

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

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Abstract

A stylized fact of technical change in developing economies is that of Harrod-neutral labor augmenting technical change arising from capital deepening. While in the aggregate this pattern of technical change is widely observed, at the firm level a variety of channels of technical change and factor biases are possible. Using a large set of firm-level panel data for China's industrial enterprises, this paper identifies three channels of technical change, each associated with a different pattern of factor bias and underlying firm objective. Autonomous, time-dependent capital-using technical change drives the neoclassical growth process. Robustly labor-using and capital- and energy-savings in-house R&D capitalizes on China's comparative advantage, and the purchase of imported technologies, which are comparatively capital using, focuses on new product development. As part of its task, internal R&D adapts imported technology to make it more "appropriate" (i.e. less capital using). 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

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Introduction

A central theme of the conditional convergence literature is that differences in technology play a critical role in explaining persistent disparities in cross-country living standards (Parente and Prescott, 1994; Mankiw, Romer and Weil, 1992). This finding fundamentally challenges the implicit assumption of the neoclassical growth model that technology can be characterized as a Harrod-neutral, homogeneous public good that is universally accessible to all economies. By modeling processes of technical change, endogenous growth theory allows for differences in levels of technological advance across countries. Due to country differences in the parameters that frame the processes of deliberate technical innovation in the firm sector and spillovers that ensue from the accumulation of physical and human capital, technical change proceeds at different rates across countries. These studies, however, assume also that *within* each country, technology is homogeneous and of the labor-saving Harrod-neutral variety.

What is not adequately stressed in the endogenous growth literature are the persistent cross-country differences in the factor bias of technologies employed in different countries. Acemoglu and Zilibotti (2001), for instance, identify significant differences in relative factor productivities across countries even when countries have equal access to technologies. Some studies, including that of Atkinson and Stiglitz (1969) attempt to explain country differences in the factor bias of technologies. A common argument of these papers is that differences in the comparative factor advantage of economies are critical to shaping the factor bias of the technologies used in those economies. Yet, the fundamental drivers of technical change may be more complex and varied than simple comparative advantage. Acemoglu (2002) argues that if the “price effect,” i.e. incentives to develop technologies used to produce more expensive goods, outweighs the “market effect,” i.e., incentives to develop technologies that are using in the more abundant factor of production, we could see an economy adopting technologies that – counter to comparative factor advantage – are using in the scarce factor.

These theories of the factor bias of technological change, however, focus on the aggregate economy. At the firm level, both across firms and within individual firms, we can casually observe the simultaneous adoption of technologies with different factor biases. This pattern is especially prevalent within developing economies in which markets are segmented and the pace of technical change is uneven. China, in particular, is one developing country in which firms are attempting to improve the efficient production of existing products while simultaneously

adopting more capital intensive technologies that focus on the development of new products for the international market.

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 accumulates through spending on new plant, equipment, and workers that embody new vintages of technology. 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 internal R&D operations or they may be used to purchase imported technologies. While each of these sources of technology development may reflect identical patterns of factor bias, the localization hypothesis of Atkinson and Stiglitz, for example, would lead us to expect that within China internal R&D programs focus on relatively labor-using techniques whereas imported technologies would embody relatively capital-using techniques. As a result, we explicitly distinguish between innovation resources that are spent on internal R&D operations and those spend on imported technology.

Our analysis finds that each of these three sources of technical change 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 not supported by R&D spending, is driving Chinese industry along a path of capital deepening 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 internal R&D is strikingly different from that of autonomous technical change. R&D expenditures exhibit labor and material-using and capital and energy-saving biases. By comparison, imported technology exhibits a capital-using bias and other factor biases that change over time. We explore the reasons why these two technologies – R&D and foreign technology transfer, which involve deliberate technical change but different factor biases – co-exist with each other and with the forces of autonomous change. Internal 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 tends to reflect the comparative advantage of the more advanced economies where these technologies originate. We reconcile the co-existence of these technologies in China's industrial system by identifying their different functions. We find that internal R&D tends to be used for existing products; it therefore emphasizes cost-cutting process innovation. 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 internal R&D and imported technology. Chinese firms employ internal R&D to dampen the capital-using bias of imported technology. 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 implications for other developing countries. R&D and technology spending are essential inputs for cost reducing process innovation and product development. To the extent that it generates spillovers that translate into exogenous technical change for other firms, firm-level R&D and technology spending is also a critical ingredient for the neoclassical growth process.

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.

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.

Sources of 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. Solow's neoclassical growth model (1956) models an economic system in which technical change is exogenous. Presumably, the firms in this system that put these technologies to use acquire these technologies like "manna from heaven" as does the economic system as a whole. An important theme of the endogenous growth literature is the role of deliberate technical change, involving the firm's expenditure of R&D resources, as a source of innovation. 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. Jefferson and Bai (2004) document the growing role of R&D in China's large and medium enterprise sector. As we show in Section 3 of this paper, these firms also expend considerable resources on the purchase of imported technology. At the level of the firm, we should expect that the firm's technical advance is driven partially by deliberate technical change and, where R&D is widely used, that spillovers might also engender exogenous technical change that may be statistically independent of the firm's R&D effort. As we indicate in the introduction to this paper, however, modern growth theory does not address the potential for differences in factor bias across economic systems.

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

Hicks (1932) suggests a second perspective on the bias of technological change. According to Hicks, 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 was further developed by Ahmad (1966) with the concept of the innovation-possibility curve (IPC). The IPC is an isoquant that maps out the 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 a country to move along its IPC through the application of R&D resources that minimize production costs in accord with the revised set of factor prices. Reviewing the literature (e.g., Hayami and Ruttan, 1970; Wright, 1990; and Jorgenson and Wilcoxon, 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 the implication for the bias of R&D of a change in relative factor prices. To capture the impact of a change in relative factor prices, we first characterize the point on the economy that represents an equilibrium production technology that is consistent with the initial factor prices represented by the price line $P_a P_a$. 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.

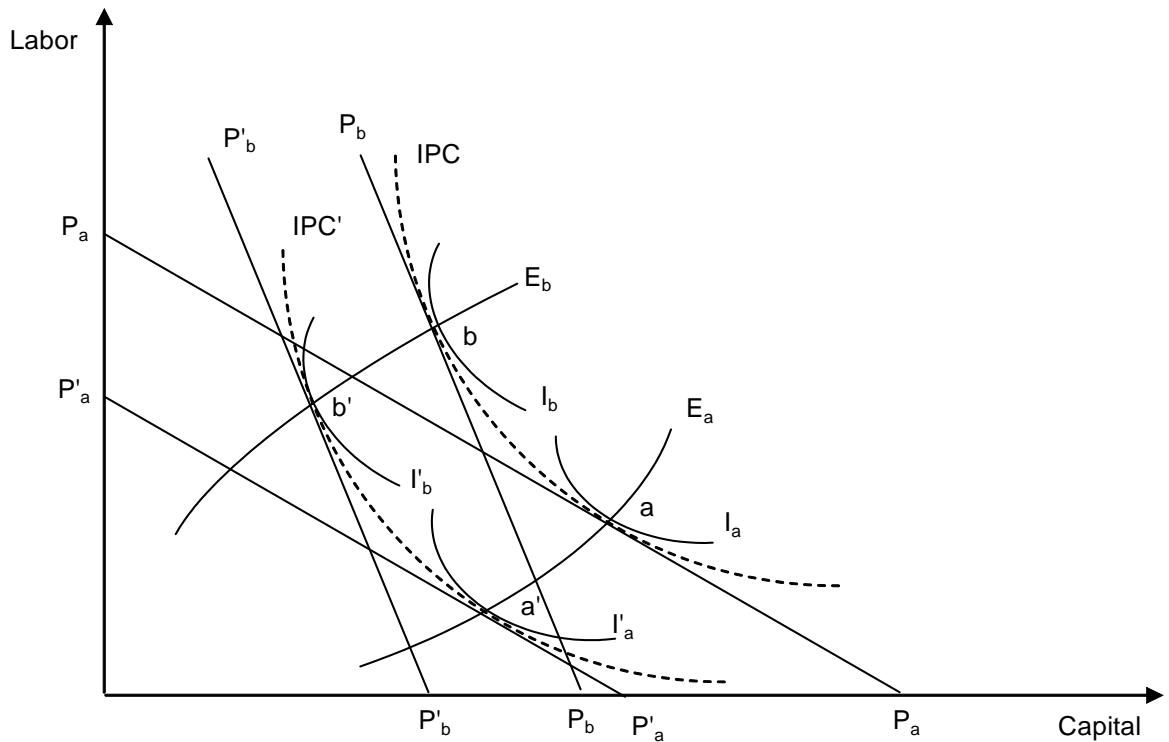


Figure 1

As a result of an increase in the relative price of capital, the price line shifts to P_b P'_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 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'_b P'_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 potentially relevant in two general ways:

- Chinese industry has exhibited the processes depicted by the neoclassical growth model, involving capital deepening, the growth of labor productivity, and wage growth. In the context of the Hicks-Ahmad model, this rise in wages, which implies a rise in the wage-

rental ratio, should be motivating new rounds of capital-using and labor-saving technical change. However, within the context of the firm level and a developing economy with an abundance of surplus labor, labor's elasticity of supply is high and wages are relatively fixed. With increases in labor productivity relative to wage, firms are motivated to invest in labor using technical change, which enables the firm to employ more workers, thereby moderating the rise in labor productivity and wages.

- At the same time, China has moved away from central planning and state ownership. During the era of central planning, through price controls and subsidies to capital and energy, Chinese industry evolved along a path whose capital and energy intensities were inconsistent with China's relative abundance of surplus labor. During the post-1980 reform period, particularly beginning in the latter 1990s, China's economy has substantially restructured. Price reform, trade liberalization, and governance reform have created pressures for Chinese producers to harden budget constraints and to achieve efficiency by more effectively exploiting their comparative advantage. These changes lead us to believe that technical change should be labor using and capital and energy saving. The marketization of China's economy should also be leading Chinese industry, which became excessively vertically integrated during the era of central planning, to outsource.

China continues to move along a path of capital deepening, labor-augmenting Harrod neutral technical change. However, given that technical change evolves from multiple sources – internal R&D and foreign technology, as well as autonomous sources – we cannot anticipate a priori the patterns of factor bias associated with each of these sources of technological development.

Multiple sources of technology development. It is often the case 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 internal R&D, 759 (50%) report purchases of imported technology, and 744 (49%) firms report using both. Only 228 firms (15%) report no expenditures on internal R&D or imported technology.

This phenomenon in which firms use both internal R&D and engage in foreign technology transfer motivates our inquiry into why firms use multiple sources of technology

development. If the bias of technologies reflects the underlying factor endowment of the economies in which they are developed, why do we observe technology transfer from rich, labor-scarce and capital-abundant economies to poor countries with very different factor endowments? 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 internal R&D and purchased technology imports reflect the factor bias of their respective countries of origin, why do Chinese companies buy 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 internal 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. Developing economy firms 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

$$\frac{\partial \pi}{\partial R_I} > \frac{\partial \pi}{\partial R_D}, \text{ where } \pi \text{ is unit (marginal) profit, } R_I \text{ is imported R\&D and } R_D \text{ is domestic R\&D.}^1$$

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 but does result in a higher cost of production that would eliminate the gain in higher output price.²

¹ Unit profit, π , may be interpreted as a discounted unit of future profit that enters into the present value of the firm.

² This is the "price effect" that together with the "market size effect" drives the composition of technology in Acemoglu's model (2002).

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

We might anticipate imported technology to be most intensively used for product innovation, which may require more advanced modes of R&D, similar to those created by OECD nations that are likely to be the first movers in new product markets. These more sophisticated imported technologies, for example, may be needed to install, utilize, and maintain the capital-intensive techniques and equipment, such as precision production machinery and quality control instrumentation, which are needed to achieve world class product quality standards.

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. We should expect that a Chinese firm purchasing imported technology would 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 internal 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 needed for both domestic and foreign technology transfer.

Returning to Figure 1, we anticipate 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, instead we 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 firm may attempt to convert the technology into an “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 internal 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 a , the point of entry of the technology, the same imported technology, once mixed with internal R&D, acquires a factor bias that becomes more labor-using and capital-saving.

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

1. Because the pattern of growth of the Chinese economy reflects the capital deepening trajectory defined by Solow’s neoclassical model of growth, overall, technical change in Chinese industry will be capital using.
2. Even as China has followed a neoclassical growth trajectory, an elastic 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 even as the country experiences an overall shift toward growing capital intensity.

3. Regardless of the factor saving bias of imported technology purchased by Chinese firms, relative to internal R&D, we expect it to be capital-using and labor-saving, and perhaps material-using.
4. Given that both China and most of the OECD economies have exhibited increases in relative energy prices, we might expect that their existing technologies exhibit energy saving biases. Whether on-going *technical change* exhibits energy-saving bias depends on the extent to which the existing techniques have fully incorporated new technologies that reflect the prevailing set of relative energy-prices and scarcities.
5. Internal R&D is used to adapt imported technology to China's relative factor endowment.
6. Relative to internal 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.

Understanding the factor biases and interactions between internal and imported technology is critical for understanding the process by which developing countries innovate and adopt technology. Due to the lack of data, previous studies have been unable to distinguish directly between internal 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 internal versus imported technology development. We use these data to measure the neutral and factor-biased effects of internal 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 the appendix that includes approximately 1,500 large and medium-size Chinese industrial enterprises and spans the years 1997-2001..

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. 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.

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 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.³ 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,⁴ we use the cost function approach.

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:

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

where

³ 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.

⁴ The data set includes both quantities and values and therefore a price can be imputed by dividing value by quantity.

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

$$B(R,T,Z) = \ln R' \cdot \beta_{RZ} \cdot \ln Z + T' \cdot \beta_{TZ} \cdot \ln Z + \sum_{t=98}^{01} \text{Year}_t \cdot \ln R' \cdot \beta_{RZt} \cdot \ln Z$$

$$\ln Z' = (\ln P_K, \ln P_L, \ln P_E, \ln P_M)$$

$$\ln R' = (\ln R_{\text{int}}, \ln R_{\text{imp}})$$

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

$$\alpha'_Z = (\alpha_{Pk}, \alpha_{Pl}, \alpha_{Pe}, \alpha_{Pm})$$

$$\alpha'_R = (\alpha_{R\text{int}}, \alpha_{R\text{imp}})$$

$$\alpha'_T = (\alpha_{98}, \alpha_{99}, \alpha_{00}, \alpha_{01})$$

$$\beta_{ZZ} = \begin{bmatrix} \beta_{KK} & \beta_{LK} & \beta_{EK} & \beta_{MK} \\ \beta_{KL} & \beta_{LL} & \beta_{EL} & \beta_{ML} \\ \beta_{KE} & \beta_{LE} & \beta_{EE} & \beta_{ME} \\ \beta_{KM} & \beta_{LM} & \beta_{EM} & \beta_{MM} \end{bmatrix}$$

$$\beta_{RZ} = \begin{bmatrix} \beta_{R\text{int}\cdot K} & \beta_{R\text{int}\cdot L} & \beta_{R\text{int}\cdot E} & \beta_{R\text{int}\cdot M} \\ \beta_{R\text{imp}\cdot K} & \beta_{R\text{imp}\cdot L} & \beta_{R\text{imp}\cdot E} & \beta_{R\text{imp}\cdot M} \end{bmatrix}$$

$$\beta_{TZ} = \begin{bmatrix} \beta_{98K} & \beta_{98L} & \beta_{98E} & \beta_{98M} \\ \beta_{99K} & \beta_{99L} & \beta_{99E} & \beta_{99M} \\ \beta_{00K} & \beta_{00L} & \beta_{00E} & \beta_{00M} \\ \beta_{01K} & \beta_{01L} & \beta_{01E} & \beta_{01M} \end{bmatrix}$$

$$\beta_{RT} = \begin{bmatrix} \beta_{R\text{int}98} & \beta_{R\text{imp}98} \\ \beta_{R\text{int}99} & \beta_{R\text{imp}99} \\ \beta_{R\text{int}00} & \beta_{R\text{imp}00} \\ \beta_{R\text{int}01} & \beta_{R\text{imp}01} \end{bmatrix}$$

$$\beta_{RZt} = \begin{bmatrix} \beta_{R\text{int}\cdot K\cdot t} & \beta_{R\text{int}\cdot L\cdot t} & \beta_{R\text{int}\cdot E\cdot t} & \beta_{R\text{int}\cdot M\cdot t} \\ \beta_{R\text{imp}\cdot K\cdot t} & \beta_{R\text{imp}\cdot L\cdot t} & \beta_{R\text{imp}\cdot E\cdot t} & \beta_{R\text{imp}\cdot M\cdot t} \end{bmatrix}$$

$$\beta'_{QZ} = (\beta_{QK}, \beta_{QL}, \beta_{QE}, \beta_{QM}).$$

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),⁵
 R_{int} \equiv stock of internal technology development expenditures, described in Section III,
 R_{imp} \equiv stock of imported technology expenditures, described in Section III, and
 $Year98, Year99, Year00, Year01$ \equiv time dummies for each year, 1997-2001 (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 . In order to avoid issues of endogeneity the two-year R&D stocks enters the cost function with a one-year lag.

From Shephard's Lemma, we know that the cost share equation associated with each factor input can be obtained by taking the derivative of the cost function with respect to the input price; i.e.,

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

Taking the derivative of the translog cost function specified in equation (1) with respect to each input price, we obtain the following cost share equations:⁶

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

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

⁵ The price deflator for GVIO was used as a proxy for the price of materials since materials account for the largest share of GVIO.

⁶ Since the cost shares must sum to one, we are able to drop one cost share equation – 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).

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

where

$$\beta'_{LT} = (\beta_{98L}, \beta_{99L}, \beta_{00L}, \beta_{01L})$$

$$\beta'_{ET} = (\beta_{98E}, \beta_{99E}, \beta_{00E}, \beta_{01E})$$

$$\beta'_{MT} = (\beta_{98M}, \beta_{99M}, \beta_{00M}, \beta_{01M})$$

$$\beta'_{RLT} = \begin{bmatrix} \beta_{Rint-L-98} & \beta_{Rint-L-99} & \beta_{Rint-L-00} & \beta_{Rint-L-01} \\ \beta_{Rimp-L-98} & \beta_{Rimp-L-99} & \beta_{Rimp-L-00} & \beta_{Rimp-L-01} \end{bmatrix}$$

$$\beta'_{RET} = \begin{bmatrix} \beta_{Rint-E-98} & \beta_{Rint-E-99} & \beta_{Rint-E-00} & \beta_{Rint-E-01} \\ \beta_{Rimp-E-98} & \beta_{Rimp-E-99} & \beta_{Rimp-E-00} & \beta_{Rimp-E-01} \end{bmatrix}$$

$$\beta'_{RMT} = \begin{bmatrix} \beta_{Rint-M-98} & \beta_{Rint-M-99} & \beta_{Rint-M-00} & \beta_{Rint-M-01} \\ \beta_{Rimp-M-98} & \beta_{Rimp-M-99} & \beta_{Rimp-M-00} & \beta_{Rimp-M-01} \end{bmatrix}$$

VL \equiv labor expenditures (equal to wage bill + welfare payments)

VE \equiv value of energy expenditures

VK \equiv value of capital (equal to value added – labor expenditures)

VM \equiv value of material expenditures (value of intermediate inputs)

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

By estimating this system of four equations, we can analyze the effect on both the rate and factor bias of technical change of deliberate technical change, as it operates through technology development expenditure, and autonomous technical change, summarized by the passage of time. As shown in the above system, we assume 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, that is technological change not occurring through deliberate purchases of R&D and imported technology, is captured by the coefficients associated with the year dummies, Year₉₈, Year₉₉, Year₀₀, Year₀₁. Factor neutral technological change, in which technical progress or regress is proportional across all inputs, is captured by the terms $\alpha'_R \cdot \ln \mathbf{R}$ and $\mathbf{T}' \cdot \alpha'_{RT} \cdot \ln \mathbf{R}$. Factor-biased technological change, which

causes movement along the isoquant, is captured by $\ln R'_t \cdot \beta_{RZ} \cdot \ln Z$ and $\sum_{t=98}^{01} \text{Year}_t \cdot \ln R'_t \cdot \beta_{RZt} \cdot \ln Z$.

Flows into the technology development stock are annual technology development expenditures.⁷

Estimation 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). To ensure the usual properties of symmetry, homogeneous of degree 1 in prices, homothetic, and constant-returns-to-scale conditions on the coefficients, we impose the following constraints:⁸

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

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

$$\beta_{ZZ} \cdot \mathbf{i} = \mathbf{0}$$

$$\beta_{RZ} \cdot \mathbf{i} = \mathbf{0}$$

$$\beta_{RTZ} \cdot \mathbf{i} = \mathbf{0}$$

$$\beta_{TZ} \cdot \mathbf{i} = \mathbf{0}$$

$$\beta_{QZ} \cdot \mathbf{i} = \mathbf{0}$$

$$\beta_{QZ} = \mathbf{0}$$

$$\alpha_Q = \mathbf{1}$$

where \mathbf{i} is a vector of ones.

We anticipate that the firms in our sample exhibit fixed effects that may be correlated with some of the variables of interest. 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 they are simultaneously able to effectively use 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 capital intensity, then we would expect the set of

⁷ Annual technology development expenditures are made up of capital, labor, energy and materials expenditures designated for technology development activities.

⁸ Estimating a system consisting of the cost function and the associated cost share equations rather than only estimating the cost function increases the estimation efficiency.

coefficients on capital and its interactive terms to suffer from downward bias, i.e. capital would appear to create more cost-saving efficiencies than it actually does.

To remedy this 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. This expectation, however, is conditional on one further condition; that is the absence of measurement error. We anticipate that measurement error is indeed 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. Moreover, prices are exceedingly difficult to measure, since we either use proxies or prices that are derived from other variables (i.e., values and quantities) that may also be subject to measurement error. In principle, instrumental variables should be able to address both the fixed effects problem and the problem of measurement error. Lacking a suitable set of instrumental variables, we rely on the fixed effects estimator to minimize the problem of upward bias associated with endogeneity.

Results

Table 1 presents two sets of estimation results – columns (1) through (3) pool the data; 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 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), internal 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 technology development. In columns (2) and (3), we also see that the estimates of the neutral effects of R&D and imported technology 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 serves a specific purpose. All three include the neutral effects of the two forms of deliberate technical change – internal 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, indicates 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 internal R&D and imported R&D have negligible and virtually identical impacts on unit cost is somewhat at odds with our expectations.

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 internal R&D (α_{Rint}) becomes significantly cost saving, whereas imported technology (α_{Rimp}) is consistently cost increasing. The neutral effect of the interaction of internal R&D and imported technology

$(\alpha_{\text{Rint-Rimp}})$ is negligible in column (5). We also see from Column (5) that internal R&D is robustly labor and material using and energy saving ($\beta_{\text{Rint-L}}, \beta_{\text{Rint-E}}, \beta_{\text{Rint-M}}$). While imported technology is also energy saving ($\beta_{\text{Rimp-E}}$), it exhibits a capital using bias ($\beta_{\text{Rimp-K}}$). 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 internal R&D and imported technology ($\beta_{\text{Rint-Rimp-K}}, \beta_{\text{Rint-Rimp-L}}, \beta_{\text{Rint-Rimp-E}}, \beta_{\text{Rint-Rimp-M}}$). 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 internal 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 ($\beta_{01-K}, \beta_{01-L}, \beta_{01-E}, \beta_{01-M}$). 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.⁹

Deliberate technical change tells a different story in which internal R&D continues to be labor using (β_{Rint-L}) and energy saving (β_{Rint-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 (β_{01-K}), internal 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 (β_{Rint-K}) and more labor using (β_{Rint-L}). Moreover, it seems that a purpose of R&D is not to expand value added ratios, rather to facilitate outsourcing, as evident from the material using bias of internal R&D (β_{Rint-M}). The insignificance of the interactions of the internal factor bias terms with time ($\beta_{Rint-K-01}$, $\beta_{Rint-L-01}$, $\beta_{Rint-E-01}$, $\beta_{Rint-M-01}$) indicates that this pattern of R&D factor bias has been stable over 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 (β_{Rimp-K} , β_{Rimp-E}), shown in column (5), reinforced with the addition of autonomous factor biased technical change, but the labor-saving bias of imported technology (β_{Rimp-L}), comes into play. Unlike the pattern of internal 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 ($\beta_{Rimp-L-01}$, $\beta_{Rimp-E-01}$), the bias for materials changes from being neutral in 1997 (β_{Rimp-M}) to robustly saving in 2001 ($\beta_{Rimp-M-01}$).

Our results in column (6) show that the energy-saving bias of internal R&D and imported technology are similar in 1997 (β_{Rint-E} , β_{Rimp-E}). While the energy-saving bias of internal R&D remains stable during 1997 to 2001 (comparing β_{Rint-E} and $\beta_{Rint-E-01}$), imported R&D becomes less

⁹ 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 supply, to ensure the capital-deepening, labor augmenting outcome, we require that technical change be capital-biased.

energy saving (comparing β_{Rimp-E} and $\beta_{Rimp-E:01}$).¹⁰ One reason for the growing division between internal R&D and imported technology may have been the relative increase in energy prices within China, particularly in relation to material prices, as shown in Table A.5. 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 ($\beta_{Rint-Rimp-K}$). 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, causing internal R&D to dampen nearly two-thirds (62%) of the capital using bias 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.

Table 1
Neutral and Factor Biased of Technological Change

	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)
$\alpha_{Rint-Rimp}$	-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						
β_{01-K}	--	--	-0.010 (0.009)	--	--	0.013** (0.005)
β_{01-L}	--	--	0.006 (0.006)	--	--	-0.003 (0.005)
β_{01-E}	--	--	-0.001 (0.011)	--	--	0.008 (0.007)
β_{01-M}	--	--	0.006	--	--	-0.018**

¹⁰ 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.

			(0.012)			(0.008)
β_{Rint-K}	--	0.001*** (0.000)	-0.012*** (0.001)	--	0.000 (0.000)	-0.006*** (0.000)
β_{Rint-L}	--	0.003*** (0.000)	0.000 (0.001)	--	0.003*** (0.000)	0.003*** (0.001)
β_{Rint-E}	--	-0.003*** (0.001)	-0.004*** (0.001)	--	-0.004*** (0.001)	-0.004*** (0.001)
β_{Rint-M}	--	-0.001 (0.001)	0.016*** (0.001)	--	0.001** (0.001)	0.007*** (0.001)
β_{Rimp-K}	--	0.002** (0.001)	0.003** (0.001)	--	0.002** (0.001)	0.003*** (0.001)
β_{Rimp-L}	--	0.001 (0.000)	-0.000 (0.001)	--	-0.000 (0.001)	-0.002** (0.001)
β_{Rimp-E}	--	0.001 (0.001)	-0.001 (0.002)	--	-0.002** (0.001)	-0.003** (0.001)
β_{Rimp-M}	--	-0.004** (0.002)	-0.002 (0.002)	--	0.001 (0.001)	0.001 (0.001)
$\beta_{Rint-Rimp-K}$	--	-0.000 (0.000)	-0.000 (0.000)	--	0.000 (0.000)	-0.000** (0.000)
$\beta_{Rint-Rimp-L}$	--	-0.000* (0.000)	-0.000* (0.000)	--	-0.000 (0.000)	-0.000 (0.000)
$\beta_{Rint-Rimp-E}$	--	-0.000 (0.000)	0.000 (0.000)	--	-0.000 (0.000)	-0.000 (0.000)
$\beta_{Rint-Rimp-M}$	--	0.000 (0.000)	0.000* (0.000)	--	0.000 (0.000)	0.000** (0.000)
$\beta_{Rint-01}$	--	--	0.008* (0.005)	--	--	0.001 (0.003)
$\beta_{Rint-K-01}$	--	--	0.002* (0.001)	--	--	-0.000 (0.001)
$\beta_{Rint-L-01}$	--	--	-0.001 (0.000)	--	--	-0.001 (0.001)
$\beta_{Rint-E-01}$	--	--	0.001 (0.002)	--	--	-0.000 (0.001)
$\beta_{Rint-M-01}$	--	--	-0.002 (0.002)	--	--	0.001 (0.001)
$\beta_{Rimp-01}$	--	--	-0.004 (0.004)	--	--	-0.003 (0.003)
$\beta_{Rimp-K-01}$	--	--	-0.001 (0.001)	--	--	0.000 (0.001)
$\beta_{Rimp-L-01}$	--	--	0.000 (0.000)	--	--	0.001* (0.001)
$\beta_{Rimp-E-01}$	--	--	0.001 (0.002)	--	--	0.002* (0.001)
$\beta_{Rimp-M-01}$	--	--	-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.

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. We associate autonomous technical change largely with exogenous increases in the efficiency of available capital.

2. Both internal R&D and imported technology exhibit significant neutral impacts on cost. The former reduces cost, whereas the latter raises cost.
3. The factor bias of internal R&D is consistent with China's comparative factor endowment. Internal R&D is robustly capital and energy-saving and labor and materials-using. These biases are consistent with a shift toward China's comparative advantage.
4. The factor bias of imported technology, likewise, is generally consistent with our prior expectations regarding the factor endowment of the OECD economies. Imported technology is robustly capital using; its materials saving bias grows over time.
5. The application of internal R&D to imported technology serves to dampen the capital using bias of foreign technology transfer.

VI. Interpretation

Our model and empirical results identify three distinct patterns of non-neutral factor bias in the technical change that shapes 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. During the period 1997 to 2001, the capital-labor ratio within our sample of firms rose by nearly one-half. Our estimation results show that the principal driver of this capital deepening is autonomous technical change. We interpret this capital deepening phenomenon as resulting from increases in the availability of increasingly efficient vintages of capital. As capital's efficiency rose about its rental cost, firms expanded their investment in capital, thereby promoting capital deepening. Capital deepening, in turn, raised labor productivity. In the neoclassical model, capital deepening leads to labor augmentation. Since 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. The growth of labor supply is unchanged.

If the supply of labor were inelastic in the Chinese economy, technical change would be exclusively labor augmenting. This is not the case, however, at the firm level in a developing economy with an abundant supply of surplus labor. In China's industrial sector, we expect the supply of labor to be highly elastic. Capital deepening in the firm causes its labor productivity to rise above the prevailing wage. In the face of wage increases that are tempered by labor mobility or, in China, the layoff of millions of state workers in the later 1990s, rising labor productivity motivates firms to wish to hire in more labor. In order to effectively absorb labor, however, firms may need to focus their R&D energies on labor-using technical change that increases the quantities of labor that can be mixed with new vintages of the capital stock. In this version of the neoclassical growth model with an abundance of labor, rising wages do not motivate labor-saving R&D as predicted by the Hicks-Ahmad account of the factor bias of technical change. Rather than rising wages motivating labor saving innovation in the face of a fixed supply of labor, increases in labor productivity relative to wages motivate labor using technical change, which enables the firm to hire in more workers, thereby moderating the wage.

In addition to on-going capital deepening that reflects the process of neoclassical growth, China has been engaged in an economic transition from a system of socialist ownership and central planning to an incentivized, market oriented economy. From 1950 through the late 1970s, China's government emphasized a capital-intensive pattern of industrial development through a system of price controls and centralized resource allocation that effectively subsidized capital and energy. China's major industrial producers were uniformly state owned. Beginning in the early 1980s, albeit generally slowly and fitfully, Chinese industry by the turn of the century with its entry into the WTO had achieved substantial price reform, trade liberalization, and reform of its system of corporate governance. During the 1990s, the confluence of these changes has motivated Chinese firms to exploit more aggressively the country's comparative advantage. We briefly examine these changes:

(i) Price reform. During the 1990s, the effective price of capital rose while subsidies to energy were substantially eliminated. During the latter half of the 1990s, a hardening of the budget constraint occurred through two channels. The first was that many enterprises were converted from state-owned enterprises to non-state-owned enterprises. As a result of their

conversion, while not completely shut off from access to subsidized capital, the newly converted enterprises enjoyed less access to government grants and to low-cost bank loans than their state-owned counterparts. Moreover, among the SOEs that survived, the furlough of large portions of their workforces facilitated a hardening of budget constraints while the approach of WTO accession led to efforts to put China's financial system on a more open and competitive footing. The 1990s in China also witnessed the liberalization of energy prices. With energy prices having been controlled through the era of central planning and into the 1980s, the relaxation of controls during the early half of the decade led to substantial energy price adjustments. According to Fridley, Sinton, and Lewis (2003), "By the mid-1990s, fuel prices had risen significantly, in most cases to world levels, providing firms price signals encouraging efficiency" (p. 3).

(ii) Liberalization. From the outset of China's reforms, China's industrial landscape was transformed by the entry of new firms outside the state sector. These included township and village enterprises (TVEs), foreign joint ventures and then wholly owned foreign firms, and individual enterprises. From the 1980s, this surge of new firm formation dramatically increased competition and reduced profit margins across Chinese industry.¹¹ Over the same period, China also implemented a gradual reform of its trading system as tariffs and export subsidies were cut; this process of trade liberalization accelerated in the late 1990s as China prepared for its ascension to the World Trade Organization. Growing international competition, which is intense in most sectors of the industrial economy, has forced companies to aggressively engage in cost-cutting innovations.

(iii) Governance reform. In principle, firms should seek to cost-minimize by exploiting the country's comparative advantage irrespective of the degree of competition. Where Chinese enterprises were substantially state-owned, this was not necessarily the case. To understand the implications of enterprise reform in China, we enlist the Nelson-Winter evolutionary model (1982) in which the firm's search for new technology is set in motion when certain decision rules are violated, say when profits fall below a certain level. During the 1990s, not only were acceptable profit thresholds violated, but enterprise reform accelerated the replacement of lax rules with efficiency-based rules.

Within the population of LMEs, for example, the proportion of state-owned enterprises declined from 63 percent in 1995 to just 38 percent in 2001. Using a sample of enterprises that is

¹¹ See Naughton (1992).

drawn from the same population of LMEs from which our energy data set is drawn, Jefferson and Su (2004) analyze the impact of the conversion of state-owned enterprises to shareholding enterprises during the period 1996-2001. A key result of their study is that relative to the unconverted SOEs, the converted enterprises shift to significantly less capital-intensive production techniques. The introduction of these less capital intensive techniques substantially increased returns to capital.

The combined effect of these transitional changes – price reform, trade liberalization, and governance reform – has been to motivate Chinese firms to exploit their comparative advantage. Internal R&D has been the principal means through which firms have developed the process innovations that have led to the design and implementation of the factor-biased techniques that are serving to exploit China’s comparative advantage. Applying the standard models of neoclassical and endogenous growth to the Chinese economy in the midst of the current transition toward its comparative advantage as compared with the application of these models, say in a decade or two after the transition is completed should result in different patterns of observed factor biases in technical change. While we expect to find a robust pattern of capital using technical change, we should also expect to find conditions that suggest the use of “appropriate technologies” for China in relation to its comparative advantage.

Relative function 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, internal 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 excessive vertical integration resulting from the breakdown of markets during the era of central planning have been replaced by vibrant domestic markets and deepening foreign trade.

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 internal 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 focuses on cost reduction, which requires that technologies are developed and used to embody a factor mix that is aligned with the relevant country 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 internal 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.,

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

where

$$\begin{aligned} f(\Delta \ln R_{int}) = & \alpha_{Rint} \Delta(\ln R_{int}) + \beta_{Rint*K} \Delta(\ln R_{int} * \ln P_K) + \beta_{Rint*L} \Delta(\ln R_{int} * \ln P_L) \\ & + \beta_{Rint*E} \Delta(\ln R_{int} * \ln P_E) + \beta_{Rint*M} \Delta(\ln R_{int} * \ln P_M) + \beta_{Rint*2001} \Delta(\ln R_{int}) \\ & + \beta_{Rint*K*2001} \Delta(\ln R_{int} * \ln P_K) + \beta_{Rint*L*2001} \Delta(\ln R_{int} * \ln P_L) \\ & + \beta_{Rint*E*2001} \Delta(\ln R_{int} * \ln P_E) + \beta_{Rint*M*2001} \Delta(\ln R_{int} * \ln P_M) \\ g(\Delta \ln R_{imp}) = & \alpha_{Rimp} \Delta(\ln R_{imp}) + \beta_{Rimp*K} \Delta(\ln R_{imp} * \ln P_K) + \beta_{Rimp*L} \Delta(\ln R_{imp} * \ln P_L) \\ & + \beta_{Rimp*E} \Delta(\ln R_{imp} * \ln P_E) + \beta_{Rimp*M} \Delta(\ln R_{imp} * \ln P_M) \end{aligned}$$

$$\begin{aligned}
& + \beta_{R_{imp} * 2001} \Delta(\ln R_{imp}) + \beta_{R_{imp} * K * 2001} \Delta(\ln R_{imp} * \ln P_K) \\
& + \beta_{R_{imp} * L * 2001} \Delta(\ln R_{imp} * \ln P_L) + \beta_{R_{imp} * E * 2001} \Delta(\ln R_{imp} * \ln P_E) \\
& + \beta_{R_{imp} * M * 2001} \Delta(\ln R_{imp} * \ln P_M) \\
h(\Delta \ln R_{int} * R_{imp}) & = \alpha_{R_{int} * R_{imp}} \Delta(\ln R_{int} * \ln R_{imp}) + \beta_{R_{int} * R_{imp} * K} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_K) \\
& + \beta_{R_{int} * R_{imp} * L} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_L) \\
& + \beta_{R_{int} * R_{imp} * E} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_E) \\
& + \beta_{R_{int} * R_{imp} * M} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_M) + \beta_{R_{int} * R_{imp} * 2001} \Delta(\ln R_{int} * \ln R_{imp}) \\
& + \beta_{R_{int} * R_{imp} * K * 2001} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_K) \\
& + \beta_{R_{int} * R_{imp} * L * 2001} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_L) \\
& + \beta_{R_{int} * R_{imp} * E * 2001} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_E) \\
& + \beta_{R_{int} * R_{imp} * M * 2001} \Delta(\ln R_{int} * \ln R_{imp} * \ln P_M) \\
z(\Delta other) & = \text{change in other non-R\&D-related factors.}
\end{aligned}$$

The values of $f(\Delta \ln R_{int})$, $g(\Delta \ln R_{imp})$, $h(\Delta \ln R_{int} * R_{imp})$, converted to percent changes, are provided in the first row of Table 2, and show that the increase in internal R&D expenditures between 1997 and 2001 resulted in a negative overall impact on cost while the increase in imported technology had a positive impact on 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, which shows the impact on cost of internal R&D and imported technology from 1997 to 2001, increases in internal R&D reduced cost by 9.3 percent; increases in imported R&D raised cost by 0.3 percent; and 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 internal 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.

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

	Internal R&D	Imported tech.	Internal*Imported
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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.

The key results shown in Table 2 are that internal R&D is unambiguously cost reducing; foreign technology transfer is cost increasing. Factor bias, whether associated with internal 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.¹² 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 internal and imported R&D (normalized by total sales), year dummy variables for 1998-2001, and dummy variables representing different categories of firm ownership type and industry.¹³

¹²Due 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.

¹³Consistent 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 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.

Table 3
Determinants of New Product Development

	(a)	(b)	(c)	(d)
constant	-0.359*** (.017)	-0.365*** (.037)	-0.405*** (.038)	0.764*** (.064)
Internal 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
R²/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% level, *** Significant at the 1% level.

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 internal 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 internal 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 offer compelling evidence of why we observe firms employing technologies that embody different factor biases. Firms often simultaneously engage in multiple technology development activities. Internal 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; it is one which we believe exists in other developing economies that are in the process of integrating with the world economy. The puzzle is that although differences exist in patterns of factor bias across

different sources of technical change, we find, at least among Chinese firms, simultaneous expenditure of resources on these disparate forms of technical change.

Using a large panel of Chinese enterprises, we conclude based on our empirical results 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 internal 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 internal 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 foreign technology transfer perform distinct functions. Whereas internal 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 notably, Chinese firms employ the R&D resources to dampen the capital-using 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 identifiable, well-defined roles in the process of growth and development. Autonomous technical change is the transmission channel for neoclassical capital deepening. Internal 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 economy: exogenous, capital-biased technical change drives neoclassical growth; internal 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.

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 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 Population, Social, and Science and Technology Statistics (NBS, 2001b). These two data sets are combined with an energy data set that consists of both measures of 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.¹⁴

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 of from capital and labor to a full blown KLEM data set. To test the robustness the factor bias of various technology sources, we welcome the addition of five pair-wise factor relationships in 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

¹⁴ 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.

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. internal 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) Internal 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 4 show the distribution of technology development by internal 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 internal 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 internal and imported technology development spending. State-owned enterprises receive a much larger proportion of imported technology than non-state-owned enterprises, while internal 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	
		Internal*	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 ;

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

δ \equiv 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

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