technology inputs in production as in Basant and Fikkert (1996).[26] This section extends the analysis of the latter by introducing as additional regressors interaction terms involving the various technology inputs. If an interaction term between two variables, say R and T shows up positively (negatively), then the two share a complementary (substitute) relationship in the sense that an increase in R or T leads to an increase (decrease) in the output elasticity of T or R. Thus if a significant amount of R was needed to utilize T effectively this would tend to reveal itself in terms of a positive interaction term. If this were not the case, i.e. suppose a firm could use either R or T to obtain technical knowledge independently of the other, the interaction term would be small, zero, or even negative if diminishing returns to investing in technological knowledge were important.[27]

Table 5a and 5b detail the estimates of Cobb-Douglas production functions estimated using the fixed effects model (with a correction for AR1 errors) for various firm groupings. As the row of estimates corresponding to the interaction term between R and T reveals in Table 5a, there is no evidence of significant complementarity between stocks of R&D and imported disembodied technology in any of the four industrial groupings. The estimates at the more disaggregated two-digit industry level, detailed in Table 5b, support this with one exception. In the electrical industry, the interaction term between R and T is positive and statistically significant, consistent with the notion that own R&D allows firms in this industry to utilize their imports of disembodied technology more effectively. In addition, the estimates of Tables 5 a and b also indicate only limited complementarity between R&D stocks and imported embodied technology: of all the estimates there is only one statistically significant interaction term between R and RI^M/K (for food processing in Table 5b). On the basis of these estimates, it seems fair to say that while the imports of technology may require some in-house efforts to adapt it to local conditions, this is not as pervasive a factor in driving in-house R&D as some of the literature has claimed.

Interestingly, there is much more evidence of a complementary relationship between the shares of new imported and domestic capital goods in production: whenever the interaction terms between these shares are statistically significant in the estimates of Tables 5a and 5b, they are always positive. Apparently, new investment plans of firms require investments in both domestic

[26] While Fikkert (1996) finds evidence that any factor which raises imports of disembodied technology leads to a reduction of R&D, Raut (1988) finds the opposite. The two papers utilize similar data sets covering virtually the same time period (1975/76 to 1980/81). Therefore, it seems likely that an interplay of differences in methodology and variable construction are responsible. For example, although both papers use a simultaneous equation framework, Fikkert (1996) uses a maximum likelihood procedure to take into account the censoring of his two dependent variables, R&D and imported disembodied technology, at zero. While Raut (1988) does not take into account the censoring problem, he breaks down firms' expenditures on disembodied technology into five categories distinguishing, for example, between royalties and technical fees paid to foreign sources. Fikkert (1996), on the other hand, combines the payments for royalties and technical fees paid to foreign sources into one composite "technology purchase" variable.

[27] Suppose that either R or T could be used independently of the other for the purpose of generating useful technical knowledge. If there are diminishing returns in the generation of technical knowledge, then the larger is a firm's R or T, the smaller will be the output elasticity of R&D or imported disembodied technology. In terms of the production function estimates, this feature would show up as a negatively signed interaction term.

and imported capital goods to be most effective. Restrictions on imports of capital goods would then not only have a direct, adverse impact on productivity - as indicated by the positive and statistically significant estimate for the share of imported capital in the scientific group of industries, for example - they would also have an indirect, adverse impact by making investments in domestic capital goods less productive. This finding resonates well with the assumption made in numerous endogenous growth models that domestic and imported inputs are complements in production (Romer 1994; Lee 1995; Baldwin and Seghezza 1996). Indeed, such an assumption is crucial in these models because it provides a link whereby barriers to trade lead to inefficiencies in the accumulation of capital and ultimately tie an economy down to a lower equilibrium growth rate.

4.3 Comparison with Other Studies

There are very few studies that have estimated the impact of investments in technology on productivity using firm-level data for LDCs. In fact, those that have, have used data for India - the one LDC for which panel data on the relevant variables exists (Basant and Fikkert 1996, Raut 1995, and Ferrantino 1992). However, all three of these studies have examined only the impact of various types of disembodied technology on productivity.

Ferrantino uses panel data for 280 firms belonging to six 2 digit industries and spanning the 1975-81 period. He examines the impact of technology in the six industries by estimating an indirect cost function where technology purchase intensities enter as parameter shifters. The specification is quite general in that the technical change implied by the technology purchase intensities can lead to Hicks neutral technical change as well as affect the substitutability of capital and labor. When Ferrantino aggregates all the various components of technology into one consolidated technology share variable, he finds technology intensity to have a positive and statistically significant impact on productivity in only two industries: chemicals and light industries. However, for textiles and machinery, technology intensity has a statistically significant negative impact on productivity. By contrast, recall that the two-digit industry level estimates here indicate technology inputs to have a positive impact on productivity in the textiles industry and the two machinery producing industries (electricals and non-electricals). Moreover, the light industry estimates here yield a negative and significant impact of R&D stocks on productivity.

While it is difficult to be sure of what is driving these differences across the two papers, methodological differences could be responsible.[28] For example, the cost function used by Ferrantino assumes that both capital and labor are at their long-run equilibrium values. As pointed out in Fikkert and Hasan (1998), India's licensing regime imposed serious constraints on firms' choice of inputs, especially capital. Thus the appropriate cost function should be a short-run cost function which recognizes the quasi-fixity of capital. Indeed, estimating a long-run cost function

[28] To some extent, it is possible that the differences in the composition of the light industries may be responsible for the different estimates across the two papers for this industry. While Ferrantino includes in his light industries the producers of paper, non-metallic minerals, wood products, and leather and fur products, there are no producers of the last two product categories in the sample firms here. However, as pointed out in the text differences in methodology are playing a definite role.

in a situation where some factor is quasi-fixed induces bias in the parameters of the production technology in an indeterminate direction. Perhaps more importantly, Ferrantino does not include time effects, nor does he correct for firm-specific heterogeneity by using either a fixed effects or random effects procedure. As mentioned before, ignoring firm effects will lead to biased parameter estimates if input choices are correlated with these. Indeed, a check using data from the light industry revealed that production functions estimated without controls for time effects and firm-heterogeneity (and without corrections for autocorrelated errors) yielded a positive and statistically significant sign on the R&D stocks, consistent with the results of Ferrantino.[29]

Basant and Fikkert (1996) and Raut (1995) estimate augmented Cobb-Douglas production functions as does this paper. The results pertaining to the impact of stocks of R&D and disembodied technology import are consistent with those of Basant and Fikkert - high returns to T and low returns to R - even when the possibility of autocorrelated errors and simultaneity bias between output and inputs are taken into account as done here (see Appendix 2 and Table A1). Basant and Fikkert also find no support for the notion that R&D and imports of disembodied technology are complements in production. While this is generally found to be the case in this paper also, the analysis at the more disaggregated two-digit industry reveals that complementarities are important for electricals industry.

Unfortunately, it is not possible to make a direct comparison of the results of this paper with Raut's because he does not treat R&D and imports of technology as distinct regressors in his production function. Instead, he pools together firms' expenditures on in-house R&D and import of disembodied technology calling it R&D. He also includes a measure of the aggregate R&D conducted by other firms in order to capture the role of R&D spillovers in each of his regressions. While Raut's disembodied technology variable (R&D plus imports of disembodied technology) is almost never statistically significant even at the 10 percent level, he does get statistically significant coefficients on the spillover variable in several of his estimates. Raut conjectures that the insignificant effect of firms' stock of disembodied technology may be due to measurement error caused by the double-counting of labor and capital used to perform R&D in the variables L and K and/or the non-reporting of R&D by some firms. He notes that the latter problem may not be there in the spillover variable since this is based on information from the Department of Science and Technology which is usually considered a reliable source of R&D data.

While the issue of double counting cannot be addressed with the available data, it does not seem likely that the low estimate of disembodied technology stocks stems from utilization of R&D numbers reported by the firms in their annual reports rather than the numbers they report to the Department of Science and Technology. As explained in Section 3, the procedure used in this paper was to cross-check the R&D numbers listed in the annual reports with those reported in the Compendium of In-House R&D Centers published by the Department of Science and Technology. If a firm had R&D expenditures reported in the Compendium but not in its annual report, the former

[29] When Ferrantino separates the various categories of technology into five categories based on expenses on R&D, royalty payments to foreigners, technical fees to foreigners, royalty payments to domestic firms, and technical fees to domestic firms, the share of R&D impacts productivity positively and significantly.

numbers were used. As the production function estimates in this paper reveal, even a usage of the Department of Science and Technology R&D numbers, usually considered more reliable, does not raise the impact of R&D stocks on productivity.[30]

In addition to the fact that R&D is a difficult and risky venture which may not pay-off, the low estimates of Indian manufacturing firms' R&D, found across all of these papers, may also reflect the possibility that the Indian government's very policies to encourage private sector R&D have led firms to over-report their R&D activities. In a survey of India's R&D policy and experience, Desai (1993) argues that firms' R&D efforts were not entirely geared towards generating useful knowledge. Rather a part of the reported R&D expenditures were designed to enable firms to take advantage of the incentives - income tax breaks and favorable treatment in the granting of licenses to import technology - introduced by the Indian government for firms with R&D units certified by the Department of Science and Technology. By either interpretation of the results, the efforts of the Department of Science and Technology to raise productivity generating R&D by the private sector seem to have been ineffective.

5. Conclusion

This paper has examined the impact of firms' R&D activities, their imports of disembodied technology, and their investments in imported and domestic capital goods on productivity using a sample of Indian manufacturing firms. The estimates from production functions augmented with these technology inputs support the hypothesis that the better access to the international knowledge base that closer international integration would afford represents important opportunities for developing countries to generate productivity growth. In particular, the estimates indicate that the imports of technology, especially those of disembodied technology, make statistically significant and direct contributions to the technical efficiency of firms, especially in industries where technological opportunities and technology investments are highly prevalent - industries such as chemicals and pharmaceuticals, electrical and non-electrical machinery, and transportation equipment.

The estimates also indicate that new domestic capital goods impact productivity positively and, in fact, do so for a broader range of manufacturing industries. However, the productivity enhancing impact of new domestic capital goods itself seems to stem from imported technology: firms belonging to the domestic capital goods industry tend to be the largest and most intensive users of imported disembodied technology. Moreover, there is evidence of a complementary relationship between imported and domestic capital goods in production in a number of the specifications estimated in this paper suggesting that restrictions on firms' import of capital goods, in addition to restricting access to embodied foreign technology, may have had another adverse effect on firms' productivity: lower technical efficiency of domestic capital goods as a result of lack of complementary inputs.

[30] R&D stocks based on only the expenditures reported in the firms' annual reports were not associated with higher productivity either.

In contrast to the other technology inputs, the impact of own R&D is found to be quite low. Although this may be a result of firm heterogeneity in ability to perform R&D - the random effects estimates in this paper yield larger and sometimes statistically significant impacts on productivity - they could also result from measurement problems. In particular, the incentive schemes introduced by the Indian government to encourage R&D may have led firms to seriously over report their R&D activities. To the extent that this happened, it points to a serious flaw in the ability to implement such government efforts aimed at encouraging firms to perform R&D. Indeed, the numbers presented in this paper suggest that India's liberalization of its trade and industrial policies, begun in earnest in 1991 but still ongoing, may lead to a decline in firms' R&D efforts as firms' increase their expenditures on imported technology in the more liberalized regime. The decline in R&D may be arrested to the extent that some R&D is needed to utilize imported technologies more effectively. However, the limited complementarity found in this paper between R&D and imported technologies suggests that this is not likely to be as important a countervailing force.

In other words, proponents of India's ongoing liberalization based reform efforts should be cautious when they argue that the pro-competitive forces of liberalization will lead local firms to conduct more R&D. Reductions in R&D in the more liberalized environment may well give ammunition to opponents of liberalization, especially those who tend to look at any substitution of local efforts at technology generation with imports with great suspicion (and called "technology nationalists" by Desai, 1993). A more constructive approach, not only from the point of firms' productivity but also with regard to the generation of local technological capability, may be to accept that foreign technologies present concrete opportunities for Indian firms and that policies aimed at developing local technological capability must focus on tools other than import substitution. As Bell and Pavitt (1993) point out, local technological capability has for too long been viewed solely through the lens of trade policy in development debates.[31] Over time India has accumulated a vast body of scientific and technical personnel in government owned scientific departments and institutions of higher learning. Efforts at aligning them more closely with private sector requirements and making them less dependent on government finance and management may well be challenging, but they could lead to large pay-offs.

[31] Thus those on the right often argued that an open trade policy would encourage the development of local technological capability while those on the left argue that local technological capability would only be harnessed in closed regimes (Bell and Pavitt,1993).

Appendix 1
Construction of Capital Stocks

The procedure used in Fikkert and Hasan (1998) was followed to construct a firm specific capital stock variable, K_t, that is net of depreciation and expressed in constant 1985-86 rupees. The first step was to compute the average age of the capital stock in the first year for which a firm's data is available. This was done by using values of accumulated depreciation (AD) and total gross fixed assets (TGFA), both of which are in the data set and by making the assumption that full depreciation of a firm's capital stock takes 16 years for accounting purposes. In this case, the average age (AA_i) of a firm's capital stock is:

$$AA_i = \frac{AD_i}{TGFA_i} \cdot 16 \tag{A1.1}$$

If it is further assumed that all of the capital stock in the first year has been purchased AA_i years ago the capital stock in 1985-86 rupee value becomes:

$$K_{i0} = \frac{TGFA_{i0}}{P_{K,\,0-AA_i}} \cdot [1 - \delta]^{AA_i} \tag{A1.2}$$

where δ denotes the rate of depreciation of the capital stock, t=0 represents the first year for which a firm's data is available, and P_{Kt} is the value of the investment deflator in year t. In all future time periods (t > 0), the firm's capital stock evolves as:

$$K_{it} = I_t + K_{it-1} \cdot [1-\delta] \tag{A1.3}$$

where I_t denotes real investment and has been calculated as the difference in TGFA between years, deflated by P_{Kt}. The rate of depreciation was chosen to be 6 percent per annum as in Fikkert and Hasan.

Another way to compute firm- and time-specific net capital stocks is to simply deflate each firm's total gross fixed assets by the investment deflator:

$$K_{it} = \frac{TGFA_{it}}{P_{K,t}}. \tag{A1.4}$$

Whereas the procedure outlined in equations (A1.1) - (A1.3) makes the implicit assumption that there is no revaluation of fixed assets, the capital stocks of equation (A1.4) are based on the assumption that revaluations are made every year on the basis of replacement cost and are undertaken so that the fixed assets recorded in the balance sheet may reflect their intrinsic value.

The two capital stocks, i.e., the one based on the perpetual inventory method and that based on equation (A1.4), move closely together and using either of the capital stock measures in the empirical analysis does not lead to qualitatively different results (Hasan 1997).

Appendix 2
An Exploration of Endogeneity Issues Using GMM-IV Estimation

The various estimates presented in the paper are obtained under the assumption that the regressors - the various production inputs - are uncorrelated with the error term. If changes in output and inputs are correlated - as they would be if they were simultaneously determined - then the estimates would be subject to a simultaneity bias. Such a bias could occur on account of either demand shocks or liquidity shocks, for example.

In principle, the way to tackle the simultaneity problem is through the usage of an instrumental variable estimator. In practice, however, finding an instrument which is correlated with the independent variable(s) being instrumented but not the error term can be very difficult, particularly in the context of micro-level data such as used here. Panel data are useful in such cases because they present a potentially useful instrument: lagged values of the regressors themselves (see, for example, Griliches and Hausman 1986, Mairesse and Hall 1996, Arellano and Bond, 1991). This appendix presents estimates which control for simultaneity bias and omitted variable bias due to time-invariant firm effects. In particular, time-invariant firm effects are dealt with by first differencing the data and simultaneity is dealt with by using lagged values of right hand side variables as instruments. Estimation is via the generalized method of moments (GMM) procedure of Arellano and Bond (1991) which provides a gain in efficiency as compared to the first differenced instrumental variables method suggested by Anderson and Hsiao (1981) for the case of dynamic fixed-effects models.

As Arellano and Bond point out, estimators that assume i.i.d. errors and utilize lagged values of the potentially endogenous right hand side variables as instruments would lose their consistency if the errors were actually autocorrelated. Because the analysis of Section 4 revealed the presence of autocorrelation, it is necessary to first transform the regression equation so as to eliminate the autocorrelation. Thus if the original model is:

$$y_{it} = \beta \cdot x_{it} + u_i + v_{it}, \tag{A2.1}$$

where v_{it} is an AR1 process ($v_{it} = \rho v_{it-1} + \eta_{it}$; ρ is the autocorrelation coefficient and η_{it} is an i.i.d. error), then it is possible to re-express the equation in dynamic form as:

$$y_{it} = \rho \cdot y_{i\,t-1} + \beta \cdot x_{it} - \beta \cdot \rho \cdot x_{i\,t-1} + (1-\rho) \cdot u_i + \eta_{it}, \tag{A2.2}$$

where η_{it} is i.i.d. as before and non-linear common factor restrictions are imposed on the values of β and ρ. The term involving u_i may be removed by differencing the data. Moreover, as η_{it} is i.i.d., any correlation between the differenced right hand side variables, $\Delta y_{i\,t-1}$, Δx_{it}, and $\Delta x_{i\,t-1}$, and the differenced error term, $\Delta\eta_{it}$, may now be dealt with by choosing lagged levels of the differenced right hand side variables dated t-2 or earlier as instruments.

For estimation purposes, each of the right hand side variables is assumed to be potentially endogenous and is instrumented for using lagged values of all the right hand side variables except for capital. In the case of capital, it is assumed that in addition to simultaneity, there may be endogeneity on account of mis-measurement of capital.[32, 33] If true this would invalidate the usage of lagged values of capital as an instrument because by virtue of its construction, mis-measurement in capital at any given point of time would be carried over to the future. As argued by Westbrook and Tybout (1993) and Tybout (1992), items such as land and buildings rather than purchases of plant and equipment usually account for a large part of the error in measuring capital thereby rendering investments in plant and equipment as a possible instrument for capital. However, because simultaneity between current investments in plant and equipment and output is of concern, this paper uses lagged values of these investments as instruments. Finally, lagged values of real wages are also included as instruments as their movements are likely to have an impact on firms' decisions regarding their capital stocks.

Table A1 presents the GMM-IV estimates using the method of Arellano and Bond.[34] Because the procedure is very intensive in data, estimates are obtained using the more aggregated industrial classification, i.e., for all firms and the scientific, non-scientific, and technology-intensive industries. The table also presents results from two tests of instrument validity due to Arellano and Bond. These are a test for the absence of *second* order serial correlation, since by definition, first differencing will introduce first order serial correlation in the differenced error term: $\Delta\eta_{it} = \eta_{it} - \eta_{i\,t-1}$) and a Sargan test of over-identifying restrictions. The test statistic for second order serial correlation - based on the GMM residuals from the first-difference equation - is distributed as a standard normal with zero mean and unit variance. As the table reveals, the test statistic leads to an acceptance of the null of no second order serial correlation in all four sets of estimates. Similarly, the Sargan test of over-identifying restrictions, which is distributed as chi-squared under the null that the instruments are valid, also leads to a validation of the instruments.

The actual estimates are qualitatively similar to those of the fixed effects model corrected for autocorrelation (Table 3a of Section 4). The imports of disembodied technology are positive and statistically significant for all firms and the scientific and technology intensive industries, while the

[32] To see this, suppose that $K_{it}=K^*_{it} + w_{it}$, where K^*_{it} is the true but unobserved capital stock and w_{it} is i.i.d. measurement error. Suppose that we estimate equation (A2.2) using ΔK_{it} rather than ΔK^*_{it}, i.e. $\Delta K_{1it}=K_{it}-K_{it-1}$. Then under the assumption that w_{it} is uncorrelated with η_{it}, the actual error term of the first-difference equation is $\Delta(\eta_{it}-\beta_K \cdot w_{it})$ which is correlated with ΔK_{it} since $\Delta K_{it}=\Delta(K^*_{it}+w_{it})$. The result will be a downward bias in the coefficient on capital.

[33] The same problem may afflict the other two stock variables included in the production function, R and T. However, obtaining suitable firm and time specific instruments for these technology variables with the available data was not possible. In any case, as is shown below the tests of instrument validity did not rule out the usage of lagged R and T as instruments.

[34] The estimates are based on Arellano and Bond's one-step estimates. Consistent with Arellano and Bond's warning that while their two-step estimates are asymptotically more efficient they are susceptible to spuriously low standard errors in small samples, the two-step estimates obtained from the application here had implausibly low standard errors.

share of new domestic capital goods are positive and statistically significant for all firms and non-scientific group. The share of new imported capital goods fails to be statistically significant in any of the estimates, however. Other than that, the main difference between the GMM-IV estimates and those of the fixed effects model with correction for AR1 errors is in terms of the estimates on capital. While the estimates of capital in the scientific and technology intensive industries are statistically significant (and substantially larger than previous estimates), they are statistically insignificant for all firms and the non-scientific industry. Although this is an unfortunate feature of the GMM-IV estimates, the relative robustness of the findings for the technology related variables across very different methodologies is encouraging.

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Table 1a
Basic statistics by two-digit industry

Industry	Firms	Output (Q)	Capital (K)	Labor (L)	Materials (M)
Food	15	210,136	127,304	18,833	119,331
Textiles	48	521,903	387,101	84,599	259,748
Light	34	744,268	639,233	70,377	274,616
Metals	22	438,375	233,984	36,406	235,743
Chemicals	80	493,960	408,475	52,258	280,809
Transportation	25	1,165,106	676,990	147,334	705,510
Electricals	33	548,033	209,641	76,596	360,310
Non-Electricals	29	419,531	198,367	54,198	249,614

Note: Numbers are mean values over firm means for Q, K, L, and M. All numbers are in thousands of constant rupees.

Industry	R&D Capital (R)	Imported Disembodied Technology Capital (T)	Recent Investments in Imported Capital (RI^M)	Recent Investments in Domestic Capital (RI^D)
Food	0	0	1	20,059
Textiles	0	0	3,845	58,802
Light	1,212	671	10,301	99,956
Metals	54	1,645	2,491	26,556
Chemicals	4,197	201	3,108	47,855
Transportation	2,346	5,074	25,952	77,950
Electricals	2,267	5,821	7,854	28,456
Non-Electricals	674	5,383	5,093	41,197

Note: Numbers are median values over firm means for R, T, RI^M, and RI^D. All numbers are in thousands of constant rupees.

Table 1b
Fraction of firms with positive technology inputs

Industry	R>0	T>0	RI^M>0	RI^D>0
Food	0.40	0.13	0.53	1.00
Textiles	0.35	0.44	0.98	1.00
Light	0.74	0.68	0.97	1.00
Metals	0.50	0.86	0.86	1.00
Chemicals	0.84	0.63	0.99	1.00
Transportation	0.84	0.88	1.00	1.00
Electricals	0.88	0.88	0.94	1.00
Non-Electricals	0.59	0.93	1.00	1.00

Table 1c
Intensities of technology inputs

Industry	R/Q	T/Q	RI^M/K	RI^D/K
Food	0.000	0.000	0.000	0.180
Textiles	0.000	0.000	0.023	0.301
Light	0.003	0.001	0.032	0.257
Metals	0.000	0.004	0.022	0.227
Chemicals	0.015	0.001	0.018	0.256
Transportation	0.007	0.012	0.082	0.280
Electricals	0.007	0.012	0.049	0.229
Non-Electricals	0.001	0.017	0.039	0.324

Note: Median value over firm means

Table 2a
Cobb-Douglas production functions
(Time dummies included in all regressions)

Variables	All Firms (286)		Scientific Firms (113)		Non-Scientific Firms (173)		Technology-Intensive Firms (167)	
	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects
ln(R)	0.000[a]	0.001	0.001	0.001	0.000[a]	0.001**	0.001	0.001
	(-0.37)	(0.83)	(0.69)	(1.06)	(-0.26)	(1.64)	(1.10)	(1.37)
ln(T)	0.005*	0.004*	0.010*	0.007*	0.002**	0.002**	0.009*	0.007*
	(5.96)	(5.32)	(6.56)	(5.20)	(1.79)	(1.77)	(7.23)	(6.62)
$\ln(RI^M/K)$	0.002*	0.001	0.001	0.001	0.003*	0.002*	0.003*	0.003*
	(2.06)	(1.60)	(0.54)	(0.42)	(3.31)	(2.93)	(2.09)	(2.00)
$\ln(RI^D/K)$	0.006*	0.006*	0.014*	0.015*	0.006*	0.006*	0.014*	0.016*
	(3.35)	(3.40)	(2.21)	(2.49)	(3.66)	(3.73)	(2.64)	(3.06)
ln(K)	0.05*	0.08*	0.08*	0.08*	0.05*	0.09*	0.04*	0.06*
	(5.01)	(10.04)	(4.29)	(5.72)	(4.97)	(9.67)	(2.47)	(5.01)
ln(L)	0.29*	0.27*	0.25*	0.21*	0.36*	0.32*	0.268	0.24*
	(19.87)	(22.48)	(9.80)	(11.02)	(22.00)	(24.04)	(12.88)	(15.15)
ln(M)	0.62*	0.61*	0.69*	0.68*	0.55*	0.54*	0.67*	0.65*
	(79.72)	(83.91)	(57.16)	(60.71)	(58.21)	(62.07)	(64.53)	(68.58)
Adjusted R^2	0.98	0.91	0.98	0.93	0.99	0.92	0.98	0.93
Hausman Statistic	--	144.40	--	34.06	--	169.40	--	59.61

Note: T-statistics are in parenthesis. All Hausman Statistics are significant at the 1 percent level. Constant term not reported for random effects model. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 2b
Translog production functions
(Time dummies included in all regressions)

Variables	All Firms (286)		Scientific Firms (113)		Non-Scientific Firms (173)		Technology-Intensive Firms (167)	
	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects
ln(R)	-0.001	0.001	0.002	0.003*	-0.001	0.001	0.001	0.001
	(-0.82)	(0.80)	(1.50)	(2.04)	(-1.37)	(1.04)	(1.32)	(1.57)
ln(T)	0.005*	0.004*	0.008*	0.006*	0.001	0.000[a]	0.008*	0.006*
	(5.22)	(4.46)	(5.37)	(4.48)	(0.64)	(0.52)	(6.59)	(5.89)
$\ln(RI^M/K)$	0.002*	0.001*	0.002	0.002	0.002*	0.001**	0.003*	0.003*
	(2.32)	(2.00)	(1.05)	(1.20)	(2.34)	(1.83)	(2.55)	(2.75)
$\ln(RI^D/K)$	0.004*	0.004*	0.012*	0.013*	0.003**	0.003*	0.013*	0.014*
	(2.45)	(2.53)	(1.99)	(2.38)	(1.67)	(1.97)	(2.47)	(2.92)
Mln(K)/Mln(Q)	0.07*	0.10*	0.09*	0.09*	0.06*	0.10*	0.06*	0.08*
	(7.14)	(12.38)	(5.25)	(6.74)	(5.83)	(11.07)	(4.61)	(7.28)
Mln(L)/Mln(Q)	0.25*	0.25*	0.19*	0.19*	0.33*	0.31*	0.20*	0.21*
	(17.05)	(21.24)	(7.32)	(9.85)	(20.71)	(24.22)	(9.49)	(13.24)
Mln(M)/Mln(Q)	0.61*	0.59*	0.68*	0.66*	0.58*	0.56*	0.65*	0.63*
	(65.65)	(70.64)	(38.93)	(43.46)	(58.78)	(63.77)	(49.57)	(54.94)
Adjusted R^2	0.98	0.91	0.98	0.93	0.99	0.92	0.98	0.94
Hausman Statistic	--	239.72	--	40.40	--	261.47	--	74.25

Notes: T-statistics are in parenthesis. Output elasticities have been computed at mean values and the associated t-statistics have been computed using the delta method. All Hausman Statistics are significant at the 1 percent level. Constant term not reported for random effects model. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 3a
Cobb-Douglas production function
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	All Firms (286)	Scientific Firms (113)	Non-Scientific Firms (173)	Technology-Intensive Firms (167)
ln(R)	-0.001	0.000[a]	-0.001	0.000[a]
	(-1.15)	(0.20)	(-1.20)	(-0.39)
ln(T)	0.002**	0.003**	0.001	0.003*
	(1.91)	(1.86)	(0.66)	(2.58)
$\ln(RI^M/K)$	0.001	0.001	0.001	0.003**
	(0.88)	(0.52)	(1.22)	(1.85)
$\ln(RI^D/K)$	0.006*	0.012*	0.006*	0.013*
	(3.42)	(2.15)	(3.43)	(2.46)
ln(K)	0.03*	0.05*	0.03*	0.03*
	(2.49)	(2.73)	(2.66)	(1.98)
ln(L)	0.35*	0.31*	0.40*	0.32*
	(23.40)	(12.78)	(21.98)	(16.06)
ln(M)	0.61*	0.67*	0.53*	0.65*
	(87.89)	(72.83)	(52.10)	(79.31)
Adjusted R^2	0.97	0.97	0.97	0.97

Note: T-statistics are in parenthesis. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 3b
Translog production function
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	All Firms (286)	Scientific Firms (113)	Non-Scientific Firms (173)	Technology-Intensive Firms (167)
ln(R)	-0.001	0.001	-0.002**	0.000[a]
	(-1.35)	(0.47)	(-1.81)	(-0.40)
ln(T)	0.002**	0.002	0.001	0.003*
	(1.65)	(1.04)	(0.61)	(2.18)
$\ln(RI^M/K)$	0.001	0.001	0.001	0.003*
	(1.21)	(0.84)	(1.05)	(2.14)
$\ln(RI^D/K)$	0.003*	0.011*	0.002	0.014*
	(2.24)	(2.08)	(1.36)	(2.75)
Mln(K)/Mln(Q)	0.04*	0.05*	0.04*	0.04*
	(3.51)	(2.78)	(3.31)	(2.67)
Mln(L)/Mln(Q)	0.31*	0.23*	0.36*	0.26*
	(20.78)	(9.34)	(20.57)	(13.02)
Mln(M)/Mln(Q)	0.61*	0.69*	0.59*	0.66*
	(65.89)	(43.43)	(53.65)	(53.11)
Adjusted R^2	0.97	0.97	0.98	0.97

Note: T-statistics are in parenthesis. Output elasticities have been computed at mean values and the associated t-statistics have been computed using the delta method. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 4a
Cobb-Douglas production function
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	Food (15)	Textiles (48)	Light (34)	Metals (22)	Chemicals (80)	Transport (25)	Electricals (33)	Non-Electricals (29)
ln(R)	0.002	-0.001	-0.009*	-0.003	0.000[a]	-0.002	-0.002	0.005**
	(0.85)	(-0.57)	(-2.14)	(-1.13)	(0.19)	(-0.90)	(-0.87)	(1.73)
ln(T)	-0.006	0.003	-0.001	-0.004	0.003	-0.001	0.008*	0.010*
	(-1.01)	(1.47)	(-0.35)	(-1.47)	(1.61)	(-0.44)	(2.44)	(3.81)
$\ln(RI^M/K)$	0.000[a]	-0.001	0.002	0.001	0.003**	0.010*	-0.002	0.009*
	(-0.23)	(-0.96)	(0.75)	(0.89)	(1.79)	(3.01)	(-0.82)	(2.70)
$\ln(RI^D/K)$	0.016	0.004*	0.006	0.002	0.018**	0.020	0.010	0.003
	(1.39)	(2.01)	(1.36)	(1.18)	(1.89)	(1.60)	(1.50)	(0.12)
ln(K)	-0.11*	0.04*	0.09*	0.02*	0.04	0.08*	0.06*	-0.02
	(-2.02)	(2.35)	(2.55)	(0.89)	(1.54)	(3.04)	(1.92)	(-0.42)
ln(L)	0.35*	0.31*	0.45*	0.27*	0.36*	0.28*	0.20*	0.57*
	(5.92)	(12.51)	(9.48)	(6.62)	(11.00)	(6.82)	(5.89)	(10.48)
ln(M)	0.76*	0.66*	0.43*	0.65*	0.65*	0.64*	0.80*	0.50*
	(23.86)	(35.84)	(22.32)	(23.21)	(62.08)	(23.79)	(35.22)	(20.04)
Adjusted R^2	0.98	0.99	0.97	0.98	0.97	0.99	0.98	0.96

Note: T-statistics are in parenthesis. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 4b
Pooled Cobb-Douglas production function
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	Food (15)	Textiles (48)	Light (34)	Metals (22)	Chemicals (80)	Transport (25)	Electricals (33)	Non-Electricals (29)
ln(R)	0.003	0.004**	-0.012*	-0.003	-0.001	-0.003	0.002	0.002
	(0.85)	(1.75)	(-3.79)	(-1.31)	(-0.30)	(-1.41)	(0.76)	(0.81)
ln(T)	-0.011	0.005**	-0.001	-0.006*	0.002	-0.002	0.011*	0.010*
	(-1.61)	(1.91)	(-0.48)	(-1.97)	(0.93)	(-0.49)	(2.82)	(3.65)
$\ln(RI^M/K)$	0.000[a]	-0.001	0.001	0.002	0.003	0.010*	-0.004	0.009*
	(-0.13)	(-0.59)	(0.50)	(0.94)	(1.39)	(2.26)	(-1.28)	(2.60)
$\ln(RI^D/K)$	0.006	0.006**	0.007*	0.004**	0.013	0.034*	0.013**	-0.004
	(0.48)	(1.85)	(2.26)	(1.65)	(1.41)	(1.99)	(1.67)	(-0.20)

Note: T-statistics are in parenthesis. The parameter estimates (and their t-statistics in parenthesis) for K, L, and, M are as follows: (i) Scientific firms: 0.05 (2.75), 0.31 (12.86), 0.67 (72.27); and (ii) Non-Scientific firms: 0.02 (1.85), 0.40 (21.98), 0.53 (52.53). The adjusted R^2s for the two groups are 0.98 and 0.97, respectively. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 5a
Cobb Douglas with flexible functional form for technology stocks
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	All Firms (286)	Scientific Firms (113)	Non-Scientific Firms (173)	Technology-Intensive Firms (167)
ln(R)	-0.001	0.000[a]	-0.001	-0.002
	(-0.79)	(0.12)	(-0.32)	(-0.71)
ln(T)	0.003**	-0.001	0.003	0.000[a]
	(1.67)	(-0.29)	(1.48)	(-0.18)
ln(R)× ln(T)	0.000[a]	0.000[a]	0.000[a]	0.000[a]
	(0.44)	(0.22)	(-0.36)	(0.58)
$\ln(RI^M/K)$	0.000[a]	0.007**	0.001	0.009*
	(-0.01)	(1.67)	(0.36)	(2.77)
$\ln(RI^D/K)$	0.012*	0.060*	0.011*	0.071*
	(3.96)	(2.99)	(3.59)	(4.11)
$\ln(RI^M/K)\times\ln(RI^D/K)$	0.001*	0.003*	0.001	0.004*
	(2.27)	(2.62)	(1.99)*	(3.65)
$\ln(R)\times\ln(RI^M/K)$	0.000[a]	0.000[a]	0.000[a]	0.000[a]
	(0.04)	(-0.50)	(0.34)	(-1.31)
$\ln(R)\times\ln(RI^D/K)$	0.000[a]	0.001	0.000[a]	0.000[a]
	(0.86)	(0.83)	(0.83)	(0.66)
$\ln(T)\times\ln(RI^M/K)$	0.0003*	0.000[a]	0.0003*	0.000[a]
	(2.92)	(0.34)	(2.77)	(1.49)
$\ln(T)\times\ln(RI^D/K)$	-0.0018*	-0.003*	-0.0004*	-0.003*
	(-2.73)	(-2.85)	(-2.11)	(-3.62)
ln(K)	0.03*	0.04**	0.04*	0.02
	(2.50)	(1.93)	(2.79)	(1.27)
ln(L)	0.35*	0.31*	0.40*	0.32*
	(23.36)	(12.84)	(21.92)	(16.07)
ln(M)	0.61*	0.67*	0.53*	0.65*
	(87.64)	(72.22)	(52.27)	(79.18)
Adjusted R^2	0.97	0.97	0.97	0.97

Note: T-statistics are in parenthesis. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table 5b
Pooled Cobb Douglas with flexible functional form for technology stocks
Fixed effects model with AR1 correction
(Time dummies included in all regressions)

Variables	Food (15)	Textiles (48)	Light (34)	Metals (22)	Chemicals (80)	Transport (25)	Electricals (33)	Non-Electricals (29)
ln(R)	0.018*	0.007**	-0.014*	-0.007	0.000[a]	-0.008	-0.018*	0.003
	(2.53)	(1.76)	(-3.56)	(-0.86)	(-0.04)	(-1.59)	(-2.02)	(0.48)
ln(T)	0.107	0.005	-0.005	-0.007**	-0.001	-0.005	0.002	-0.002
	(1.24)	(1.32)	(-0.97)	(-1.72)	(-0.13)	(-0.78)	(0.29)	(-0.36)
ln(R)@ ln(T)	-0.006	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.001*	0.000[a]
	(-1.53)	(-0.39)	(0.15)	(0.13)	(-0.81)	(0.25)	(2.81)	(0.45)
$\ln(RI^M/K)$	-0.006	-0.006	0.008**	0.009**	0.010**	0.022**	0.007	0.013
	(-0.61)	(-1.63)	(1.69)	(1.70)	(1.70)	(1.77)	(0.65)	(1.48)
$\ln(RI^D/K)$	0.018	-0.007	0.017*	0.021*	0.063*	0.119*	0.052	0.145**
	(0.20)	(-0.73)	(3.19)	(3.16)	(2.50)	(2.40)	(1.37)	(1.86)
$\ln(RI^M/K)$@ $\ln(RI^D/K)$	0.000[a]	-0.003	0.002*	0.003*	0.003	0.007*	0.003	0.009
	(0.08)	(-1.39)	(2.11)	(2.38)	(1.19)	(1.96)	(1.20)	(1.06)
ln(R)@ $\ln(RI^M/K)$	0.002*	0.000[a]	0.000[a]	-0.001	0.000[a]	-0.001	-0.001	0.000[a]
	(3.59)	(0.80)	(-1.53)	(-1.36)	(-0.71)	(-0.78)	(-1.20)	(-0.14)
ln(R)@ $\ln(RI^D/K)$	-0.002	0.001	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.002
	(-0.82)	(0.53)	(-0.91)	(0.91)	(0.30)	(-0.07)	(0.04)	(0.90)
ln(T)@ $\ln(RI^M/K)$	0.007*	0.000[a]	0.000[a]	0.000[a]	0.000[a]	0.001	0.000[a]	0.000[a]
	(1.95)	(0.19)	(0.91)	(0.01)	(0.33)	(0.79)	(0.24)	(0.94)
ln(T)@ $\ln(RI^D/K)$	0.008	-0.001	-0.005*	-0.001*	-0.004*	-0.004	-0.001	-0.010*
	(0.35)	(-0.34)	(-3.61)	(-2.04)	(-2.89)	(-1.29)	(-0.29)	(-2.51)

Note: T-statistics are in parenthesis. The parameter estimates (and their t-statistics in parenthesis) for K, L, and, M are as follows: (i) Scientific firms:0.04 (2.09), 0.32 (12.93), 0.67 (71.55); and (ii) Non-Scientific firms: 0.04 (2.90), 0.39 (21.40), 0.53 (52.11). The adjusted R^2s for the two groups are 0.97 and 0.98, respectively. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant.

Table A1
Cobb-Douglas production function
GMM-IV on first differenced data
(Time dummies incorporated in all regressions)

Variables	All Firms (286)	Scientific Firms (113)	Non-Scientific Firms (173)	Technology-Intensive Firms (167)
ln(R)	-0.006	-0.003	0.002	0.000[a]
	(-1.25)	(-0.49)	(0.37)	(0.00)
ln(T)	0.014*	0.009**	0.009	0.009**
	(2.43)	(1.95)	(1.32)	(1.64)
$\ln(RI^M/K)$	-0.004	-0.001	0.005	-0.001
	(-1.56)	(-0.20)	(1.50)	(-0.49)
$\ln(RI^D/K)$	0.007*	0.006	0.012*	0.001
	(2.81)	(0.55)	(2.83)	(0.13)
ln(K)	0.02	0.13**	-0.04	0.12*
	(0.34)	(1.81)	(-0.89)	(2.04)
ln(L)	0.47*	0.23*	0.48*	0.25*
	(4.52)	(2.62)	(5.10)	(3.47)
ln(M)	0.52*	0.75*	0.44*	0.73*
	(6.64)	(15.71)	(6.14)	(18.21)
ρ	0.53*	0.40*	0.33*	0.48*
	(8.64)	(4.58)	(4.18)	(6.20)
AR(2) test	-1.20	-1.04	-0.87	-1.27
	(0.23)	(0.30)	(0.38)	(0.20)
Sargan test	241.22	106.17	166.99	160.62
	(0.12)	(0.32)	(0.22)	(0.34)
Years [b]	1981-87	1982-87	1982-87	1982-87
Instrument lags [c]	3 to 6	3 to 4	3 to 5	3 to 5

Note: Numbers in parenthesis are t-statistics except in case of tests for AR2 and over-identifying restrictions (Sargan test) where they correspond to P-values. * Significant at 0.05 level in a two-tailed test. ** Significant at 0.10 level in a two-tailed test. [a] The parameter estimate is 0 when rounded to the third decimal place and statistically insignificant. [b, c] The use of lagged variables as instruments necessitates sacrificing initial years of data. Additionally, because the degrees of freedom vary with the number of observations, different lag lengths can be used across the four sets of estimates. The procedure used here is to choose longer lag lengths where possible so as to improve efficiency.