Technology Diversity and Development: Evidence from China's Industrial Enterprises*

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Abstract

This paper investigates the phenomenon of individual firms simultaneously developing and adopting technical change with varying factor biases. Firms in a large panel of Chinese industrial enterprise data exhibit three channels of technical change, each associated with different patterns of firm-level factor bias and strategic purpose. The neo-classical growth process, associated with Harrod-neutral technical change, drives capital deepening. In-house R&D is found to be robustly labor-using and capital- and energy-saving thereby capitalizing on China's comparative advantage. Finally, the purchase of imported technologies, which are comparatively capital-using, focuses on new product development. These diversified channels of technical change reveal a pattern of developing country technical change that is far more diversified than that suggested by the conventional growth literature.

Keywords: R&D, technological change, factor bias, China
JEL codes: Q4, P2

I. Introduction

A central theme of the conditional convergence literature is that differences in levels of technological advance play a critical role in explaining persistent disparities in cross-country living standards (Parente and Prescott, 1994; Mankiw, Romer and Weil, 1992). Whether technical change is characterized as being exogenous or endogenous to the economic system, most growth models assume the presence across countries of homogeneous Harrod-neutral, labor-augmenting technical change. While some models explain differences in factor bias due to local conditions, none of these explains the phenomenon in which individual firms are observed to be simultaneously developing and adopting technologies with different factor biases. China is an interesting case of a developing country where firms are simultaneously investing in the in-house development and acquisition of a variety of technologies that serve different strategic purposes of the firm.

Using a translog cost function and a panel of large and medium-sized industrial enterprises in China for the years 1997-2001, we examine the role of factor bias in China and attempt to explain the role of technological diversity in China's economy. We model a firm which potentially acquires technology from multiple sources. Technical change may be autonomous if, without the expenditure of R&D resources, it is associated with the passage of time and accumulation of new vintages of plant, equipment, and workers that embody new technologies. Alternatively, technical change may be deliberate in the sense that it entails the expenditure of R&D resources. Such expenditures may be used to support in-house R&D operations or they may be used to purchase imported technologies.

Our analysis finds that each of these three sources of technical change – autonomous, in-house R&D, and purchases of imported technology – plays a distinct and significant role in driving the technological advance of Chinese industry. We first confirm that robust capital-using autonomous technical change, seemingly independent of R&D spending, is driving Chinese industry along a path of capital-deepening, labor-augmenting neoclassical growth. The equally robust material-saving bias also implies that the combination of capital-using and material-saving technical change is driving Chinese production up the value chain.

Our results further show that the pattern of factor-saving bias for in-house R&D is strikingly different from that of autonomous technical change. Firm-level in-house R&D expenditures exhibit labor and material-using and capital and energy-saving biases. By comparison, expenditures on imported technology exhibit distinct capital-using and labor- and energy-saving biases. We explore the reasons why these two technologies – in-house R&D and foreign technology transfer, which involve deliberate technical change but different factor biases – co-exist. In-house R&D, whose factor bias is consistent with China's comparative advantage, exhibits a clear cost cutting effect on production. By contrast, the capital-using, labor- and energy-saving bias of imported technologies reflects the comparative advantage of the more advanced economies where these technologies originate. The imported technologies tend to raise production costs but presumably also the quality and price of the goods they produce. We reconcile the co-existence of these three technology types in China's industrial system by identifying their different purposes. We find that in-house R&D tends to be used for existing products; it therefore emphasizes cost-cutting process innovation. As such it tends to alter the capital-using, labor neutral bias of autonomous technical change to be more consistent with China's comparative advantage. Foreign technology transfer, by contrast, focuses on new product development. Because new products tend to be of higher quality and command higher prices, they can support the relatively capital-intensive, cost-increasing technologies used to produce them.

We also find interesting interactions between in-house R&D and imported technology. Chinese firms employ in-house R&D to dampen the capital-using bias of imported technology to be more consistent with China's comparative advantage. Our results also show that over time, imported technology becomes more material-saving, suggesting that like autonomous technical change, foreign technology transfer is facilitating the movement of product development in China up the value chain. Together these findings underscore the importance of diverse channels of technical change in driving the economic growth and development of China with likely implications for other developing countries.

The paper is organized as follows. Section II reviews the literature on the factor bias of technical change and synthesizes various theoretical perspectives on induced innovation that frame our research. Section III derives the empirical model used in the analysis and Section IV describes our estimation approach. Sections V and VI present and interpret the results from our econometric analysis. Section VII offers concluding remarks. Appendix A provides a detailed description of the data used in our analysis.

II. Theories on the Factor Bias of Technological Change

In this section we draw on the theoretical and empirical literature to frame the questions that motivate this paper: (i) what are the principal sources of technical change within China's industrial firms?, (ii) what is the factor bias of these various forms of technical change?, and (iii) why do we find the simultaneous use of technologies that exhibit substantial differences in factor bias? We examine below the literature that relates to each of these questions.

Incentives for technical change. In general, modern growth theory is concerned with the growth of economic systems; only recently has the role of the firm in the growth of economic systems received explicit attention. Aghion and Howitt (1998), for example, model the firm's decision in allocating its stock of labor between manufacturing and research. The allocation of labor is determined by an arbitrage condition in which the expected value of an hour in research – the flow probability of an innovation times its value – is set equal to the value of an hour in manufacturing.

During the past 25 years, China's science and technology system has been moving away from a state dominated system to one in which the locus of innovation has devolved to the level of the firm, research institute, and university. In 2003, 60.1 percent of total R&D funding was provided by China's enterprise sector while 62.4 percent of total R&D activity was performed at the enterprise level. These funding and performance proportions are now similar to those of many OECD economies. The large and medium-size industrial enterprise sector on which we focus in this paper accounts for approximately 75 percent of total R&D spending by China's enterprise sector. At the same time, technology markets have been rapidly developing in China, so that the purchase by enterprises of imported technology, such as blueprints and licenses, in 2003 amounted to about one-third of total intramural R&D spending.[1] As a result of this decentralization of managerial control rights for R&D spending, China's industrial enterprises are increasingly engaged in intertemporal resource allocation decisions such as that characterized by Aghion and Howitt. We posit that China's enterprise restructuring has not only caused China's firms to become substantially more profit oriented and focused on the future gains associated with current innovative activity, but within a context of shifting comparative advantage and underlying relative factor prices, the restructuring has also caused these firms to become responsive to the potential gains associated with appropriate factor biases of innovative activity.

Sources of factor bias. Various theories have been proposed to explain the bias and direction of technological change. We focus on three of these: the first is the role of comparative advantage, including the "localization" of technical change suggested by Atkinson and Stiglitz (1969); the second theory is the effect of changes in relative factor prices, introduced by Hicks (1932) and formalized by Ahmad (1966); the third account as introduced by Acemoglu (2002) distinguishes between technical change which is driven by the "price effect" (i.e. product innovation) and that driven by the "market effect" (i.e. process innovation).

Atkinson and Stiglitz (1969) stress a path dependent view of technical change in which "knowledge acquired through learning by doing will be located at the point where the firm (or economy) is now operating" (p. 574). While the firm should not behave completely myopically in designing its R&D program – that is, it should take into account the value of the increase in knowledge associated with each technique – Atkinson and Stiglitz stress that the nature of new knowledge will be highly localized in the sense that the relevant learning will reflect the existing factor endowment and relative factor prices. Using cross-country data for 40 countries and six five-year intervals over the period 1970-1995, Caselli and Wilson (2003) find empirical support for their finding that in equilibrium the technology profile of capital in a country reflects the factor abundance of complementary inputs, namely skilled labor.

This comparative advantage perspective tells a persuasive story concerning the factor bias of existing technologies in use. In equilibrium, however, there will be no incentive to alter the factor bias of the technologies; technical change should be neutral in the sense that it proportionally raises the marginal productivities of each of the factors. In the absence of

[1] China S&T Yearbook (2004), p. 7, 104.

changing comparative advantage and relative factor prices, the comparative advantage approach does not predict factor bias for on-going technical change.

Hicks (1932) presents a more dynamic view of technical innovation in which technical change is "directed at economizing on the use of a factor, which has become relatively expensive" (pp. 124-125). This idea of economizing on the factor whose relative price increases is embodied in the analytical technique of the innovation-possibility curve (IPC), as developed by Ahmad (1966) The IPC is an isoquant that maps out the envelope of various technology options prior to the application of a certain level of R&D effort. A change in the prevailing set of relative factor prices causes individual firms and whole economies to use their R&D resources to create production techniques (i.e. isoquants) that embody cost minimizing choices consistent with the revised set of prices. Reviewing the literature (e.g., Hayami and Ruttan, 1970; Wright, 1990; and Jorgenson and Wilcoxen, 1993), Ruttan (2001) finds strong support for the Hicks-Ahmad factor price model in agriculture and natural resource and raw material-using industries, both in the U.S. and abroad.

We show below in Figure 1 how a change in relative factor prices biases the application of R&D. To illustrate the impact of a change in relative factor prices, we first characterize an equilibrium production technology that is consistent with the initial factor prices represented by the price line P_aP_a. The initial equilibrium is at *a*. At *a*, the point of intersection between the price line, the innovation possibilities curve, and the isoquant, production is relatively capital intensive.

As a result of an increase in the relative price of capital, the price line shifts to P_bP_b. To reduce costs, the firm can move along its IPC and with the use of R&D make point *b* an attainable point of production. Alternatively, the firm can apply a larger bundle of R&D

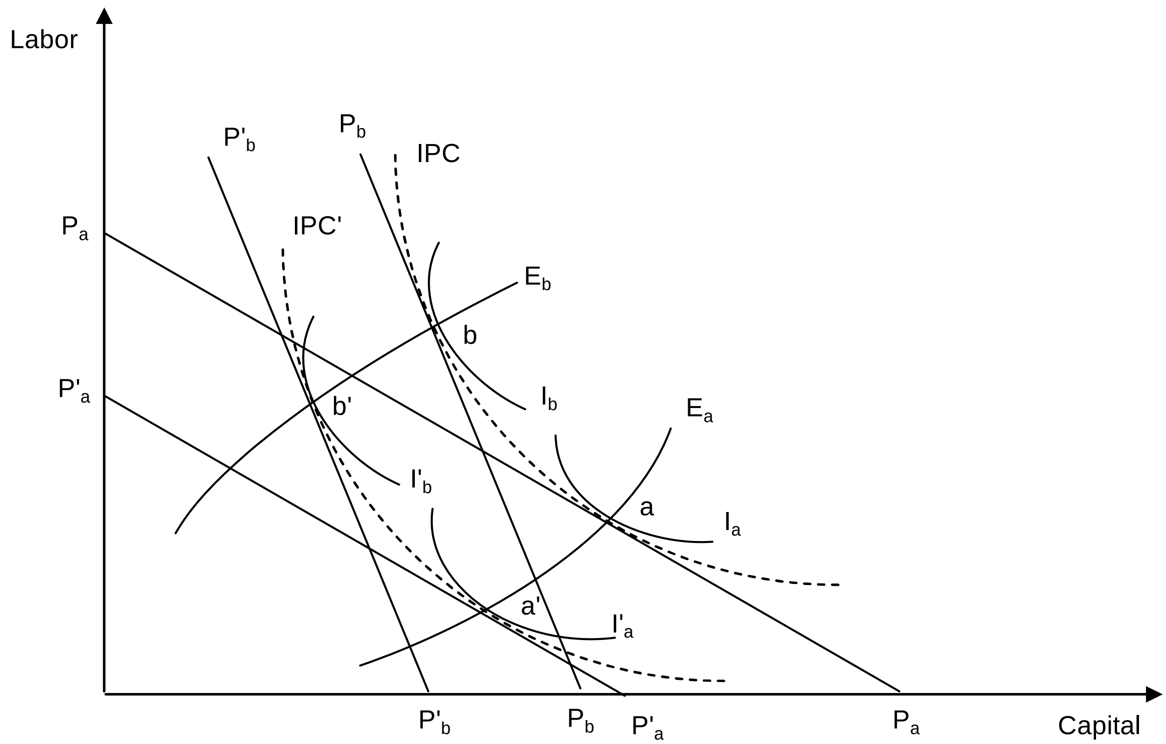

Figure 1

resources and achieve some combination of neutral and factor biased technical change on IPC', say at *b'*. During the transition from *a* to *b'*, technical change is labor using and capital saving. Thereafter, in the absence of further changes in the factor price line, $P'_bP'_b$, technical change originating at b' will be neutral, causing the firm to move along the expansion path E_b.

How does this scheme potentially relate to a developing economy like China? As a developing economy and an economy in transition from central planning to an incentivized market economy, the Hicks-Ahmad model is particularly relevant for anticipating the impact of China's price and trade liberalization on innovation. In particular, in combination with China's large supply of untapped surplus labor, the shift in relative factor prices – toward lower labor costs and higher capital and energy – can motivate a move from a to b' thereby creating technical change with factor biases that are labor-using and capital and energy-saving.

Hicks and Ahmad provide a useful analytical tool for anticipating the factor bias in China's industrial innovation, however, it does not provide a context for understanding why multiple sources of technical change may simultaneously exist. As an empirical matter, we find that Chinese firms simultaneously engage in different types of technology development. Within our sample of 1,518 large and medium-size enterprises, we find that 1,275 (84%) firms report expenditures on in-house R&D, 759 (50%) report purchases of imported technology, and 744 (49%) firms report using both. Only 228 firms (15%) report no expenditures on in-house R&D or imported technology. We would expect the technologies that are domestically developed with the use of in-house R&D funds and those that are imported to exhibit different factor biases.

This phenomenon in which firms both use in-house R&D and engage in foreign technology transfer motivates our inquiry into why firms use multiple sources of technology development. Acemoglu and Zilibotti (2001) identify as a major challenge for developing countries the fact that technology is typically developed in the North, thus reflecting the resource scarcities in these countries, not LDCs. If indeed, China's in-house R&D and purchased technology imports reflect the factor bias of their respective countries of origin, why do Chinese companies acquire both of these? What are the respective economic functions of these different technology sources and how, if at all, do they interact?

The relatively rudimentary R&D operations of many developing country firms limit the scope of their innovation capabilities. If, as Atkinson and Stiglitz argue, a firm's set of innovation opportunities is constrained by learning from the use of its existing production techniques, then the ability to employ new production techniques that embody new combinations of factor intensities may lie beyond the in-house R&D capabilities of most developing economy firms. This localization phenomenon inhibits the ability of firms to innovate more sophisticated technologies that are able to support the development of new products. Firms operating in developing economies are left with assessing the option of importing technology from more advanced foreign countries with different factor abundances.

In general, a firm will choose imported technology over domestic technology if $\frac{\partial \pi}{\partial R_I} > \frac{\partial \pi}{\partial R_D}$, where π is unit (marginal) profit, R_I is imported R&D and R_D is domestic R&D.[2] Unit profit is defined as $P_Q - C$ where P_Q is the unit price of output and C is the unit cost. This implies $\frac{\partial \pi}{\partial R} = \frac{\partial P_Q}{\partial R} - \frac{\partial C}{\partial R}$. Therefore, the firm will choose the imported technology if (a) it lowers cost more than domestic technology but does not result in a product that earns a lower output price, which would offset the gain in lower cost, or (b) it results in a product that commands a higher output price while not causing higher production costs that would eliminate the gain from the higher output price.[3]

For either of these purposes, cost-reducing process innovation or value-enhancing product development, the firm may employ imported technology. However, if "process innovation" technologies are chosen based on their use of the more abundant factor, thereby serving to raise profits by reducing costs, then "product innovation" technologies may be chosen for their ability to produce goods that command higher prices, even at the expense of greater cost. This result is consistent with Acemoglu's (2002) explanation of why a country would choose "inappropriate" technology. A firm's adoption of an "inappropriate" imported

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[2] Unit profit, π, may be interpreted as a discounted unit of future profit that enters into the present value of the firm.
[3] This is the "price effect" that together with the "market size effect" drives the composition of technology in Acemoglu's model (2002).

technology may reflect its intent to develop new products or quality improvements of existing products, both of which may command higher output prices.

Whether imported technology is used for process or product innovation, there is no reason to expect that the factor biases that are embodied in the imported technology at the time of purchase will be consistent with the home country firm's optimal production technique. A Chinese firm purchasing imported technology might therefore wish to adapt the technology, which was likely to have been developed in an OECD economy, to be more consistent with the factor mix of the firm's existing production structure and with the factor endowment of China generally. That this adaptation may be feasible is consistent with the findings of Atkinson and Stiglitz (1969) and Basu and Weil (1998) who conclude that technological inappropriateness can be reduced over time through learning or through deliberate in-house technology development. This idea was further articulated in the literature on "absorptive capacity" which argues that in order to exploit fully the benefits of R&D imported from other countries (in particular, developed countries), a country must build absorptive capacity through domestic R&D activities (Cohen and Levinthal (1989), Griffith, Redding and Van Reenan (2003)). In their study of China, Hu, Jefferson, and Qian (2004) find absorptive capacity, i.e., the establishment of a firm-level R&D operation, to be a precondition for both domestic and foreign technology transfer.[4]

[4] We can use Figure 1 to depict this use of in-house R&D resources to modify the factor bias of imported technology. Suppose that that imported technology was developed in the OECD economies to support production and technical change along the expansion path E_a. To understand the process of foreign technology absorption, we reinterpret *a* and *b*'. Whereas in the Hicks-Ahmad account, these production loci represent different points in time within the same country, we instead associate these observations with different countries. In the Hicks-Ahmad account, events occurring over time that lead to changes in the underlying factor endowment and relative factor prices might include trade liberalization, migration, or, in the case of energy, an embargo. In our reinterpretation of the shift of the price line and the IPC, the critical change is the transfer of the technology across geographic space from one country to another, which leads to a change in the mix of underlying factor endowments and their associated relative factor prices. The technology at *a*, for example, may be a package of technology developed in the U.S. As such, its embodied factor bias is capital-using and labor-saving. When the technology is transferred across an economic boundary, say to China, where the underlying factor endowment is relatively abundant in labor and scarce in capital, production at *a* may be technically feasible for the Chinese producer, but it is highly economically inefficient. In order to economize, the Chinese firm may attempt to convert the technology into an

From this synthesis, we can identify for China a set of hypotheses that we anticipate will characterize patterns of technology development and factor bias at the firm level in Chinese industry. The six hypotheses are:

1. Because the overall pattern of growth of the Chinese economy exhibits the trend toward capital deepening predicted by Solow's neoclassical model of growth, autonomous technical change in our sample of Chinese industrial enterprises will be capital using.
2. Even as China has followed a neoclassical growth trajectory, an abundant supply of labor, market and trade liberalization, and greater incentivization have created forces for China to exploit more effectively its comparative advantage. One or more sources of technical change may be dedicated to exploiting China's comparative advantage, e.g. labor-using, even as industry experiences an overall shift toward growing capital intensity.
3. Relative to in-house R&D, we expect imported technology that is purchased by Chinese firms to be capital-using and labor-saving.
4. Given several circumstances, including China's growing domestic competition and international market exposure following China's excessive energy intensity during the era of central planning as well as rising energy prices during the mid-1990s, we expect in-house R&D to be energy-saving.
5. In-house R&D is used to adapt imported technology to China's relative factor endowment.
6. Relative to in-house R&D, the net effect of imported technology is to support product development, which may entail higher unit costs, resulting from its relative capital intensity.

"appropriate" technology in the sense that it is consistent with the endowment and factor price mix faced by the firm as represented by the expansion ray E_b. With the application of in-house R&D resources, the firm is able to adapt the imported technology, so that it embodies a modified mix of factor bias. In relation to the factor mix embodied at

Due to the lack of data, previous studies have been unable to distinguish directly between in-house technology development and imported technology. Most studies use proxies, such as the imports of machinery and equipment, to represent foreign technology transfer (e.g., Coe, Helpman, and Hoffmaister, 1997). The problem with this approach is that it is difficult to distinguish between imports that truly serve the purpose of technology development and imports used for other non-R&D purposes. Our firm-level data set contains specific data on firm-level technology development expenditures including expenditures on in-house versus imported technology development. We use these data to measure the neutral and factor-biased effects of in-house R&D and foreign technology transfer, as well as the interaction among these different sources of technology development. We test the six hypotheses above using a data set, described in Appendix A, that includes approximately 1,500 large and medium-size Chinese industrial enterprises and spans the years 1997-2001.

III. The Model

The standard approach to measuring the neutral and factor bias of technological change involves the estimation of production functions or dual cost functions.[5] The theoretical connection between production or cost functions and factor demands makes this approach fitting for the measurement of the factor bias of technological change. The choice of whether to use the production function approach or the cost function approach depends on the relevant set of

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a, the point of entry of the technology, the same imported technology, once mixed with in-house R&D, acquires a factor bias that becomes more labor-using and capital-saving.

[5] The majority of the studies highlighted in Section II use cross-country data either to estimate Cobb-Douglas or constant elasticity of substitution (CES) production functions, or to estimate equations that include measures of total factor productivity that have been derived from the estimation of a production function. As discussed in Berndt (1991), the estimation of production or cost functions arise from the desire to estimate the marginal products, to explain movements in labor productivity, and to estimate elasticities of substitution across inputs and returns to scale.

exogeneity assumptions. For the production function formulation – which incorporates quantities of output and inputs – input quantities are assumed to be exogenous, whereas input prices are assumed to be exogenous in the cost function formulation.[6] In highly aggregated data sets like the cross-country data used in the studies highlighted in section II, input prices are likely to be endogenous and therefore a production function may be more appropriate. At the firm level, however, choices of factor inputs are likely to be endogenous while factor prices are more likely to be set in the market and therefore plausibly exogenous. Since our data set allows us to impute factor input prices for the individual firms,[7] we use the cost function approach. However, to test the assumption of price exogeneity, we also use wages and capital costs aggregated to the provincial levels to re-estimate our model.

Our next decision involves the choice of functional form. Since it is the most flexible of functional forms, we adopt the following translog cost function:

$$(1)\quad \ln C = \alpha_0 + A(R,T) + \boldsymbol{\alpha'_Z} \cdot \mathbf{lnZ} + \alpha_Q \cdot \ln Q + B(R,T,Z) + \tfrac{1}{2} \cdot \mathbf{lnZ'} \cdot \boldsymbol{\beta_{ZZ}} \cdot \mathbf{lnZ} + \ln Q \cdot \boldsymbol{\beta'_{QZ}} \cdot \mathbf{lnZ} + \varepsilon_Q$$

where

$$A(R,T) = \boldsymbol{\alpha'_R} \cdot \mathbf{lnR} + \boldsymbol{\alpha'_T} \cdot \mathbf{T} + \mathbf{T'} \cdot \boldsymbol{\beta_{RT}} \cdot \mathbf{lnR}$$

$$B(R,T,Z) = \mathbf{lnR'} \cdot \boldsymbol{\beta_{RZ}} \cdot \mathbf{lnZ} + \mathbf{T'} \cdot \boldsymbol{\beta_{TZ}} \cdot \mathbf{lnZ} + \sum_{t=98}^{01} \mathrm{Year}_t \cdot \mathbf{lnR'} \cdot \boldsymbol{\beta_{RZt}} \cdot \mathbf{lnZ}$$

$$\mathbf{lnZ'} = (\ln P_K, \ln P_L, \ln P_E, \ln P_M)$$

$$\mathbf{lnR'} = (\ln R_{int}, \ln R_{imp})$$

$$\mathbf{T'} = (\mathrm{Year}_{98}, \mathrm{Year}_{99}, \mathrm{Year}_{00}, \mathrm{Year}_{01})$$

[6] An alternative to the pure production function or cost function approach is the adjustment cost model,which distinguishes between variable costs and fixed factors. In this formulation, variable costs are represented as a function of input prices whereas fixed costs are represented as a function of quantities of the fixed factors. This approach only allows for cost share equations in the variable inputs and less flexibility with respect to parameter restrictions. Since we are interested in the factor bias of all four factors (i.e., K, L, E, M) including capital, we need a cost share equation for capital where if we were to adopt the adjustment cost model formulation this would not be possible.

[7] The data set includes both quantities and values and therefore a price can be imputed by dividing value by quantity.

$\alpha'_{\mathbf{Z}} = (\alpha_{Pk}, \alpha_{Pl}, \alpha_{Pe}, \alpha_{Pm})$

$\alpha'_{\mathbf{R}} = (\alpha_{Rint}, \alpha_{Rimp})$

$\alpha'_{\mathbf{T}} = (\alpha_{98}, \alpha_{99}, \alpha_{00}, \alpha_{01})$

And furthermore:

$C \equiv$ total cost of production,

$Q \equiv$ gross value of industrial output in constant prices,

$P_K \equiv$ price of fixed assets , which is calculated as (value added - wage bill - welfare payments)/(net value fixed assets),

$P_L \equiv$ price of labor, which is calculated as (wage bill + welfare payments)/employment),

$P_E \equiv$ price of aggregate energy, which is calculated as (energy expenditures)/(quantity of energy purchased in standard coal equivalent (SCE)),

$P_M \equiv$ price of materials, which is calculated as (current gross value industrial output/constant gross value of industrial output),[8]

$Rint \equiv$ stock of in-house technology development expenditures, described in Appendix A, and

$Rimp \equiv$ stock of imported technology expenditures, described in Appendix A.

Finally, Year98, Year99, Year00, Year01 are time dummies for the period 1997-2001, for which 1997 is the reference year. The function A(R,T) in equation (1) represents the neutral productivity effects of deliberate technology development (R) and time (T), while the function B(R,T,Z) represents the factor-biased productivity effects of R and T. Rather than use contemporaneous R&D expenditures, in order to incorporate a more plausible time structure between R&D inputs and outputs and to limit endogeneity, we construct R&D stock variables using the perpetual inventory method. Details of the construction of these R&D stock variables are provided in Appendix A.

Using Shephard's Lemma, we derive the cost share equation associated with each factor input by taking the derivative of the cost function with respect to the relevant input price; i.e.,

$$\frac{\partial \ln C}{\partial \ln P_i} = \frac{P_i X_i}{C} \quad i = \mathrm{K, L, E, M}$$

Specifically, taking the derivative of equation (1) with respect to each input price, we obtain the following cost share equations:

(2) $VL / VC = \alpha_L + \beta_{LL}\ln P_L + \beta_{LK}\ln P_K + \beta_{LE}\ln P_E + \beta_{LM}\ln P_M + \beta_{RintL}\ln Rint + \beta_{RimpL}\ln Rimp + \beta_{QL}\ln Q + \boldsymbol{\beta'_{LT}T} + \mathbf{T'\boldsymbol{\beta}_{RLT}\ln R} + \varepsilon_L$

(3) $VE / VC = \alpha_E + \beta_{EE}\ln P_E + \beta_{EK}\ln P_K + \beta_{EL}\ln P_L + \beta_{EM}\ln P_M + \beta_{RintE}\ln Rint + \beta_{RimpE}\ln Rimp + \beta_{QE}\ln Q + \boldsymbol{\beta'_{ET}T} + \mathbf{T'\boldsymbol{\beta}_{RTE}\ln R} + \varepsilon_E$

(4) $VM / VC = \alpha_M + \beta_{KM}\ln P_K + \beta_{LM}\ln P_L + \beta_{EM}\ln P_E + \beta_{MM}\ln P_M + \beta_{RintM}\ln Rint + \beta_{RimpM}\ln Rimp + \beta_{QM}\ln Q + \boldsymbol{\beta'_{MT}T} + \mathbf{T'\boldsymbol{\beta}_{RTM}\ln R} + \varepsilon_M$

where

VL ≡ value of labor expenditures (equal to wage bill + welfare payments)

VE ≡ value of energy expenditures

VK ≡ value of capital (equal to value added – VL)

VM ≡ value of material expenditures (value of intermediate inputs - VE)

VC ≡ value of total cost (equal to VK+VL+VE+VM)

[8] The price deflator for GVIO was used as a proxy for the price of materials, since the share of materials in GVIO is approximately 60 percent.

Dropping the capital share equation and estimating this system of four equations,[9] we can analyze the effect on deliberate technical change and the passage of time on both the rate and factor bias of technical change of deliberate technical change. As shown in the above four-equation system, we assume that technology development enters a firm's production function through the factor-neutral and factor-biased productivity terms. Autonomous factor-neutral and factor-biased technological change, i.e., technological change occurring through processes other than deliberate purchases of R&D and imported technology, are captured by the coefficients associated with the year dummies, $Year_{98}$, $Year_{99}$, $Year_{00}$, $Year_{01}$. Factor-neutral technological change, in which technical progress or regress is proportional across all inputs, is captured by the terms $\boldsymbol{\alpha}'_{\mathbf{R}}\cdot\mathbf{lnR}$ and $\mathbf{T}'\cdot\boldsymbol{\alpha}'_{\mathbf{RT}}\cdot\mathbf{lnR}$. Factor-biased technological change, which causes movement along the isoquant, is captured by $\mathbf{lnR}'\cdot\boldsymbol{\beta}_{\mathbf{RZ}}\cdot\mathbf{lnZ}$ and $\sum_{t=98}^{01} Year_t\cdot\mathbf{lnR}'\cdot\boldsymbol{\beta}_{\mathbf{RZt}}\cdot\mathbf{lnZ}$.

IV. Estimation Issues and Strategy

Because equations (1) – (4) represent a system of equations in which shocks to the factor shares are likely to be correlated across the error structure of the model, the system is estimated as a seemingly-unrelated regression (SUR).[10] To ensure the usual properties of symmetry, homogeneous of degree one in prices, homothetic, and constant-returns-to-scale conditions on the coefficients, we impose the following constraints:

$\beta_{a,b} = \beta_{b,a}$

$\mathbf{i}'\cdot \boldsymbol{\alpha}_{\mathbf{Z}} = \mathbf{1}$

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[9]Since the cost shares must sum to one, we drop one of the cost share equations – the cost share equation for capital. Coefficient estimates and standard errors will be invariant to the choice of which cost share equation is dropped (see Berndt,1991).

[10] By using information associated with cross-equation correlations of the error structure, estimating a system consisting of the cost function and the associated cost share equations increases the estimation efficiency.

$\boldsymbol{\beta}_{ZZ} \cdot \mathbf{i} = \mathbf{0}$

$\boldsymbol{\beta}_{RZ} \cdot \mathbf{i} = \mathbf{0}$

$\boldsymbol{\beta}_{RTZ} \cdot \mathbf{i} = \mathbf{0}$

$\boldsymbol{\beta}_{TZ} \cdot \mathbf{i} = \mathbf{0}$

$\boldsymbol{\beta}_{QZ} \cdot \mathbf{i} = \mathbf{0}$

$\boldsymbol{\beta}_{QZ} = \mathbf{0}$

$\alpha_Q = 1$

where i is a vector of ones.

We expect the cost function error term to include permanent (i.e., non-time varying) unobserved productivity differences across firms, transitory (i.e., time varying) unobserved productivity differences, and measurement error. In the case of permanent unobserved productivity differences, issues of simultaneity exist, since these unobserved permanent productivity differences are known to the firm when variable and fixed input choices are made. For example, unobserved variation in managerial quality is likely to be associated with cost. If high quality managers achieve low cost production, which is reflected in the firm's error structure, and high quality managers are simultaneously able to use effectively R&D resources, then the unobserved heterogeneous managerial quality will lead to a spurious association between low cost and the use of R&D inputs. Furthermore, if high quality managerial services are associated with high labor quality (reflected in the price of labor), then we would expect the set of coefficients on labor and its interactive terms to suffer from downward bias, i.e. labor would appear to create more cost-saving efficiencies than it actually does.

To remedy the fixed effects problem, we use a fixed effects estimation procedure. We do this by incorporating into our estimation procedure a dummy for each of the N firms that appears in the panel data set. Provided that our firm effects are indeed fixed, we anticipate that our estimates will be unbiased and consistent. However, we expect the error term also to include unobserved time varying productivity differences. In this case, issues of simultaneity exist, since these unobserved transitory productivity differences will affect a firm's choice of variable (but not fixed) inputs. For example, increases in labor productivity may induce firms to hire more skilled labor. Since the price of labor at the firm level is calculated by dividing the total wage bill by total employment, the price of labor will reflect changes in the composition of high skilled versus low skilled labor employed by the firm. Therefore, time varying and permanent unobserved productivity differences may be correlated with the price of labor. To test the seriousness of the issue, we run the regression using provincial level average wage rates. Since provincial-level wage rates can be considered truly exogenous to the firm, this eliminates the simultaneity issue between time-varying unobserved productivity differences and the price of labor. We find that the results presented in Section V are robust to this alternative provincial wide measure of the wage. To achieve a greater level of firm-level variation, we chose to retain firm-level prices in our regressions.[11]

Lastly, we anticipate that measurement error is a problem in our data set. Our measures of R&D expenditure and imported technology purchases, even if accurately reported, are but approximations of the true quality of R&D effort and the true quality of imported technology purchases. In particular, the errors-in-variables problem will result in underestimates of the β coefficients, which only serve to strengthen our results in Section V.

Another issue that arises in our analysis is sample selection bias. Within the population of China's industrial enterprises, our sample includes only large- and medium-size industrial enterprises, whose energy consumption exceeds 10,000 tons standard coal equivalent (SCE).

[11] Due to the fixity of capital, time-varying unobserved productivitiy differences are unlikely to be correlated with the price of capital which reflects changes in the composition of capital quality. To test this, we also ran the regression using provincial-level capital prices and, similar to the price of labor, found the results in Section V to be robust to this different assumption regarding the price of capital.

This minimum energy consumption threshold limits our ability to generalize the results of this paper to smaller industrial firms and those that are less energy consuming. As discussed in Appendix A, the importance of measuring the energy bias of R&D requires us to work with the smaller, less representative sample. Since the energy sample criterion is based on levels and not intensity of energy consumed, the sample includes both energy intensive firms (firms with a higher energy/sales ratio) and firms that may be less energy intensive, but are large enough to consume more than 10,000 tons SCE of energy. As shown in Table A.1 in Appendix A, although the sample represents only one percent of total industrial enterprises, it captures 20 percent of total industrial assets, 15 percent of total industrial employment and 40 percent of total industrial energy consumption. Our findings, therefore, are limited to this sub-sample of China's total industry.

An additional limitation on the data results from our use of a balanced set of data from which firms with missing R&D, economic or energy data in any of the five years are omitted. Firms may not report in all five years for any of several reasons. First, in each year a significant number of firms drop out of the data set. Specifically, firms that have undergone a change in their formal ownership designation, been merged or acquired, or changed industry or location are often assigned new enterprise identification numbers, so that we are unable to track the firm. Furthermore, from time to time firms consume levels of energy that fall below the required 10,000 SCE threshold and hence are omitted from the survey. In order to focus as much as possible on a stable set of firms and to limit the influence of exit and entry on the technology choice, we require that the included firms survive the full five-year period. We do this for two reasons. First, while our energy data only include the years 1997-2001, our data set includes R&D and technology import data beginning in 1995. As described in Appendix A, we use the

1995 technology development expenditures to create an estimate of the initial stock of R&D in 1995 and then use subsequent measures of annual technology development expenditure to update the initial stock estimate. By 1997, the first year of our regression sample, we expect that three years of data on R&D investment and imported technology purchases provide a reasonable representation of the actual underlying stock of R&D capital. Firms that enter after 1999 or enter, then exit, in less than three years yield estimates of their R&D stock that are likely to exhibit substantial measurement error in relation to the firms with longer durations. Moreover, because we use a fixed-effects estimator that consumes a year's observation for each firm, we effectively require 4 years of observations for each firm. These considerations – the use of three-years of data to construct the appropriate technology development stocks and an additional one year for the fixed effects approach – cause us to conduct our analysis using a balanced data set.

Sample selection bias can arise if firms are "exiting" the data set due to closure, where exit is correlated with unobserved poor productivity performance. In this case, an estimator similar to the Olley-Pakes estimator for production functions (Olley Pakes, 1996) could be used to correct for this bias. While we anticipate that the phenomenon of exit and entry may result in some change in technology orientation, our analysis shows that within our data set firms that exit or enter the data set do not as a group exhibit lower levels of productivity than the surviving firms.[12] While the phenomenon of exit and entry may not significantly affect estimates of neutral productivity change, their exclusion of exit and entering firms may affect the factor-saving bias of technological change. However, correcting for bias in the estimates of factor-saving technological change resulting from the excluded firms is beyond the scope of this paper. Hence, we limit our claim of the relevance of our results to our sample of surviving large and medium-size enterprises.

V. Results

Table 1 presents two sets of estimation results using the pooled data for 1997-2001. Columns (1) through (3) report the pooled cross-section estimates; columns (4) through (6) incorporate a dummy for each firm to control for the unobserved fixed effects. We report results for the pooled and fixed effects estimators for three different functional forms. In the first, shown in columns (1) and (4), technical change, both autonomous and deliberate, is assumed to be neutral. The second functional form, shown in columns (2) and (5), incorporates estimates of the factor bias of technical change. Finally, the third set of estimation equations, shown in columns (3) and (6), allows for autonomous time-driven changes in the factor bias of technical change. We present both pooled cross section and fixed effects results for each of the three functional forms.

Neutral technical change. In the pooled regression that restricts technology development to be neutral, shown in column (1), in-house R&D (α_{Rint}) exhibits a negative and significant effect on costs while imported technology (α_{Rimp}) exhibits a positive and significant cost effect. That the estimate on the time dummy, α_{01}, is statistically insignificant while those for the measures of deliberate technical change are statistically robust suggests that neutral technical change in Chinese industry is driven by deliberate activity. Using the fixed effects estimator, the results in column (4) completely reverse this result – autonomous neutral technical change appears to capture the impacts that had previously been attributed to deliberate technical change. This difference between columns (1) and (4) is consistent with our belief that there are firm-specific characteristics, such as heterogeneous management qualities, that are correlated with

[12] Results are available from the authors upon request.

technology development. In columns (2) and (3), we also see that the estimates of the neutral effects of in-house R&D exceed the corresponding estimates in columns (5) and (6). Absent controls for fixed effects, estimates of the impacts of technology development on production cost, it seems, are overstated. For this reason, we concentrate on the fixed effects results, i.e. columns (4), (5), and (6).

Columns (4), (5), and (6) each serve a specific purpose. All three include the neutral effects of the two forms of deliberate technical change – in-house R&D and imported technology. All three also include channels through which neutral autonomous technical change potentially operates. Our estimates in column (4), which includes these potential drivers of neutral technical change, indicate that deliberate technical change has no effect on cost. While cost is but one side of the profit maximization calculus – firms may also develop products or employ market strategies to increase marginal revenue – the estimate showing that in-house R&D and imported R&D have negligible and virtually identical impacts on unit cost is somewhat at odds with our expectations. Subsequent results clarify this anomaly.

In columns (5) and (6), we expand our functional form to include factor biased technical change, both deliberate and autonomous. Column (5) is expanded to include the terms that capture the impact of *deliberate* factor biased technical change. Column (6) includes the terms in column (5); it also includes factor-biased *autonomous* technical change and interactions between the deliberate factor-biased technical change terms and time. These latter terms represent autonomous, time-driven change in the factor bias of deliberate technical change. Put another way, these estimates of factor bias interacted with time dummies shown in column (6) test the stability of the average factor bias estimates shown in column (5).

Factor-biased technical change. Allowing for factor bias substantially alters the story of how technical change operates in China's firms. Column (5) shows that with the expansion of the functional form to allow for factor bias, our estimate of the neutral effect of in-house R&D (α_{Rint}) becomes significantly cost saving, whereas imported technology (α_{Rimp}) is consistently cost increasing. The neutral effect of the interaction of in-house R&D and imported technology ($\alpha_{Rint \cdot Rimp}$) is negligible in column (5). We also see from Column (5) that in-house R&D is robustly labor and material using and energy saving ($\beta_{Rint \cdot L}$, $\beta_{Rint \cdot E,}$ $\beta_{Rint \cdot M}$). While imported technology is also energy saving ($\beta_{Rimp \cdot E}$), it exhibits a capital using bias ($\beta_{Rimp \cdot K}$). These results are consistent with our priors that deliberate technical change will exhibit factor-saving biases that reflect the comparative advantage of the economies in which the technologies originate. The pattern of estimates is consistent with the comparative advantage hypothesis.

Column (5) also includes estimates of the factor bias of interactions between in-house R&D and imported technology ($\beta_{Rint \cdot Rimp \cdot K}$, $\beta_{Rint \cdot Rimp \cdot L}$, $\beta_{Rint \cdot Rimp \cdot E}$, $\beta_{Rint \cdot Rimp \cdot M}$). The results indicate that, like the estimate of the neutral effect of the interaction, the estimates of the factor bias of the interaction terms are also insignificant. These results seem to indicate that, whether measured in terms of their neutral or factor bias effects, interactions of in-house and imported technology are incidental to the firm's efforts to control costs. We test whether these and our other results hold with the addition of the autonomous channels of technical change.

Factor-biased technical change with autonomous effects. Column (6) tests for the stability of the impact of deliberate technical change on unit cost. None of the magnitudes or estimates of the results shown in column (5) becomes less significant in column (6). Overall, the addition of autonomous time dummies appears to magnify the factor bias of deliberate technical change.

First, we report the estimates of factor biased autonomous, time driven technical change ($\beta_{01\cdot K}$, $\beta_{01\cdot L}$, $\beta_{01\cdot E}$, $\beta_{01\cdot M}$). These estimates, shown in column (6), indicate that autonomous technical change is significantly capital using and material savings. The capital using bias may simply represent the process of neoclassical growth in which we observe capital deepening over time. The material saving bias may reflect the tendency of Chinese companies to move up the value chain, thereby increasing their value added ratios and economizing on intermediate inputs.

By definition, autonomous technical change is statistically unrelated to deliberate technical change associated with R&D and technology purchases. We therefore interpret autonomous technical change as largely exogenous to the firm. We also interpret it as largely capital biased, associated with the introduction within the Chinese economy of new vintages of increasingly efficient plant and equipment. By elevating capital's marginal product and potential returns to investment, capital-biased technical change motivates new capital deepening (i.e. using) investment, with labor-augmenting effects.[13]

Deliberate technical change tells a different story in which in-house R&D continues to be labor using ($\beta_{Rint\cdot L}$) and energy saving ($\beta_{Rint\cdot E}$). In contrast with the estimates shown in column (5), however, the estimates in column (6) further accentuate the focus of deliberate technical change on comparative advantage. While autonomous technical change represents the underlying tendency of the Chinese economy to become more capital using ($\beta_{01\cdot K}$), in-house R&D seems to play an aggressive role in moderating this effect by enabling firms to develop and deploy technologies that are less capital using ($\beta_{Rint\cdot K}$) and more labor using ($\beta_{Rint\cdot L}$). Moreover, it seems that a purpose of R&D is not to expand value added ratios, rather to facilitate

[13] In the standard Solow model, with the assumption of a CRS Cobb-Douglas technology, regardless of its factor bias technical change induces Harrod-neutral labor-augmenting outcomes. The supply of labor is exogenously determined and inelastic. At the firm level, however, particularly in a developing economy with an elastic labor

outsourcing, as evident from the material-using bias of in-house R&D ($\beta_{Rint \cdot M}$). The insignificance of the interactions of the in-house factor bias terms with time ($\beta_{Rint \cdot K \cdot 01}$, $\beta_{Rint \cdot L \cdot 01}$, $\beta_{Rint \cdot E \cdot 01}$, $\beta_{Rint \cdot M \cdot 01}$) indicates that this pattern of R&D factor bias has been stable over the duration of our sample.

With the addition of autonomous technical change, the pattern of factor bias in imported technology also more fully reflects the comparative advantage of its origins, i.e., the OECD economies. Not only are the capital using and energy saving biases of imported technology ($\beta_{Rimp \cdot K}$, $\beta_{Rimp \cdot E}$), shown in column (5), reinforced with the addition of autonomous factor biased technical change, but the labor-saving bias of imported technology ($\beta_{Rimp \cdot L}$), comes into play. Unlike the pattern of in-house R&D, which appears to be stable over the sample period, the pattern of factor bias of imported technology changes. While the technological bias of imported technology becomes marginally more labor and energy using over time ($\beta_{Rimp \cdot L \cdot 01}$, $\beta_{Rimp \cdot E \cdot 01}$), the bias for materials changes from being neutral in 1997 ($\beta_{Rimp \cdot M}$) to robustly saving in 2001 ($\beta_{Rimp \cdot M \cdot 01}$).

Our results in column (6) show that the energy-saving bias of in-house R&D and imported technology are similar in 1997 ($\beta_{Rint \cdot E}$, $\beta_{Rimp \cdot E}$). While the energy-saving bias of in-house R&D remains stable during 1997 to 2001 (comparing $\beta_{Rint \cdot E}$ and $\beta_{Rint \cdot E \cdot 01}$), imported R&D becomes less energy saving (comparing $\beta_{Rimp \cdot E}$ and $\beta_{Rimp \cdot E \cdot 01}$).[14] One reason for the growing division between in-house R&D and imported technology may have been the rapid increase in energy prices within China in the early to mid-1990s as domestic energy prices were

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supply, to ensure the capital-deepening, labor augmenting outcome, we require that technical change be capital-biased.

[14] The estimate of imported technology's energy-saving bias declines from 0.003 in 1997 to 0.001 (i.e. 0.003 – 0.002) in 2001.

liberalized.[15] During this same period, real energy prices were generally stable or falling within the OECD economies.

Finally, we find that by incorporating the representation of autonomous technical change in column (6), the interaction between R&D and imported technology becomes significantly capital saving ($\beta_{Rint \cdot Rimp \cdot K}$). That is, it seems that R&D is used in part to alter the factor bias of imported technology to be less capital using and more material using. While the magnitude of the estimate appears to be quite small, the coefficient translates into a marginal cost effect of -0.0013, which implies that in-house R&D dampens by nearly two-thirds (62%) the capital-using bias of the strength of imported technology that was operating in 1997. Our results show that most of the adaptation of the "inappropriate" bias of imported technology is achieved through autonomous time-dependent change in the factor bias of imported technology. Specifically, the results show that over time, imported technology becomes less labor-saving (more using) and less energy-saving (more using). It also becomes highly material saving.

We summarize below our regression results shown in Table 1, column (6):

1. Autonomous technical change exhibits large and highly significant effects on capital deepening that are consistent with the process of neoclassical growth. Corresponding with the capital-using factor bias, materials exhibit a factor-saving bias, which suggests that the investment process is associated with increases in the value added ratio of production.
2. The factor bias of in-house R&D is consistent with China's comparative factor endowment. In-house R&D is robustly capital and energy-saving and labor and materials- using. These biases exhibit the deliberate effort by China's industrial firms to orient production toward China's comparative advantage.

[15] Energy prices in China rose by 20% between 1990 and 1994 (Lawrence Berkeley National Laboratory, 2004).

3. The factor bias of imported technology, likewise, is generally consistent with our prior expectations regarding the factor endowment of the OECD economies. Relative to in-house R&D, imported technology is robustly capital using and labor saving; its material-saving bias grows over time.
4. The factor biases of in-house R&D and imported technology purchases are significantly energy saving.
5. The application of in-house R&D to imported technology serves to dampen the capital-using bias of foreign technology transfer.
6. Both in-house R&D and imported technology exhibit significant impacts on cost. The former reduces cost, whereas the latter raises cost. The cost-increasing effect of imported technology is associated with the development of new products.

VI. Interpretation

Our model and empirical results identify three distinct patterns of non-neutral factor bias in the technical change that drives Chinese industry. In this section we interpret these results in relation to the theoretical framework that we developed in Section II.

*Sources of factor bias***.** As with all high growth developing economies, China has exhibited a rapid rise in its capital-labor ratio. This is the central prediction of Solow's neoclassical growth model in which the consequence of technical change is to raise income and savings per capita, which translates into new investment and capital deepening. Capital deepening, in turn, leads to labor-augmenting technical change and rising labor productivity. Since in the canonical Solow model, the growth of the labor force is exogenously fixed and inelastic, capital deepening simply leads to higher rates of labor productivity, wages, and living standards.

If the supply of labor were inelastic in the Chinese economy, technical change would be exclusively labor augmenting. However, at the firm level with China's abundant supply of surplus labor, this is not the case. In China's industrial sector, we expect the supply of labor to be at least somewhat elastic, particularly within the context of the furlough of millions of workers from the state sector during the latter half of the 1990s. In order to effectively absorb labor, however, firms may need to focus their R&D resources on incorporating labor-using techniques into new vintages of capital stock. In support of this proposition, Jefferson and Su (2006) find that relative to state-owned enterprises, restructured firms in which non-state shareholders have increased their control exhibit significant increases in R&D intensity and a re-orientation toward investment in labor-using capital.

*The role of imported R&D and technology transfer***.** Our results support the theory of "appropriate technology" as presented in Atkinson and Stiglitz (1969), Basu and Weil (1998) and Caselli and Wilson (2003). They are also consistent with the theoretical perspectives and empirical findings of others – e.g., Acemoglu and Zilibotti (2001) – who find that technology is typically developed in the North and therefore reflects the relative resource scarcities of these countries. We find that in Chinese industry, in-house R&D is used to shift the factor bias of production toward China's comparative advantage, that is, toward labor and materials and away from capital and energy. The labor-using bias serves to dampen the underlying forces that drive capital deepening in China. The material-saving bias is associated with outsourcing that we would expect as vibrant domestic markets and expanding foreign trade have replaced the excessive vertical integration that resulted from the breakdown of markets during the era of central planning.

The models presented in the literature, however, assume that a country has a single objective when it comes to technology development. Our results suggest that firms in China employ in-house R&D and imported technologies to support different or multiple objectives. Similar to Acemoglu's (2002) price versus market effects, the choice of technology depends on two competing technology objectives. The first is *process innovation*, which by focusing on cost reduction requires that technology development embodies a factor mix that is corresponds to the relevant country's comparative advantage. The second technology objective is *product innovation* for which technologies are chosen based on their ability to produce goods that command a higher price. Our results seem to suggest that in-house R&D is largely dedicated to the objective of process innovation, since it is largely cost reducing, whereas imported technology is largely purchased for the purpose of supporting product innovation, which may raise costs but also increases product quality, sale prices, and revenues.

As discussed in Section II, a firm will choose imported technology over domestic technology if $\frac{\partial \pi}{\partial R_I} > \frac{\partial \pi}{\partial R_D}$, where π is the unit (marginal) profit, R_I is imported R&D and R_D is domestic R&D. Unit profit is defined as $P_Q - C$ where P_Q is the unit price of output and C is the unit cost. This implies $\frac{\partial \pi}{\partial R} = \frac{\partial P_Q}{\partial R} - \frac{\partial C}{\partial R}$. If innovation does not change the price of output, then the difference in marginal profit between the two types of technology development investments depends on the relative impact of R&D and imported technology on marginal cost. Given the translog cost function, this will depend on relative factor prices. Using the coefficients in Table 1, column (6) and the appropriate mean values, we account for the percentage change in total cost attributed to each type of technology development by subtracting the cost function in equation (1) evaluated in 1997 from the same cost function evaluated in 2001, and combine terms; i.e.,

$$\Delta lnC = f(\Delta lnR_{int}) + g(\Delta lnR_{imp}) + h(\Delta lnR_{int}{*}R_{imp}) + z(\Delta other)$$

where

$$\begin{aligned}
f(\Delta lnR_{int}) = {} & \alpha_{Rint}\Delta(lnR_{int}) + \beta_{Rint*K}\Delta(lnR_{int}{*}lnP_K) + \beta_{Rint*L}\Delta(lnR_{int}{*}lnP_L) \\
& + \beta_{Rint*E}\Delta(lnR_{int}{*}lnP_E) + \beta_{Rint*M}\Delta(lnR_{int}{*}lnP_M) + \beta_{Rint*2001}\Delta(lnR_{int}) \\
& + \beta_{Rint*K*2001}\Delta(lnR_{int}{*}lnP_K) + \beta_{Rint*L*2001}\Delta(lnR_{int}{*}lnP_L) \\
& + \beta_{Rint*E*2001}\Delta(lnR_{int}{*}lnP_E) + \beta_{Rint*M*2001}\Delta(lnR_{int}{*}lnP_M) \\
g(\Delta lnR_{imp}) = {} & \alpha_{Rimp}\Delta(lnR_{imp}) + \beta_{Rimp*K}\Delta(lnR_{imp}{*}lnP_K) + \beta_{Rimp*L}\Delta(lnR_{imp}{*}lnP_L) \\
& + \beta_{Rimp*E}\Delta(lnR_{imp}{*}lnP_E) + \beta_{Rimp*M}\Delta(lnR_{imp}{*}lnP_M) \\
& + \beta_{Rimp*2001}\Delta(lnR_{imp}) + \beta_{Rimp*K*2001}\Delta(lnR_{imp}{*}lnP_K) \\
& + \beta_{Rimp*L*2001}\Delta(lnR_{imp}{*}lnP_L) + \beta_{Rimp*E*2001}\Delta(lnR_{imp}{*}lnP_E) \\
& + \beta_{Rimp*M*2001}\Delta(lnR_{imp}{*}lnP_M) \\
h(\Delta lnR_{int}{*}R_{imp}) = {} & \alpha_{Rint*Rimp}\Delta(lnR_{int}{*}lnR_{imp}) + \beta_{Rint*Rimp\ *K}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_K) \\
& + \beta_{Rint*Rimp\ *L}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_L) \\
& + \beta_{Rint*Rimp*E}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_E) \\
& + \beta_{Rint*Rimp*M}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_M) + \beta_{Rint*Rimp\ *2001}\Delta(lnR_{int}{*}lnR_{imp}) \\
& + \beta_{Rint*Rimp\ *K*2001}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_K) \\
& + \beta_{Rint*Rimp*L*2001}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_L) \\
& + \beta_{Rint*Rimp\ *E*2001}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_E) \\
& + \beta_{Rint*Rimp*M*2001}\Delta(lnR_{int}{*}lnR_{imp}{*}lnP_M) \\
z(\Delta other) = {} & \text{change in other non-R\&D-related factors.}
\end{aligned}$$

The values of $f(\Delta lnR_{int})$, $g(\Delta lnR_{imp})$, $h(\Delta lnR_{int}{*}R_{imp})$, converted to percent changes, are provided in the first row of Table 2, and show that increases in in-house R&D expenditures between 1997 and 2001 tended to reduce overall cost while increases in imported technology had raised cost. The interaction between these two types of R&D (shown in the last column) exhibits a negative impact on cost. According to Table 2, increases in in-house R&D reduced cost by 9.3

percent, while increases in imported R&D raised cost by 0.3 percent. Increases in both types of R&D reduced cost by 0.6 percent.

The last two rows of Table 2 break out this total contribution in terms of neutral and factor biased effects. The cost reducing effect of in-house R&D is almost evenly split between neutral and factor biased effects. Imported R&D, on the other hand, had a strong positive neutral effect on cost, which is offset by the cost-saving factor bias effects. Lastly, the comparatively large neutral cost-saving effect of the interaction between the two types of technology development is only partial offset by a cost-increasing factor bias effect.

The key results shown in Table 2 are that in-house R&D is unambiguously cost reducing; foreign technology transfer is cost increasing. Factor bias, whether associated with in-house R&D or imported technology, is generally cost-reducing. Because imported technology is not cost reducing, firms using imported technology are more likely to use it for product development or quality improvements that can be passed on in the form of higher prices.

Technology transfer for new product development. We test this hypothesis – the association of imported technology with new product development – by investigating whether imported technology intensity, measured as the ratio of the lagged stock of imported R&D expenditures to total sales, positively affects the probability that the firm is a new product developer.[16] To do this, we estimate a probit model with the dependent variable defined as 1 if new product sales are nonzero, 0 otherwise. The right-hand-side variables include the intensities of in-house and imported R&D (normalized by total sales), year dummy variables for 1998-

[16]Due to noisiness in the new product sales data, we choose to estimate a model that predicts the likelihood that a firm is a new product developer.

2001, and dummy variables representing different categories of firm ownership type and industry.[17]

The results in Table 3 confirm our hypothesis. Regardless of which set of dummy variables are included in the estimate, the intensity of imported technology is a good predictor of whether or not a firm is a new product developer. While the results are generally stable across specifications, the significance of in-house R&D intensity as a predictor of product development activity disappears when the industry dummies are included (column (d)). This latter result suggests that industry-specific factors are more important than the intensity of in-house R&D in predicting whether a firm is more or less likely to be a new product developer. Imported technology, however, retains its predictive power.

Tables 2 and 3 provide a plausible account of why we observe firms employing technologies that embody different factor biases. Firms often simultaneously engage in multiple technology development activities. In-house R&D tends to be dedicated to cost-reducing process innovation; imported technologies are more likely to be used to develop products of higher quality and price, whose factor content may be more oriented toward the countries that originally designed and developed these higher quality products.

VII. Conclusions

This paper investigates an empirical puzzle observed in Chinese industry; one which we anticipate exists in other developing economies that are involved in economic transformation, including the processes of domestic liberalization, trade and financial market integration, and

[17] Consistent with our expectations, we find evidence to support the fact that new products result in higher output prices. Controlling for industry factors, we regress the change in a firm's output price index between 1997 and 2001 on a dummy variable representing whether or not the intensity of new product sales (normalized by total sales) grew

technology transfer. The puzzle that we explore is why Chinese firms simultaneously expend resources on disparate forms of technical change that embody different, often conflicting, factor biases.

Using a large panel of Chinese enterprises, we conclude that capital-using autonomous technical change is driving Chinese industry along the path of capital deepening neoclassical growth. The associated material-saving bias of autonomous change implies that investment is moving Chinese industry up the value chain. The pattern of factor saving bias for in-house R&D is strikingly different from that of autonomous technical change. The robust consistency of these factor biases with China's comparative advantage leads us to conclude that a critical function of in-house R&D is to develop and apply the "appropriate technologies" that enable firms to play effectively on their comparative advantage.

While the factor bias of foreign technology is largely consistent with the capital-deepening dynamics of autonomous technical change, it also displays clear distinctions. R&D and expenditures on foreign technology transfer perform distinct functions. Whereas in-house R&D focuses on existing products, thereby emphasizing cost-cutting process innovation, foreign technology transfer emphasizes new product development. Because new products tend to be of higher quality and command higher prices, they can support the relatively capital-intensive, cost-increasing technologies used to produce them. Also, over time, imported technology is becoming more material saving, suggesting that technology transfer is facilitating the movement of product development in China up the value chain. Notwithstanding these different emphases of R&D and imported technology, we do find predictable interactions between them. Most

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between 1997 and 2001. Our estimation generates a coefficient of .034 with a standard error of .017 (prob > |t| =.048), implying that increases in output price are correlated with increases in the share of new product sales.

notably, our results suggest that Chinese firms employ in-house R&D resources to dampen the capital-using material-saving bias of imported technology.

The most striking finding in this paper is the tendency for different forms of technical change to co-exist and to perform distinct and identifiable roles in the process of growth and development. Autonomous technical change is the transmission channel for neoclassical capital deepening. In-house R&D focuses on exploiting China's cost-cutting comparative advantage, including adapting imported technologies to make them more "appropriate." Foreign technology transfer focuses on new product development, providing the technologies that are in short supply within China for comparatively capital intensive, high value added products. In conclusion, we view the three sources of technical change and their respective factor biases that we identify in this paper as each being aligned with a distinct and critical function of China's industrial transformation: exogenous, capital-biased technical change drives neoclassical growth; in-house R&D drives efficiency based on comparative advantage, and the deliberate acquisition of foreign technology is driving new product development and China's quest to compete in the upper end of the international product market. While one-sector growth models focus our attention on the long-run determinants and properties of capital-deepening, our findings lead us to believe that at the firm level within developing countries multiple channels of technical change are operating simultaneously to achieve a variety of economic objectives.

Table 1
Neutral and Factor Biased of Technological Change[a]

	Pooled			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Neutral effects						
α_{01}	0.000 (0.001)	-0.003 (0.010)	-0.032 (0.032)	0.002** (0.001)	-0.058*** (0.005)	-0.007 (0.019)
α_{Rint}	-0.000** (0.000)	-0.021*** (0.002)	-0.041*** (0.003)	-0.000 (0.000)	-0.008*** (0.002)	-0.021*** (0.002)
α_{Rimp}	0.000* (0.000)	-0.001 (0.004)	-0.001 (0.004)	0.000 (0.000)	0.010*** (0.003)	0.011*** (0.003)
$\alpha_{Rint \cdot Rimp}$	-0.000 (0.000)	0.000 (0.000)	0.001 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Factor biased effects						
$\beta_{01 \cdot K}$	--	--	-0.010 (0.009)	--	--	0.013** (0.005)
$\beta_{01 \cdot L}$	--	--	0.006 (0.006)	--	--	-0.003 (0.005)
$\beta_{01 \cdot E}$	--	--	-0.001 (0.011)	--	--	0.008 (0.007)
$\beta_{01 \cdot M}$	--	--	0.006 (0.012)	--	--	-0.018** (0.008)
$\beta_{Rint \cdot K}$	--	0.001*** (0.000)	-0.012*** (0.001)	--	0.000 (0.000)	-0.006*** (0.000)
$\beta_{Rint \cdot L}$	--	0.003*** (0.000)	0.000 (0.001)	--	0.003*** (0.000)	0.003*** (0.001)
$\beta_{Rint \cdot E}$	--	-0.003*** (0.001)	-0.004*** (0.001)	--	-0.004*** (0.001)	-0.004*** (0.001)
$\beta_{Rint \cdot M}$	--	-0.001 (0.001)	0.016*** (0.001)	--	0.001** (0.001)	0.007*** (0.001)
$\beta_{Rimp \cdot K}$	--	0.002** (0.001)	0.003** (0.001)	--	0.002** (0.001)	0.003*** (0.001)
$\beta_{Rimp \cdot L}$	--	0.001 (0.000)	-0.000 (0.001)	--	-0.000 (0.001)	-0.002** (0.001)
$\beta_{Rimp \cdot E}$	--	0.001 (0.001)	-0.001 (0.002)	--	-0.002** (0.001)	-0.003** (0.001)
$\beta_{Rimp \cdot M}$	--	-0.004** (0.002)	-0.002 (0.002)	--	0.001 (0.001)	0.001 (0.001)
$\beta_{Rint \cdot Rimp \cdot K}$	--	-0.000 (0.000)	-0.000 (0.000)	--	0.000 (0.000)	-0.000** (0.000)
$\beta_{Rint \cdot Rimp \cdot L}$	--	-0.000* (0.000)	-0.000* (0.000)	--	-0.000 (0.000)	-0.000 (0.000)
$\beta_{Rint \cdot Rimp \cdot E}$	--	-0.000 (0.000)	0.000 (0.000)	--	-0.000 (0.000)	-0.000 (0.000)
$\beta_{Rint \cdot Rimp \cdot M}$	--	0.000 (0.000)	0.000* (0.000)	--	0.000 (0.000)	0.000** (0.000)
$\beta_{Rint \cdot 01}$	--	--	0.008* (0.005)	--	--	0.001 (0.003)
$\beta_{Rint \cdot K \cdot 01}$	--	--	0.002* (0.001)	--	--	-0.000 (0.001)
$\beta_{Rint \cdot L \cdot 01}$	--	--	-0.001 (0.000)	--	--	-0.001 (0.001)

$\beta_{Rint\cdot E\cdot 01}$	--	--	0.001 (0.002)	--	--	-0.000 (0.001)
$\beta_{Rint\cdot M\cdot 01}$	--	--	-0.002 (0.002)	--	--	0.001 (0.001)
$\beta_{Rimp\cdot 01}$	--	--	-0.004 (0.004)	--	--	-0.003 (0.003)
$\beta_{Rimp\cdot K\cdot 01}$	--	--	-0.001 (0.001)	--	--	0.000 (0.001)
$\beta_{Rimp\cdot L\cdot 01}$	--	--	0.000 (0.000)	--	--	0.001* (0.001)
$\beta_{Rimp\cdot E\cdot 01}$	--	--	0.001 (0.002)	--	--	0.002* (0.001)
$\beta_{Rimp\cdot M\cdot 01}$	--	--	-0.000 (0.002)	--	--	-0.003*** (0.001)

Note: the standard errors are in parentheses. * Significant at the 10% level, ** Significant at the 5% level, ***Significant at the 1% level.

[a] Given the large number of variables included in the estimated translog cost function, we chose to only present the coefficients associated with autonomous (represented by the year dummy variables) and deliberate technology development (represented by the stock variable, R). We only present the coefficients associated with the year 2001 dummy variable because we are primarily interested in the change over the entire time period (1997-2001).

Table 2
Contribution of R&D to % Change in Total Cost*

	In-house R&D	Imported tech.	Interaction In-house *Imported
Contribution to % change in total cost	-9.29% (-9.79%)	0.33% (0.31%)	-0.60% (0.47%)
Of which: Neutral effect	-4.09% (-4.09%)	1.57% (1.57%)	-0.75% (0.00%)
Factor bias effect	-5.19% (-5.69%)	-1.24% (-1.26%)	0.15% (0.47%)

*Results incorporating only the statistically significant coefficient estimates are shown in parentheses.

Table 3
Determinants of New Product Development – Probit analysis

	(a)	(b)	(c)	(d)
constant	-0.359*** (.017)	-0.365*** (.037)	-0.405*** (.038)	0.764*** (.064)
In-house R&D/ Sales	0.138** (.062)	0.141** (.062)	0.143** (.063)	0.046 (0.076)
Imported tech./ Sales	0.245*** (.052)	0.244*** (.052)	0.234*** (.053)	0.208*** (.059)
Other included dummies	None	Year only	Year, ownership	Year, ownership, industry
R^2/obs	0.003 (6,247)	0.004 (6,247)	0.019 (6,247)	0.211 (6,247)

* Significant at the 10% level, ** Significant at the 5% l evel, *** Significant at the 1% level.

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Appendix A: The Data

The empirical tests of the hypotheses developed in this paper are based on a data set that includes approximately 1,500 large and medium-size Chinese industrial enterprises and spans the years 1997-2001. The data set combines three constituent data sets that are updated annually by the National Bureau of Statistics (NBS) in China. The first is a set of economic and financial data, collected by the Bureau's Department of Industrial and Transportation Statistics (NBS, 2001a), that includes all of China's approximately 22,000 large and medium-size enterprises (LMEs) over the years 1995-2001. The second data set consisting of the same firm population and including a large number of R&D measures – both innovation inputs and outputs – is maintained and updated annually by the Bureau's Department of Social and Science and Technology Statistics (NBS, 2001b). These two data sets are combined with an energy data set that includes measures of approximately 20 individual energy types and aggregate measures of both the value and physical quantity of energy consumption. We derive price data from these value and quantity measures. Because this energy data set includes only the most energy intensive enterprises among the population of large and medium-size enterprises over the years 1997-2001, our combined data set includes significantly fewer observations than the two data sets from which the individual firms are drawn.[18]

Although by combining the first two data sets with the energy data set we lose a significant number of observations, the combined data set expands our set of factor inputs from capital and labor to a full blown KLEM data set. To test the robustness of the factor bias of various technology sources, we welcome the addition of five pair-wise factor relationships in

[18] The number of enterprises covered in the energy survey range from a low of 3,746 enterprises in 1998 to 10,166 enterprises in 2001. A part of this variation reflects changes in capacity utilization and energy consumption over the business cycle. A total of 1,518 enterprises appear in all five years.

addition to the conventional capital-labor substitution possibilities. The inclusion of energy in our data set will allow us to investigate how energy fits into the pattern of factor bias in China's technology development.

Table A.1 compares levels of sales, employment, fixed assets and energy consumption in our sample (i.e., the "KLEM sample") with both total industry and with the full population of 22,000 large and medium-size enterprises. As shown, although our sample represents but one percent of the number of China's industrial enterprises with annual sales in excess of five million yuan (approximately $600,000), within this group, it captures 13 percent of industrial sales, 15 percent of industrial employment, 20 percent of industrial assets, and 40 percent of industrial energy consumption.

The NBS data set classifies enterprises into 37 industrial categories. For the purposes of this analysis, we group the 37 industrial classifications into 12 industry categories. This industry distribution is shown in Table A.2. Not surprisingly, relative to the distribution of total industry and LMEs, the energy sample includes high proportions of enterprises in the more energy-intensive industries, including the chemical and electric power industries.

Table A.1
Shares of LMEs and energy sample in aggregate industry, 1999
(% of total industry)

Measure	All industry[1]	Of which: L&M Enterprises[2]	Of which: KLEM sample
Sales (100 million yuan)	69,851 (100%)	41,166 (59%)	9,062 (13%)
Employment (10,000 persons)	4,428 (100%)	3,061 (69%)	679 (15%)
Assets[3] (100 million yuan)	71,847 (100%)	53,070 (74%)	14,428 (20%)
Energy consumption (10,000 tons of standard coal (SCE))	130,119 (100%)	90,797 (70%)	36,285 (40%)
No. of enterprises	162,033 (100%)	22,000 (14%)	1,518 (1%)

[1] Industrial state owned and non-state owned enterprises with annual sales over 5 million Yuan. Source: China Statistical Yearbook, 2000 [NBS, 2000]. [2] Source: NBS (2001a). [3] Original value fixed assets

The NBS data set also classifies enterprises into seven ownership classifications, consisting of state-owned enterprises and the six other non-state classifications shown in Table A.3. In 1999, our sample is largely concentrated in the state-owned sector, i.e. 62 percent of total sales in our sample originated with SOEs. This SOE ownership bias in our sample is not surprising, since a large portion of China's energy intensive firms that occupy the capital-intensive sectors are state-owned.

The data set classifies technology development expenditures by two broad types of expenditure, i.e. in-house technology development expenditure and imported technology. These are defined as follows:

Table A.2
Industry distribution, 1999 (%)

Industry classification (2-digit SIC)	**Total industry[1]**	**LMEs**	**KLEM sample only**
Mining (06-10,12)	7,257 [4%]	829 [4%]	113 [7%]
Food and Beverage (13-16)	20,125 [12%]	2,593 [11%]	123 [8%]
Textile, apparel, and leather products (17-19)	20,784 [13%]	2,637 [12%]	93 [6%]
Timber, furniture, and paper products (20-24)	12,374 [8%]	1,332 [6%]	69 [5%]
Petroleum processing and coking (25)	988 [1%]	120 [1%]	39 [3%]
Chemicals (26-28)	15,412 [10%]	2,760 [12%]	297 [20%]
Rubber and plastic products (29-30)	7,852 [5%]	893 [4%]	28 [2%]
Non-metal products (31)	14,366 [9%]	1,699 [8%]	242 [16%]
Metal processing and products (32-34)	13,644 [8%]	1,429 [6%]	70 [5%]
Machinery, equipment, and instruments (35-37,39-42)	29,955 [18%]	6,287 [28%]	162 [11%]
Electric power (44)	4,941 [3%]	1,039 [5%]	213 [14%]
Other industry (43,45,46)	14,335 [9%]	971 [4%]	60 [4%]
Total	162,033 [100%]	22,589 [100%]	1,518 [100%]

[1] Includes all state and non-state enterprises with annual sales above 5 million yuan. Source: NBS (2000).

Table A.3
Ownership distribution, 1999 (%)

Ownership type	Total industry[1]	LMEs	KLEM sample only
State-owned	61,301 [38%]	10,451 [46%]	1,045 [69%]
Collective-owned	42,585 [26%]	3,381 [15%]	64 [4%]
Hong-Kong, Macao, Taiwan	15,783 [10%]	1,567 [7%]	64 [4%]
Foreign	11,054 [7%]	1,966 [9%]	70 [5%]
Shareholding	4,480 [3%]	4120 [18%]	263 [17%]
Private	26,830 [17%]	316 [1%]	2 [0%]
Other domestic		792 [4%]	10 [1%]
Total	162,033 [100%]	22,111 [100%]	1,518 [100%]

[1] Includes all state and non-state enterprises with annual sales above 5 million yuan.

(1) In-house technology development (*jishu kaifa jingfei zhichu*) is technology development expenditure that is conducted within the firm. The scope of this measure is broader than the standard measure of research and development expenditure. In addition to R&D spending, it includes expenditure for a wider range of process innovation activity and for improving the quality of existing products.

(2) Technology imports (*jishu yinjin jingfei zhichu*) i.e., purchased technology that originates from another country. These technology imports include equipment that is used to support domestic firm technology development operations (e.g. lab equipment) as well as blueprints and licenses for foreign technology.

Although we use technology development expenditures to measure the level and bias of innovation effort, we use the terms "technology development" and "R&D" interchangeably.

The first column of Table A.4 shows the intensity of technology development expenditures – defined as the ratio of total development expenditure to sales revenue. This table shows that, notwithstanding the fact that SOEs capture a larger proportion of total technology development expenditure, due to their comparatively large sales volume, the intensity of technology development for SOEs is smaller than that for non-SOEs.

For each of the two technology development expenditure categories, the last two columns in Table A.4 show the distribution of technology development by in-house R&D and by purchases of imported technology. The industries for which the share of imported technology is relatively large are food and beverage, timber furniture and paper products, and metal processing and petroleum processing industries. While the metal processing industry accounts for nearly one-third of total imported technology purchases, the two industries that follow – machinery and chemicals – use proportionately more in-house R&D. Because these two industries stand out as those with the most overall technology development intensity, combined with chemicals, they account for the largest shares of both in-house and imported technology development spending. State-owned enterprises receive a much larger proportion of imported technology than non-state-owned enterprises, while in-house technology development is more evenly divided between the two ownership types.

Table A.4
Shares of Technology Development Expenditures
By Industry and Ownership Type, 1997-2001

	Total Technology Development Expenditures		
	Relative to sales revenue	Of which	
		In-house*	Imported*
Mining	1.0	84 (9)	16 (4)
Food and beverage	1.5	41 (4)	59 (12)
Textiles, apparel and leather products	1.9	66 (3)	34 (3)
Timber, furniture, and paper products	2.1	49 (1)	51 (4)
Petroleum processing and coking	1.8	58 (4)	42 (6)
Chemicals	2.5	68 (14)	32 (13)
Rubber and plastic products	2.0	73 (2)	27 (1)
Non-metal products	1.8	75 (4)	25 (3)
Metal processing and products	1.7	57 (20)	43 (32)
Machinery, equipment and instruments	3.4	78 (32)	22 (19)
Electric power	0.7	78 (5)	22 (3)
Other industry	1.0	85 (1)	15 (<1)
Total industry	2.0	67 (100)	33 (100)
State-owned enterprises	1.7	64 (52)	36 (63)
Non-state-owned enterprises	2.3	72 (48)	28 (37)

*Figures not in parentheses are average firm shares (rows sum to 100%); figures in parentheses are shares within the total sample (columns sum to 100%).

For estimation purposes, we use the perpetual inventory method to construct stocks of technology development expenditure for each firm in our data set. The stocks are constructed as the accumulation of reported technology development expenditures minus depreciation; i.e.

$$K_{R,i,t} = (1-\delta)K_{R,i,t-1} + I_{R,i,t-1}$$

where

$K_{R,i,t} \equiv$ stock of R&D of firm i at time t;

$I_{R,i,t-1}$ ≡ flow of R&D expenditures of firm I at time t-1; and

δ ≡ depreciation rate (assumed to be 15%).

The NBS data set supplies technology development expenditures for the years 1995-2001. We estimate the initial R&D stock in 1995 as,

$$K_{R,i,1995} = I_{R,i,1995} / (\delta+\gamma)$$

where γ is the growth rate of I_R estimated as the average annual growth rate of the 2-digit industry of firm i.

Table A.5 provides input price indices, input value shares, and input intensities for the years 1997 and 2001, averaged over the firms in our sample**.** Overall, we find that labor prices increased over the sample period while the relative prices of energy and materials fell. Input quantities of capital, energy and materials rose while labor fell; however, in terms of value shares, the value shares of capital and energy fell while materials increased and labor stayed constant. Controlling for changes in output levels, we find that the input intensities of labor and energy fell while capital and materials rose. These data indicate that, relative to the other inputs, firms are, on average, economizing on energy.

Table A.5
Sample Statistics—Mean values

		1997	2001
Input price indices (relative to the year 1997)	Capital	1.00	0.99
	Labor	1.00	1.30
	Energy	1.00	0.95
	Materials	1.00	0.96
Input quantities (relative to the year 1997)	Capital	1.00	1.18
	Labor	1.00	0.79
	Energy	1.00	1.10
	Materials	1.00	1.34
Input value shares	Capital	0.152	0.146
	Labor	0.126	0.127
	Energy	0.216	0.210
	Materials	0.506	0.517
Input intensities--input quantities/ constant GVIO (relative to the year 1997)	Capital	1.00	1.08
	Labor	1.00	0.76
	Energy	1.00	0.86
	Materials	1.00	1.02