

# What Will a Science and Technology Takeoff in China Mean for Energy Use and Carbon Emissions?<sup>1</sup>

Karen Fisher-Vanden<sup>2</sup>  
Dartmouth College

Mun S. Ho  
Resources for the Future

---

<sup>1</sup> This work was supported by the Office of Science (BER), U.S. Department of Energy, Grant no. DE-FG02-04ER63930 and the National Science Foundation (project/grant #450823).

<sup>2</sup> Corresponding author: Dartmouth College, 6182 Fairchild Hall, Hanover, NH 03755; phone: 603-646-0213; fax: 603-646-1682; email: [kfv@Dartmouth.edu](mailto:kfv@Dartmouth.edu).

# What Will a Science and Technology Takeoff in China Mean for Energy Use and Carbon Emissions?”

## ABSTRACT

In an attempt to move their economies up the value chain, many developing countries have emphasized improvements in their science and technology (S&T) capabilities. What could a science and technology takeoff in a developing country, however, mean for energy use and carbon emissions, a growing global concern? Some have argued for more technology development as a way to lower emissions in developing countries since the incorporation of new technologies will likely result in lower energy intensities at the firm level. However, an S&T takeoff will also shift the relative size of the energy intensive industries—i.e., structural change—and lead to higher economic growth and incomes which will result in a greater consumption of goods including energy. The net effect therefore is unclear. In this paper, we simulate the effects of an S&T takeoff on sectoral total factor productivity and energy intensity using a model of China that incorporates econometric estimates from 1500 industrial enterprises in China. We find that an S&T takeoff will lead to lower prices overall, but a larger drop in energy prices due to the energy-saving bias of R&D. The outcome is higher investment and economic growth; a substitution of energy for other factors of production; and greater energy consumption by households. Energy use and carbon emissions, therefore, are higher in an S&T takeoff scenario. Our findings underscore the importance of considering the economy-wide implications of a technology policy, recognizing that better technology does not necessarily imply a cleaner environment.

JEL Classification: O10, P21, D58, Q00

Keywords: China, carbon emissions, global climate change, computable general equilibrium, technological change.

## 1. Introduction

Increasing a developing country's science and technology (S&T) capability is often cited as an important factor for economic development (UNDP, 2001; Dahlman and Aubert, 2001; OECD, 2002). As discussed in Jefferson (2005), there is a marked difference in R&D intensities—defined as total annual R&D expenditures divided by GDP—among upper-, middle- and lower-income countries. By 1997, the R&D intensities of most higher-income countries exceeded two percent while the R&D intensities of lower-income countries averaged 0.7 percent (UNDP, 2001; Gao and Jefferson, 2005). Gao and Jefferson (2005) find that most lower-income countries transitioning to higher-income status experience an acceleration in R&D intensity—a “science and technology (S&T) takeoff.” Most S&T takeoffs occur within a decade—e.g., the U.S.'s R&D intensity grew rapidly from one to two percent within 10 years, while this change only took 5 years in South Korea (Gao and Jefferson, 2005).

Although China is still considered a lower-income country with a GDP per capita of \$1,150 in 2003 (\$4,980 in purchasing power parity (PPP) terms), China's R&D intensity has accelerated rapidly in recent years, from 0.6 in 1996 to 1.3 in 2003 (World Bank, 2006). This rapid acceleration has caused some to wonder whether China is currently experiencing an S&T takeoff (e.g., Jefferson, 2005). The prospect of an S&T takeoff is further supported by the Chinese government's recent campaign to move the Chinese economy up the value chain through improvements in China's innovation capabilities. The recent release of China's “National Medium- and Long-Term Programme for Scientific and Technological Development (2006-2020)” calls for dramatic increases in China's R&D spending as a percentage of GDP to levels similar to those of OECD countries (The Economist, 2006).

Given that countries like China are soon to be the largest source of global carbon emissions and currently face no limit on emissions, it is important to understand how a science and technology takeoff will affect energy use and carbon emissions in these countries. There are three channels through which this may occur. First, the incorporation of new technologies may alter the factor intensities of production; for instance, new technologies may be more or less energy intensive than current technologies. Second, a science and technology takeoff may lead to changes in relative output prices and hence changes in the allocation of capital and labor across industries, i.e., a structural change of the economy. If this shift results in a relative decline in the size of the energy intensive industries, then the overall energy intensity of the economy will fall. Lastly, a science and technology takeoff will likely lead to higher economic growth and income levels. This will result in an outward shift in the demand for energy, and a corresponding shift in carbon emissions. Whether a science and technology takeoff will lead to higher or lower energy use and carbon emissions on net, therefore, depends on the relative contribution of each of these channels.

In this paper, we examine this question using a model of China that explicitly allows for all three effects. In our dynamic computable general equilibrium (CGE) model, R&D spending in the current period leads to both higher productivity and shifts in factor intensities in future periods. This model is also multi-sectoral, allowing us to trace how future prices, relative output levels, and the allocation of capital and labor are affected by investment in R&D at the industry level.

We parameterize the effects of R&D in the model using econometric results based on Fisher-Vanden and Jefferson (2006). Using a data set consisting of approximately 1500 Chinese industrial enterprises, we estimate industry cost functions that allow for “deliberate” technical

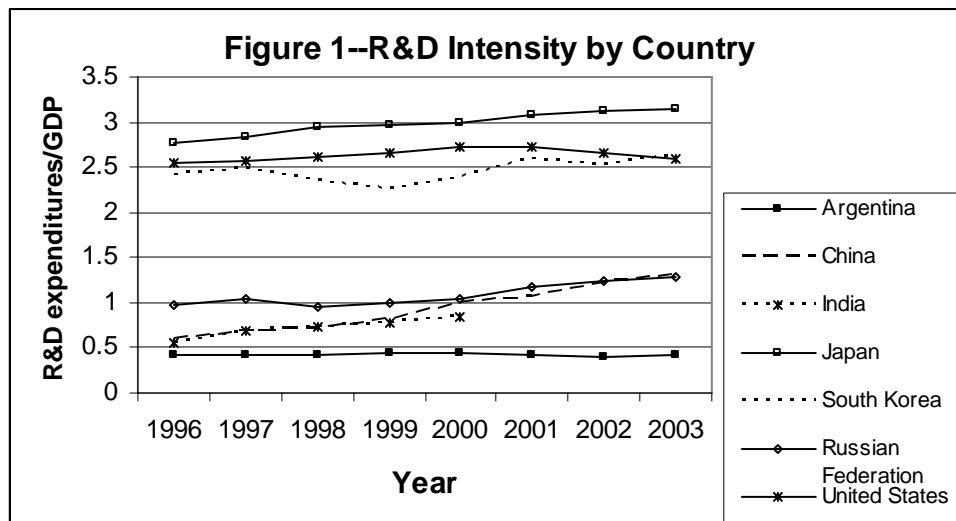
change (i.e., the cumulative effects of previous R&D activities) and “autonomous” technical change (i.e., the cumulative effects of time captured in the usual Solow residual). These functions also allow for factor-biased technical change; for example, changes in the capital:labor ratio over time due to autonomous or deliberate technical change rather than changes in input prices.

Our simulation results show that a science and technology takeoff in China will result in lower prices overall relative to wages, but a much larger drop in energy prices due to the energy-saving bias of R&D. These changes lead to higher investment and economic growth; a substitution of energy for other factors of production; and greater energy consumption by households. The net effect is higher energy use and carbon emissions than if no S&T takeoff occurred.

The paper is organized as follows. Section 2 provides an overview of the science and technology story in China. Section 3 describes the numerical model including an overview of the econometric results that were incorporated in the CGE model of China and the adjustments made to account for changes in product quality. Section 4 presents the simulation results and Section 5 provides concluding remarks.

## 2. Background: Science and Technology Takeoff in China

Figure 1 below provides the R&D intensities of seven selected countries over the period 1996-2003 from World Bank (2006). As Gao and Jefferson (2005) have pointed out, there is a stark demarcation between the R&D intensities of the lower-income countries (e.g., China, India, Argentina) and the higher-income countries (e.g., Japan, South Korea, U.S.). Although the R&D intensities of most countries have stayed flat over this time period, the R&D intensity of China has risen significantly, from 0.6 in 1996 to 1.3 in 2003. China's recently released "National Medium- and Long-Term Programme for Scientific and Technological Development (2006-2020)" sets a R&D intensity goal of 2.5% by 2020, a level similar to that of the higher-income countries shown in Figure 1.<sup>3</sup>



Source: World Bank, 2006.

Historically, R&D activities in China have occurred primarily in government-run R&D institutes; however, this has changed dramatically in recent years as these institutes have been forced to seek non-governmental funding and R&D efforts have shifted to the enterprises

themselves. As shown in Table 1, the shift from government institutes to enterprises as the main source of R&D expenditures has been quite rapid, with the share from enterprises rising from 32% in 1994 to 49% in 1999.

**Table 1**  
**R&D Expenditures by Performing Organizations in China, 1994-1999**

	1994	1996	1998	1999
<b>Government R&amp;D institutes</b>	43.2%	41.1%	42.6%	38.5%
<b>Universities and colleges</b>	14.5%	13.0%	10.4%	9.3%
<b>Enterprises</b>	32.4%	36.8%	44.8%	49.5%
<b>Others</b>	9.9%	9.1%	2.2%	2.6%
<b>Total</b>	100%	100%	100%	100%

Source: Dahlman and Aubert, 2001

Although this sectoral breakdown of R&D expenditures in China is changing over time, it still differs significantly from the situation in countries like the U.S. where approximately 75% of total R&D expenditures comes from enterprises, 10% from government, and 15% from universities (OECD, 2002). A major focus of China's tenth five-year plan (covering 2001-2005) had been to reform the R&D system in anticipation of WTO entry with language targeting the technological upgrading of industry and the increasing role of universities in scientific research. Therefore, although R&D activities are increasingly being undertaken by the firms themselves, these activities are still the result of central government directives, as evidenced by the government's current campaign to significantly increase China's innovation capabilities nationally (The Economist, 2006).

---

<sup>3</sup> This is an ambitious target. Even if per capita income in China were to grow at 5% per year, per capita income will reach approximately US\$11,000 by 2020 in PPP terms, roughly the per capita income level of Argentina or Poland

It should be noted, however, that China's science and technology capabilities are not spread uniformly across the country. As discussed in Dahlman and Aubert (2001), nine administrative regions out of 31 comprise 74% of national R&D expenditures in 1999. Although this is partly explained by differences in regional GDP, cities like Beijing have benefited immensely from governmental efforts to make the city a national science and technology center.

What might an S&T takeoff mean for China? First, we expect that an acceleration of R&D will lead to greater efficiency and higher economic growth. Hu and Jefferson (2004) and Hu et al (forthcoming) in their studies of China's industrial enterprises find that the accumulation of R&D has a strong positive effect on a firm's productivity and profitability. In this case, the income effect from higher productivity will lead to higher energy use and carbon emissions in China. We also expect an increase in China's R&D intensity will lead to a shift in the factor composition of production. Fisher-Vanden and Jefferson (2006) find that domestic R&D generate changes that tend to be labor-using and capital- and energy-saving, consistent with China's comparative advantage. Therefore, we expect that an increase in China's R&D intensity will shift production to be more labor-intensive and less capital- and energy-intensive (and thus less carbon-intensive). Lastly, we expect an S&T takeoff will lead to a shift in the industry composition of total output and employment —i.e., structural change. Industries engaged in relatively more R&D activities will experience greater total factor productivity growth which, in a competitive economy, leads to lower output prices. Lower output prices should result in output growth that is higher in the industries with larger R&D activities. Depending upon which industries are more engaged in R&D activities—energy-intensive industries versus less energy-intensive industries—China's energy- and carbon-intensity may be higher or lower.

---

currently.

China is currently the second largest emitter of carbon and is predicted to surpass the largest emitter, the U.S., by 2020 (USDOE/EIA, 2006). This, coupled with the fact that China currently faces no limit on emissions under the Kyoto Protocol, means that China's future emissions will likely be a serious contributor to global greenhouse gas emissions. Depending upon which effect of a science and technology takeoff dominates—energy efficiency gains, higher incomes, or shifts in industry composition—a science and technology takeoff may raise or lower China's future emissions trajectory. To assess what an acceleration of R&D means for energy use and carbon emissions in China, we develop a model of China that explicitly represents each of these three effects of R&D.

### **3. An Economic-Energy Model of China**

#### **3.1. Model Overview**

To simulate the effects of a science and technology takeoff in China on energy use and carbon emissions, we develop a model of the Chinese economy that explicitly includes the neutral and factor-bias effects of R&D. The model used in this analysis is a dynamic recursive computable general equilibrium (CGE) model where the complex interactions between the four economic agents—producers, households, government and the foreign sector—lead to changes in investment and productivity growth. On the production side there are 33 sectors consisting of agriculture, 6 energy sectors, 17 nonenergy manufacturing sectors, construction, transportation, and seven service sectors (see Table A-1). The inter-industry structure of the model allows both direct and indirect effects of policy to be captured. Output in the 33 industries is produced assuming constant returns to scale production technology and profit maximization.

Household demand of each of the 33 commodities is determined by utility maximization, where household income is derived from labor income, capital income and transfers. As in the Solow growth model, the household savings rate is set exogenously. The government sector collects taxes, allocates subsidized capital, purchases goods and services, and redistributes resources. The foreign sector is modeled using the standard one-country Armington approach. Carbon emissions are estimated in the model based on the amount and type of fossil fuel consumed by each of the three domestic economic actors.

The primary source of data for the construction of model parameters is a social accounting matrix (SAM) constructed using the official 1997 input-output tables for China, and supplemented by data on government finances, trade, labor and energy. Further details on the model structure, parameter construction, and data sources are provided in Appendix A. In the

remainder of this section, we highlight the features of the model that allow for the neutral and factor-biased effects of R&D to be represented.

Output of industry  $j$  at time  $t$  ( $QO_{j,t}$ ) is represented by the following Cobb-Douglas production function:

$$QO_{j,t} = A(t, R_{j,t}) KD_{j,t}^{\alpha_{K,j,t}} LD_{j,t}^{\alpha_{L,j,t}} TD_{j,t}^{\alpha_{T,j,t}} E_{j,t}^{\alpha_{E,j,t}} M_{j,t}^{\alpha_{M,j,t}} \quad (1)$$

where  $KD_{j,t}$ ,  $LD_{j,t}$ ,  $TD_{j,t}$ ,  $E_{j,t}$  and  $M_{j,t}$  are the capital, labor, land, energy, and non-energy material inputs, respectively, of industry  $j$  at time  $t$ . The parameters  $\alpha_{K,j,t}$ ,  $\alpha_{L,j,t}$ ,  $\alpha_{T,j,t}$ ,  $\alpha_{E,j,t}$  and  $\alpha_{M,j,t}$  are the value shares of capital input, labor input, land input, energy input, and non-energy material input, respectively.  $A(t, R_{j,t})$  is the neutral productivity term which is dependent on time and the R&D stock of industry  $j$  at time  $t$ .

Autonomous and deliberate technical change affect production by altering the input value share parameters,  $\alpha_{X,j,t}$ , and the  $A(t, R_{j,t})$  term which captures the neutral effect of technical change. In our model, with constant returns to scale and perfect competition, we incorporate these effects of technical change into the zero profit equation which equates output price ( $PO_{j,t}$ ) with the unit cost dual of the production function in (1):

$$\ln PO_{j,t} = \alpha_{K,j,t} \ln PK_t + \alpha_{L,j,t} \ln PL_t + \alpha_{T,j,t} \ln PT_t + \alpha_{E,j,t} \ln PE_t + \alpha_{M,j,t} \ln PM_t + g(t, R_{j,t}) \quad (2)$$

where  $PX_t$  is the price of input  $X$  at time  $t$ ,  $X=K,L,T,E,M$  and  $g(t, R_{j,t})$  represents neutral productivity change, i.e. the change in unit cost due to autonomous and deliberate technical progress.

We assume that this neutral impact of autonomous and deliberate technology development on costs in industry  $j$  may be written as:

$$g(h_b, R_{j,t}) = \gamma_{A,j} h_t + \gamma_{R,j} R_{j,t} \quad (2a)$$

where

$\gamma_{A,j} \equiv$  neutral productivity effect of autonomous technology development ;

$h_t \equiv$  index of autonomous technology development;

$\gamma_{R,j} \equiv$  neutral productivity effect of deliberate technology development ; and

$R_{j,t} \equiv$  index of the stock of deliberate technology development in industry  $j$  at time  $t$ .<sup>4</sup>

We also build into the model the effects of technology development on factor use in production. By altering the input share parameters ( $\alpha$ ), which are typically set exogenously in most models, autonomous and deliberate technical change have factor bias effects on production. The input share parameters, therefore, are defined as the following functions of autonomous and deliberate technical change:

$$\alpha_{Z,j,t} = \alpha_{Z,j,0} + \beta_{A,Z,j} * h_t + \beta_{R,Z,j} * R_{j,t} \quad \text{where } Z= K,L,T,E,M. \quad (2b)$$

This equation implies that the value share of factor  $Z$  at time  $t$  is equal to the value share in the base year, plus adjustments attributable to autonomous and deliberate technical change.

### 3.2. Econometric estimation of R&D parameters

The model requires a number of parameters, most of which are determined through calibration as discussed in the appendix (Section A.7). The R&D parameters given in equations (2a) and (2b), however, were acquired through econometric estimation. Following Fisher-Vanden and Jefferson (2006), we employ a firm-level data set of ~1500 industrial enterprises in China over the years 1995-2001 to measure the factor bias of autonomous and deliberate technology development activities by estimating a translog cost function for each industry  $j$  with prices, an index of R&D stock (representing deliberate technical change) and an index of time

---

<sup>4</sup> The model is calibrated to the 1997 input-output table which is chosen as the base year. The cost function in (2) is normalized such that  $g(h_t, R_{j,t})$  is zero in the base year and the input shares at  $t=1997$  are set to the value shares found in the 1997 benchmark IO table. The  $g(h_t, R_{j,t})$  term in subsequent years reflects the effects of the *change* in the autonomous and deliberate technology development stocks between years.

(representing autonomous technical change) on the right-hand side.<sup>5</sup> In a manner similar to the cost equation included in the model (i.e., equation (2)), the total cost of producing output  $QO$  for enterprise  $i$  in industry  $j$  at time  $t$  is represented as:<sup>6</sup>

$$\ln TC_{i,j,t} = \alpha_{0,j} + \alpha_{1,i,j} + A(h_t, R_{i,j,t}) + \alpha'_{z,j,0} \cdot \ln Z_{i,j,t} + \alpha_{Q,j} \cdot \ln Q_{i,j,t} + B(h_t, R_{i,j,t}, Z_{i,j,t}) + \frac{1}{2} \cdot \ln Z_{i,j,t}' \cdot \beta_{ZZ,j} \cdot \ln Z_{i,j,t} + \ln Q_{i,j,t} \cdot \beta'_{QZ,j} \cdot \ln Z_{i,j,t} + \varepsilon_{Q} \quad (3)$$

where

$$A(h_t, R_{i,j,t}) = \gamma_{A,j} \cdot h_t + \gamma_{R,j} \cdot \ln R_{i,j,t} \text{ (similar to model equation (2a))}$$

$$\ln Z_{i,j,t}' = (\ln PK_{i,j,t}, \ln PL_{i,j,t}, \ln PE_{i,j,t}, \ln PM_{i,j,t}), \text{ (vector of input prices as in equation (2))}$$

$$\alpha'_z = (\alpha_{K,j,0}, \alpha_{L,j,0}, \alpha_{E,j,0}, \alpha_{M,j,0}) \text{ (similar to the intercept term in equation (2b))}$$

$$B(h_t, R_{i,j,t}, Z_{i,j,t}) = h_t \cdot \beta_{A,Z,j} \cdot \ln Z_{i,j,t} + \ln R_{i,j,t} \cdot \beta_{R,Z,j} \cdot \ln Z_{i,j,t} \text{ (corresponding to the technical change components in equation (2b))}$$

$h_t$  = time trend

$R_{i,j,t} \equiv$  enterprise  $i$ 's stock of deliberate technology in industry  $j$  at time  $t$ ; proxied by cumulated R&D expenditures,

$Q_{i,j,t} \equiv$  gross value of industrial output (in constant prices) of enterprise  $i$  in industry  $j$  at time  $t$ ,

$PK_{i,j,t} \equiv$  enterprise  $i$ 's price of capital input; calculated as (value added - wage bill - welfare payments)/(net value fixed assets),

$PL_{i,j,t} \equiv$  enterprise  $i$ 's price of labor; calculated as (wage bill + welfare payments) / employment,

$PE_{i,j,t} \equiv$  enterprise  $i$ 's price of aggregate energy; calculated as (energy expenditures)/(quantity of energy purchased in standard coal equivalent (SCE)),<sup>7</sup>

<sup>5</sup> Autonomous technology development refers to the effects of time whereas deliberate technology development refers to the effects of technology development activities represented by expenditures on technology development. See Fisher-Vanden and Jefferson (2006) for further details on the econometric estimation.

<sup>6</sup> Unlike model equation (2), this estimation equation does not include the price of land, PT, due to the lack of data.

$PM_{i,j,t}$   $\equiv$  enterprise  $i$ 's price of materials; set as the price deflator for gross value of industrial output.<sup>8</sup>

The function  $A(h_t, R_{i,j,t})$  in equation (3) represents the neutral productivity effects of deliberate technology development ( $R_{i,j,t}$ ) and autonomous technology development ( $h_t$ ), where  $\gamma_{A,j}$  and  $\gamma_{R,j}$  correspond to the neutral productivity parameters used in model equation (2a). The function  $B(R, T, Z)$  represents the factor-bias of deliberate and autonomous technical change, where  $\beta_{A,z,j}$  and  $\beta_{R,z,j}$  correspond to the parameters used in model equation (2b). Similar to other studies, we use the translog form of the cost function since it provides linear share equations derived from first-order conditions that can be estimated together with equation (3) to identify the technology parameters used in the model. The estimation equation includes enterprise dummy variables to control for enterprise fixed effects and is estimated for each industry to acquire the industry-specific technology parameters required by the model.

Tables 2 and 3 provide the econometric results from this exercise. Table 2 shows the neutral and factor-bias effects of deliberate technology development by industry. Deliberate technology development exhibits an energy-saving bias for all industries except for food, petroleum, and electric power. However, in many cases, the neutral effect of deliberate technology development is positive, seeming to suggest that increasing technology development will increase unit cost; that is, a decrease in total factor productivity. Under what conditions would technology development lead to higher cost?

In general, a firm will choose to engage in R&D if marginal profit is positive, i.e. if

$\frac{\partial \pi}{\partial R} > 0$ , where  $\pi$  is unit profit and  $R$  is R&D expenditures.<sup>9</sup> Unit profit, when constant returns

---

<sup>7</sup> This aggregate energy value is the sum of coal, oil, gas and electricity consumed (in value terms and in SCE).

to scale is assumed, is output price minus unit cost,  $P_Q - C$ ; therefore,  $\frac{\partial \pi}{\partial R} = \frac{\partial P_Q}{\partial R} - \frac{\partial C}{\partial R}$ . From

this, we see that the firm will choose the technology if (a) it lowers cost 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, high enough to offset the higher cost of production.<sup>10</sup>

**Table 2**  
**Neutral and factor-biased effects of deliberate technology development**  
**(by industry  $j$ )**

	Neutral effect on cost ( $\gamma_{R,j}$ )	Factor-bias			
		Capital ( $\beta_{R,K,j}$ )	Labor ( $\beta_{R,L,j}$ )	Energy ( $\beta_{R,E,j}$ )	Material ( $\beta_{R,M,j}$ )
<b>Mining</b>	.010**	.004***	-.004***	-.005***	.005***
<b>Food</b>	.005**	.004***	.001	.002***	-.006***
<b>Textile</b>	-.007***	.003***	.005***	-.001*	-.006***
<b>Paper</b>	.012***	.004***	-.002***	-.001	-.001
<b>Petroleum</b>	.036***	.005	-.003**	.011**	-.013***
<b>Chemicals</b>	-.004*	.000	.001***	-.004***	.003***
<b>Rubber</b>	.003	.001	-.002	-.0004	.001
<b>Nonmetal</b>	-.003	.003***	.001***	-.005***	.001
<b>Metal</b>	-.005	.003***	-.0001	-.009***	.006***
<b>Machinery</b>	-.009***	-.003***	.002***	-.002***	.003***
<b>Electric power</b>	.028***	.005***	-.002***	.006***	-.010***
<b>Other industry</b>	.013**	.005***	-.001*	-.002	-.002

\* Significant at the 10% level, \*\* Significant at the 5% level, \*\*\*Significant at the 1% level.

For either of these purposes, cost-reducing process innovation or value-enhancing product development, the firm may employ new technology. One may say that “process

<sup>8</sup> Industrial output refers to manufacturing and mining. The price deflator for GVIO was used as a proxy for the price of materials since industrial goods account for the dominant share of non-energy intermediate input value (30-90% in the manufacturing industries).

<sup>9</sup> Strictly speaking, since the effects of R&D extend over many periods, profit or costs should be given in terms of discounted future profit and costs. For present purposes we may simply think of cost as current cost given by equation (3).

innovation” technologies are chosen based on their use of the cheaper, more abundant, input factor, thereby serving to raise profits by reducing costs, and “product innovation” technologies are 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” technology may reflect its intent to develop new products or improve the quality of existing products, both of which may command higher output prices. Fisher-Vanden and Jefferson (2006) have provided evidence of this in the case of imported technology. Using data on imported technology development expenditures and new product development, they find that China’s industrial enterprises seem to be importing technology for the purpose of new product development.

Table 2 shows that the mining, food, paper, petroleum, electric power, and other industry sectors exhibit a positive neutral effect of deliberate technology development on cost. In each case, a story of technology development targeting quality improvements or new product development can be told. For instance, certain sectors are increasingly requiring higher quality materials from the mining, paper and petroleum sectors to produce newer and higher quality products downstream. Furthermore, as incomes rise, Chinese consumers are increasingly demanding newer and higher quality products from the food sector and the electric power sector is seeking to improve the quality of delivered electric power and pollution control.

Table 3 provides the neutral and factor-biased effects of autonomous technology development. Unlike the effects of deliberate technology development, autonomous technology development has few significant factor-bias effects. Autonomous technology development

---

<sup>10</sup> This is the “price effect” that together with the “market size effect” drives the composition of technology in Acemoglu’s model (2002).

primarily exhibits neutral effects on cost. In most cases, autonomous technology development exhibits a negative effect on cost, suggesting significant improvements in efficiency over time.

**Table 3**  
**Neutral and factor-biased effects of autonomous technology development (by industry)**

	Neutral effect on cost ( $\gamma_{A,j}$ )	Factor-bias			
		Capital ( $\beta_{A,K,j}$ )	Labor ( $\beta_{A,L,j}$ )	Energy ( $\beta_{A,E,j}$ )	Material ( $\beta_{A,M,j}$ )
<b>Mining</b>	-.001	.001	-.003	.004	-.002
<b>Food</b>	-.009*	-.002	.001	-.001	.003
<b>Textile</b>	-.018**	.003	.004**	.0004	-.007**
<b>Paper</b>	.006	-.003	-.007***	-.001	.010***
<b>Petroleum</b>	.002	.010	-.004	-.012	.006
<b>Chemicals</b>	-.005	.006***	-.001	.003	-.007***
<b>Rubber</b>	-.026**	.001	.004	-.004	-.0005
<b>Nonmetal</b>	-.008*	.0006	-.003***	.006***	-.004
<b>Metal</b>	-.029***	.001	.0008	-.001	-.0008
<b>Machinery</b>	-.026***	.002	.002	-.001	-.003
<b>Electric power</b>	-.047***	-.004	.0006	-.007*	.010**
<b>Other industry</b>	.054***	.005	.006**	.0003	-.011**

\* Significant at the 10% level, \*\* Significant at the 5% level, \*\*\*Significant at the 1% level.

In the next section we describe how high cost quality improvements are taken into account when we incorporate these econometric results into the model described in Section 3.1.

### 3.3. Accounting for changes in product quality<sup>11</sup>

As discussed in Section 3.2, our econometric results suggest that the neutral effect of technology development on unit cost may be positive in certain industries (i.e.,  $\gamma_{R,t} > 0$  and/or  $\gamma_{A,t} > 0$ ), likely reflecting an increase in unmeasured product quality. In this case, technology development would have the effect of increasing the output price when adjustments are not made to account for quality improvements. In this case, the cost function is mis-specified which would

lead to a fall in GDP when technology development increases. Given this, the model must allow for the case where technology development is being directed at new product development or improving product quality, cases that are not currently reflected in the price data. To do this, we must first distinguish between the effects of technology development on improving efficiency (which would result in a lower unit cost and thus a lower output price in the zero profit equation) and the effects of technology development on product quality (which would result in a higher unit cost and thus a higher price for a unit of mis-measured output).

Improving product quality can be thought of as increasing the product's "quality-adjusted" units. For example, in the case of computers, we would want to measure output in terms of, say, computing power rather than physical units. This implies that the quantity of output is higher after incorporating improvements in the quality of a physical unit of observed output. This would imply,

$$Q_{\text{qualadj}} = Q_{\text{observed}} * \exp(\eta_{\text{quality}})$$

That is, output measured in quality-adjusted units is greater than observed output quantity by an amount attributable to quality improvements. The value of output can be interpreted as follows,

$$P_{\text{observed}} * Q_{\text{observed}} = P_{\text{qualadj}} * Q_{\text{qualadj}}$$

where  $P_{\text{qualadj}}$  is the quality adjusted price.

This implies,

$$P_{\text{qualadj}} = P_{\text{observed}} * \exp(-\eta_{\text{quality}})$$

and, therefore,

$$\ln(P_{\text{qualadj}}) = \ln(P_{\text{observed}}) - \eta_{\text{quality}} \tag{4}$$

To compare across time periods in the model, we must hold the units of output constant. That is, we must adjust output prices to reflect output in quality-adjusted units. Our regression

---

<sup>11</sup> A detailed theoretical treatment of this modeling issue is provided in Fisher-Vanden and Sue Wing (2006).

results in Section 3.2, however, provide the effects of technology development on the observed price of output and not on the quality-adjusted price. The neutral productivity coefficients associated with autonomous and deliberate technology in the regression results,  $\gamma_{A,j}$  and  $\gamma_{R,j}$ , reflect the aggregation of effects on efficiency improvements and quality improvements. Using  $\gamma_{Ae,j}, \gamma_{Re,j}$  to denote the efficiency components and  $\gamma_{Aq,j}, \gamma_{Rq,j}$  the quality improvement components, we express this as:

$$\gamma_{A,j} * h_t = (\gamma_{Ae,j} + \gamma_{Aq,j}) * h_t \quad (5)$$

$$\gamma_{R,j} * R_{i,j,t} = (\gamma_{Re,j} + \gamma_{Rq,j}) * R_{i,j,t} \quad (6)$$

If technology development improves efficiency, then we assume the effect will be negative on the observed price of output; i.e., both  $\gamma_{Ae,j}$  and  $\gamma_{Re,j}$  will be negative. If technology development improves quality, however, we assume the effect will be positive on observed output; i.e., both  $\gamma_{Aq,j}$  and  $\gamma_{Rq,j}$  will be positive. That is, if the estimated  $\gamma_{A,j}$  coefficient is negative, we assume that the efficiency effect outweighs the quality effect,  $|\gamma_{Ae,j}| > \gamma_{Aq,j}$ . Similarly, a negative estimated  $\gamma_{R,j}$  for the effect of deliberate technology change implies  $|\gamma_{Re,j}| > \gamma_{Rq,j}$ . Conversely, a positive  $\gamma_{A,j}$  and  $\gamma_{R,j}$  regression result implies  $|\gamma_{Ae,j}| < \gamma_{Aq,j}$  and  $|\gamma_{Re,j}| < \gamma_{Rq,j}$ , respectively; i.e., the quality effect outweighs the efficiency effect.

Thus, in order to incorporate the econometric results, we need to assume that a positive neutral productivity growth is the result of pure efficiency improvements with zero quality improvements, and a negative neutral productivity growth is the result of quality improvements and zero efficiency improvements. These are clearly strong assumptions, but necessary since intermediate cases cannot be distinguished with the available data.

Although the regression results are in terms of observed prices, the model is in terms of quality-adjusted prices. To incorporate the econometric results into the model—i.e., to convert

from observed prices to quality-adjusted prices—we must assume that a positive effect on the observed price of output will have an equal negative effect on the quality-adjusted price, as implied by equation (4). Therefore, combining equations (4) and (3), we get the zero profit equation (i.e., equation (2)) in terms of the price of output in quality-adjusted units:

$$\ln PO_{j,t}^{qualadj} = \ln PO_{j,t} - \eta^{quality}$$

or,

$$\begin{aligned} \ln PO_{qual,j,t} &= \alpha_{K,j,t} \cdot \ln PK_t + \alpha_{L,j,t} \cdot \ln PL_t + \alpha_{T,j,t} \cdot \ln PT_t + \alpha_{E,j,t} \cdot \ln PE_t + \alpha_{M,j,t} \cdot \ln PM_t \\ &\quad + \gamma_{A,j}^{qualadj} \cdot h_t + \gamma_{R,j}^{qualadj} \cdot R_{j,t} \end{aligned}$$

where the technology terms are given by:

$$\gamma_{A,j}^{qualadj} \cdot h_t = \gamma_{Ae,j,t}^{qualadj} \cdot h_t - \gamma_{Aq,j,t}^{qualadj} \cdot h_t \quad (7)$$

$$\gamma_{R,j}^{qualadj} \cdot h_t = \gamma_{Re,j,t}^{qualadj} \cdot R_{j,t} - \gamma_{Rq,j,t}^{qualadj} \cdot R_{j,t} \quad (8)$$

We set the coefficients for the quality adjusted terms in equations (7) and (8) by implementing the above assumptions as:

$$\gamma_{A,j}^{qualadj} = -abs(\gamma_{A,j}) = -abs(\gamma_{Ae,j}) - abs(\gamma_{Aq,j}) = \gamma_{Ae,j}^{qualadj} - \gamma_{Aq,j}^{qualadj}$$

$$\gamma_{R,j}^{qualadj} = -abs(\gamma_{R,j}) = -abs(\gamma_{Re,j}) - abs(\gamma_{Rq,j}) = \gamma_{Re,j}^{qualadj} - \gamma_{Rq,j}^{qualadj}$$

where  $\gamma_{Ae,j,t}^{qualadj} < 0$ ,  $\gamma_{Re,j,t}^{qualadj} < 0$  and  $\gamma_{Aq,j,t}^{qualadj} > 0$ ,  $\gamma_{Rq,j,t}^{qualadj} > 0$ .

This implies that both improvements in efficiency and improvements in quality will have a negative effect on the quality-adjusted price of output in the model. This quality-adjusted zero profit equation is adopted in our model and is reflected in the simulation results below.

## 4. Simulation Results

To assess the impacts of an S&T takeoff on energy use and carbon emissions, we compare the results from a simulation with an S&T takeoff (“Takeoff”) to the results from a simulation where no S&T takeoff occurs (“No Takeoff”). We define an S&T takeoff as a rapid increase in R&D intensification over a short period of time.<sup>12</sup> To represent an S&T takeoff in the model, we parameterize the following logistic curve of R&D/GDP as a function of GDP per capita to approximate the trend in R&D intensity during 1997-2002 and, using the model’s projections of GDP per capita, approach an R&D intensity level of 2.5% by 2020:<sup>13</sup>

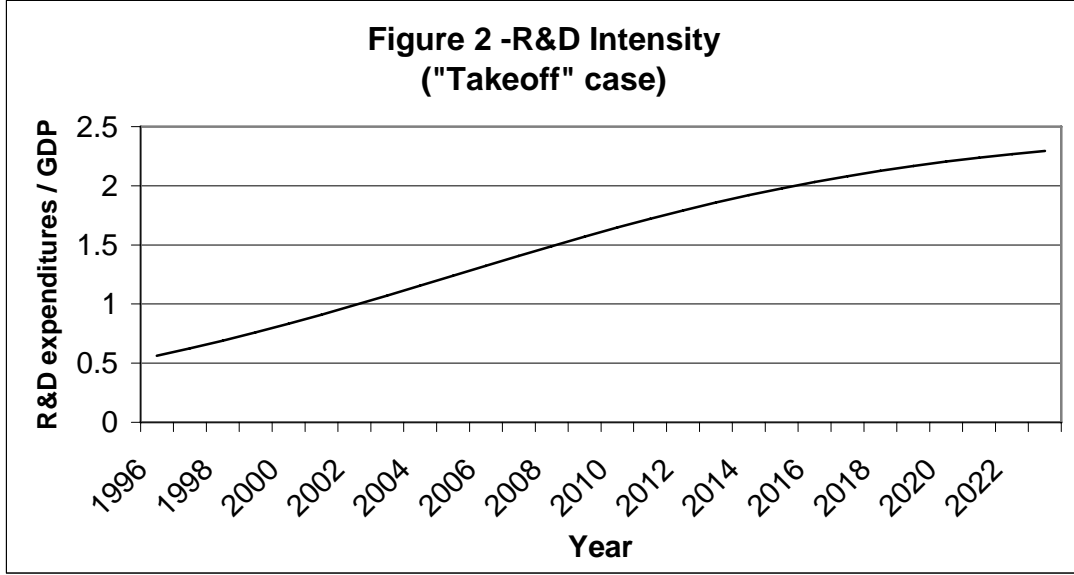
$$\left(\frac{R \& D}{GDP}\right)_k = \frac{b_1}{\left(1 + b_4 e^{-b_2 \left(\left(\frac{GDP}{POP}\right)_k - b_3\right)}\right)} \quad (9)$$

The parameters chosen to approximate this trend are  $b_1 = 2.5$ ,  $b_2 = .135$ ,  $b_3 = 5$ , and  $b_4 = 2$ . Figure 2 shows the trajectory of R&D intensity over time in the “takeoff” case.

---

<sup>12</sup> As discussed in the introduction, Gao and Jefferson (2005), using cross-country data, regress the ratio of R&D expenditures to GDP on GDP per capita and find that this ratio follows an S-shaped logistic curve, supporting a period of rapid increase in China’s R&D intensity.

<sup>13</sup> This is consistent with China’s “National Medium- and Long-term Programme for Scientific and Technological Development (2006-2020)” which calls for an increase in R&D spending from 1.23% of GDP in 2006 to 2.5% by 2020 (The Economist, 2006). This is similar to the R&D intensity levels of the high-income countries shown in Figure 1, although China would not be regarded as a high-income country by 2020, as noted in footnote 3.



As described in section 3.1, the model requires an index of R&D stock by industry.

Using the perpetual inventory model, we construct these stocks,  $K_{j,t+1}^R$ , as the accumulation of R&D expenditures minus depreciation in industry  $j$  over time; i.e.,

$$K_{j,t+1}^R = (1 - \delta_R)K_{j,t}^R + I_{j,t+1}^R \quad (10)$$

where  $I_{j,t+1}^R$  is the flow of R&D expenditures in industry  $j$  at time  $t$  and  $\delta_R$  is the depreciation rate on R&D stock (set equal to 15% as in Fisher-Vanden and Jefferson (2006)). Given this, the growth rate of R&D stock in a given year,  $g_{j,t}^{KR}$ , is simply:

$$g_{j,t}^{KR} + \delta_R = \frac{I_{j,t+1}^R}{K_{j,t}^R}$$

Therefore, we can approximate base year R&D stock for a specific industry as base year R&D expenditures divided by the average growth rate in R&D expenditures in the industry over the period 1995-2001,  $avgg_{j,1995-2001}^{KR}$ , plus the depreciation rate; i.e.,

$$K_{j,0}^R = \frac{I_{j,1}^R}{avgg_{j,1995-2001}^{KR} + \delta_R}$$

We calculate R&D expenditures by industry in the model as follows. In a given period  $t$ , aggregate R&D intensity is derived from equation (9) applying the parameters above and the previous year's GDP per capita. Multiplying this aggregate R&D intensity by lagged GDP, we obtain aggregate R&D expenditures at  $t$ . The firm-level data set used in our econometric estimation described in section 3.2 allows us to compute the average share of national R&D expenditures by industry for the years 1997-2001. We apply these industry shares from the data to the aggregate expenditures to obtain R&D expenditures by industry which are then used to construct the stocks of R&D via equation (10).<sup>14</sup> These stocks are then used to derive the indexes  $R_j(t)$  in model equations (2a) and (2b). We assume that the base year (1997) input-output data used to calibrate the model reflects aggregate R&D spending in this year; therefore, R&D spending is captured in the observed tax rates and government spending in the base year data. R&D spending above the base year level in future years is assumed to be funded through a non-distortionary lump sum tax on household income.

The “no takeoff” case only differs from the “takeoff” case in our assumption about the R&D intensity parameter. In the “no takeoff” case, we assume China's R&D intensity stays constant at the 1997 value. The same neutral and factor-biased technical change parameters are used in both cases.

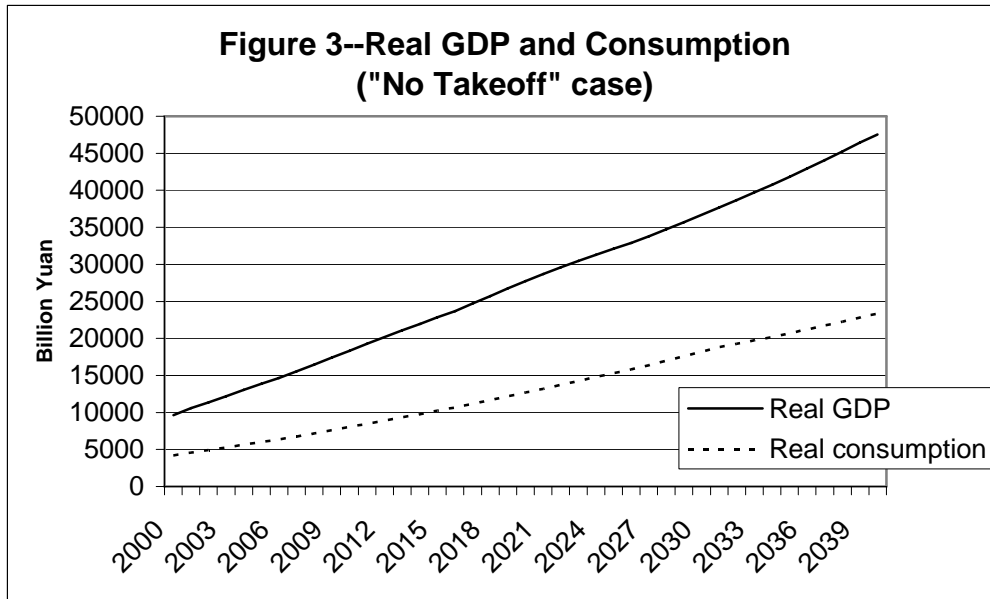
#### **4.1. “No Takeoff” Case**

Figure 3 shows the growth of real GDP and consumption in the “no takeoff” case over the modeling period. The average annual growth rate of real GDP between 2000 and 2030 is 4.6% while the average annual growth rate of real consumption is 5.0%. Figure 4 shows a

---

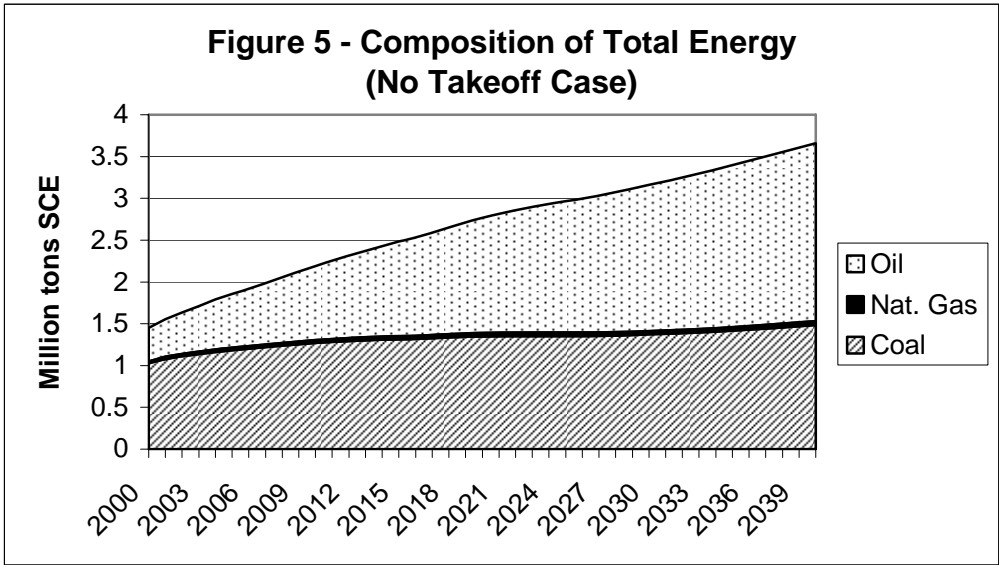
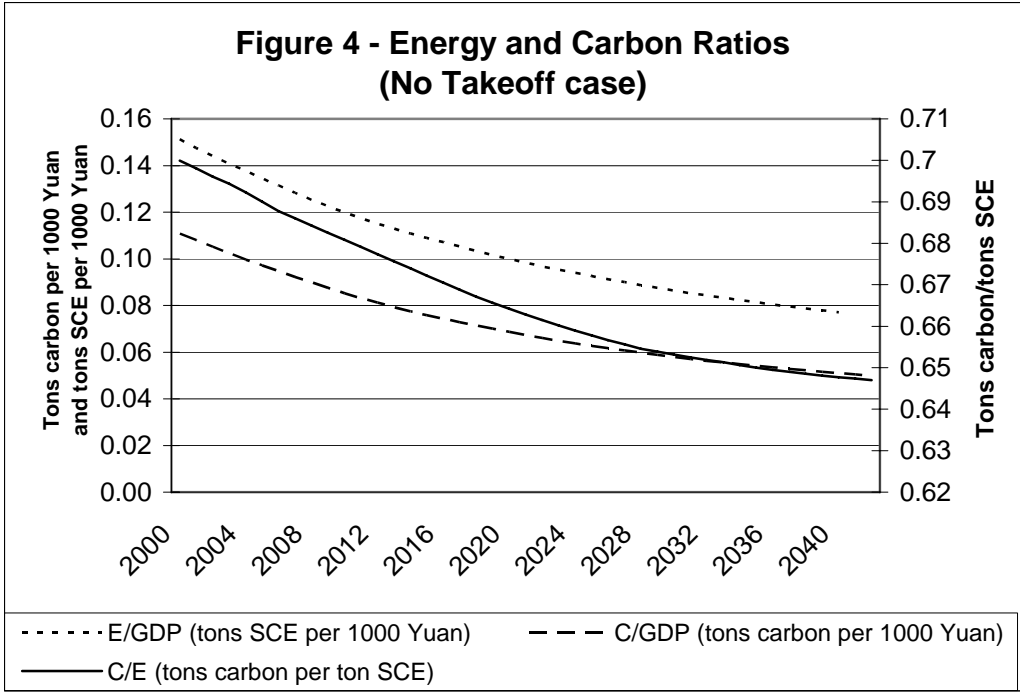
<sup>14</sup> As discussed in Section 2, historically R&D has been conducted by government-run R&D institutes and diffused to the firms. Although this has been changing over time, with a large percentage of R&D activities now occurring at the firm level, these activities are still largely in response to government directives. Thus, we chose not to model

dramatic fall in China's energy intensity (E/GDP) and carbon intensity (C/GDP) over the modeling period.<sup>15</sup> Figure 4 also shows a dramatic decline in China's carbon to energy ratio over time which can be explained by a fall in the share of coal in total energy (Figure 5). However, the absolute level of energy use is rising as shown in Figure 5.



R&D as a choice variable of the firm, but rather determined at the aggregate level and distributed to industries based on historical trends.

<sup>15</sup> See Appendix A, equations (A.34) and (A.35), for details on how total energy and carbon emissions are calculated.



To understand what is driving this increase in carbon emissions over time, we decompose the effects of factor substitution and output substitution on the change in carbon emissions

between the years 2000 and 2040 by employing the following multiplicative form of the Divisia decomposition method:<sup>16</sup>

$$\ln(C_{2040}) = \ln(C_{2000}) + \ln\left(\frac{Q_{2040}}{Q_{2000}}\right) + \frac{1}{2} \sum_{i=1}^N \left(\frac{C_{2000,i}}{C_{2000}} + \frac{C_{2040,i}}{C_{2040}}\right) \ln\left(\frac{I_{2040,i}}{I_{2000,i}}\right) + \frac{1}{2} \sum_{i=1}^N \left(\frac{C_{2000,i}}{C_{2000}} + \frac{C_{2040,i}}{C_{2040}}\right) \ln\left(\frac{S_{2040,i}}{S_{2000,i}}\right) + R \quad (11)$$

or, in level form (in millions of tons carbon),

$$C_{2040} = C_{2000} \cdot \left(\frac{Q_{2040}}{Q_{2000}}\right) \cdot \exp\left(\frac{1}{2} \sum_{i=1}^N \left(\frac{C_{2000,i}}{C_{2000}} + \frac{C_{2040,i}}{C_{2040}}\right) \ln\left(\frac{I_{2040,i}}{I_{2000,i}}\right)\right) \cdot \exp\left(\frac{1}{2} \sum_{i=1}^N \left(\frac{C_{2000,i}}{C_{2000}} + \frac{C_{2040,i}}{C_{2040}}\right) \ln\left(\frac{S_{2040,i}}{S_{2000,i}}\right)\right) \cdot \exp(R) \quad (11a)$$

where

$C_t \equiv$  total carbon emissions (in millions of tons) in year  $t$ ,  $t=2000,2040$ ;

$Q_t \equiv$  total output (equal to the sum of industry output,  $QO_{j,t}$ , from equation (1)) in year  $t$ ;

$C_{t,i} \equiv$  total carbon emissions (in millions of tons) in sector  $i$  in year  $t$ ;

$I_t \equiv$  total carbon intensity ( $C/Q$ ) in year  $t$ ;

$I_{t,i} \equiv$  total carbon intensity of sector  $i$  in year  $t$ ;

$S_{t,i} \equiv$  sector  $i$ 's share of total output in year  $t$ ; and

$R \equiv$  approximation residual.

The first two terms, which can be combined as  $\left(\frac{C_{2000}}{Q_{2000}}\right)Q_{2040}$ , represent carbon emissions

in 2040, conditional on output in the year 2040 being produced at the same carbon intensity as in the year 2000. The third term captures the change in carbon emissions between the years 2000 and 2040 due to changes in industrial sector carbon intensity. The fourth term represents the change in total carbon emissions due to changes in the sectoral composition of total industrial output. Since this decomposition method is an approximation, the last term captures the residual change.

<sup>16</sup> A derivation of this equation can be found in Ang and Zhang (2000).

The decomposition of the increase in carbon emissions between the years 2000 and 2040 in the “no takeoff” case, as given in equation (11a), is provided in Table 4. By combining the first two terms, we see that if the carbon intensity was the same as in the year 2000, carbon emissions would be 4.92 times higher due solely to the growth in output. However, a fall in the within-industry carbon intensity dampens this increase in emissions. The third term of the Divisia decomposition implies that emissions are only 46.12% of what they would otherwise be if there was no fall in within-industry carbon intensity. A shift in the composition of output (i.e., structural change) has a small upward effect on emissions, due to the expansion of manufacturing relative to agriculture. In sum, the rise in carbon emissions from 1014 mil. tons in 2000 to 2373 mil. tons in 2040 is primarily due to the increase in total output; however, emissions would have been 11700 mil. tons if it were not for the significant fall in within-industry carbon intensity.

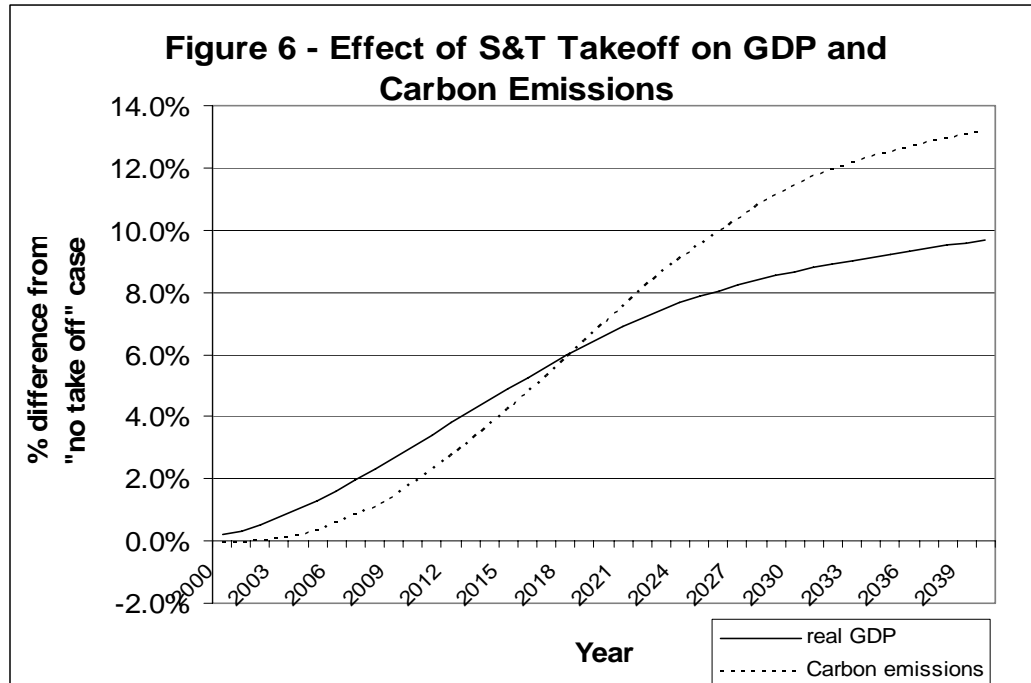
**Table 4**  
**Divisia decomposition of changes in carbon emissions between 2000 and 2040**

Terms in Divisia Equation	No Takeoff Case	S&T Takeoff Case
<b>First term</b> —Year 2000 carbon emissions (mil. tons)	1014	1014
<b>Second term</b> —change in output levels	4.922	5.443
<b>Third term</b> —change in within industry carbon intensity	0.4612	0.4327
<b>Fourth term</b> —change in industry composition of total output	1.044	1.148
Total of above four terms (mil. tons)	2404	2742
Projected year 2040 emissions (mil. tons)	2373	2694
Decomposition residual (mil. tons)	-31	-48

## 4.2. “Takeoff” Case

In the S&T “takeoff” case where we assume the R&D intensity of the Chinese economy follows the trajectory depicted in Figure 2, the decomposition results tell a story similar to the “no takeoff” case. As shown in the last column of Table 4, the increase in output levels is driving the increase in emissions between 2000 and 2040; however, this is dampened by a large fall in within-industry carbon intensity. The growth in output is higher in the “takeoff” case, so the upward pressure on emissions is greater. The downward pressure from the fall in within-industry carbon intensity, however, is larger than in the “no takeoff” case; i.e., emissions are only 43.3% of what they would otherwise be if there was no fall in within-industry carbon intensity. However, the downward pressure on emissions due to the fall in the within-industry carbon intensity is not enough to compensate for the larger upward pressures on emissions due to output growth and changes in industry composition, reflected in the second and fourth terms of the Divisia decomposition equation. Therefore, carbon emissions are greater in the “takeoff” case than the “no takeoff” case.

Figure 6 shows the differences in real GDP and carbon emissions between the “takeoff” and “no takeoff” cases. Prior to 2020, the difference in carbon emissions between the two cases is smaller than the difference in real GDP. This implies that the carbon intensity in the “takeoff” case is lower than in the “no takeoff” case. This changes after 2020 when the difference in carbon emissions is greater than the difference in real GDP between the two cases, implying that the carbon intensity in the “takeoff” case is higher than in the “no takeoff” case.



This is reflected in the carbon and energy intensities of GDP provided in Figure 7. This figure shows that the carbon intensity is lower in the takeoff case in the years prior to 2020 and higher afterwards. The carbon intensity of output is a function of the energy intensity of output and the carbon intensity of energy; i.e.,  $C/Q = E/Q * C/E$ . From Figure 7, we see that most of the changes in carbon intensity of output ( $C/Q$ ) over the modeling period is due to changes in the energy intensity of output ( $E/Q$ ). The carbon intensity of output diverges from the energy intensity of output in the later periods due to an increase in the carbon intensity of energy. Although in both cases the share of coal in total primary energy is falling over time, this share is falling faster in the “no takeoff” case. As explained further below, this is due to differences in the relative price of coal between the two cases.

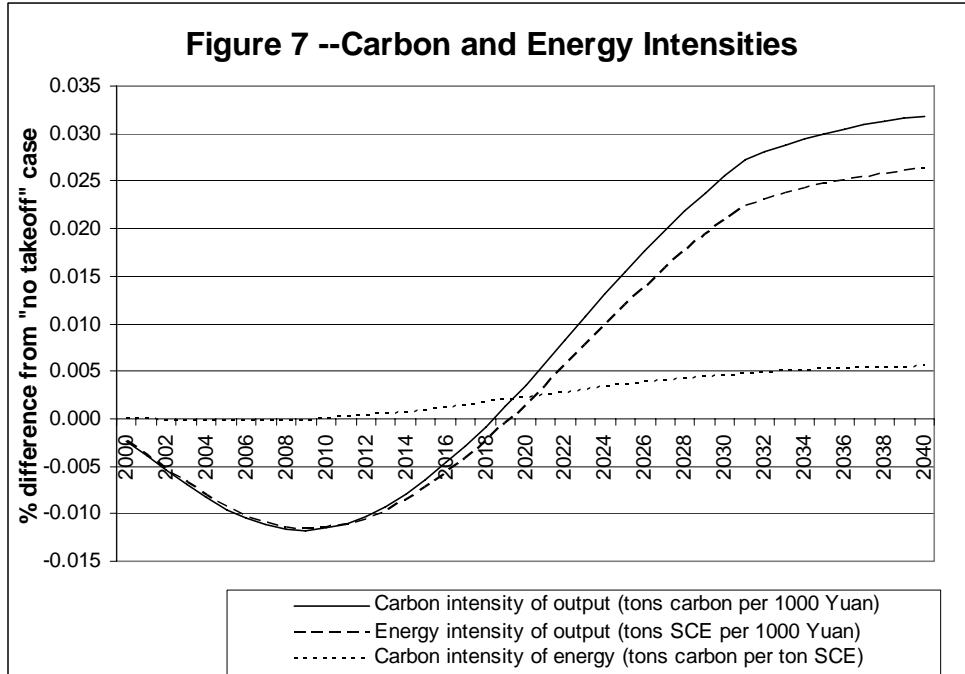


Table 5 provides the percent difference in the Divisia decomposition terms between the two cases in years 2010, 2020, and 2040. Since carbon intensity is a function of the within industry carbon intensity and the composition of industry output, the percent difference in carbon intensity between the “takeoff” and “no takeoff” cases can be computed by adding the third and fourth terms of the Divisia decomposition equation. In 2010, we see that the difference in within industry carbon intensity is larger than the difference in industry composition, which leads to a lower overall carbon intensity in the “takeoff” case. This changes, however, after 2020 when the difference in industry composition is larger than the difference in within industry carbon intensity, leading to a higher carbon intensity in the “takeoff” case.

**Table 5**  
**Percent Difference in Divisia Results**  
**(% difference from “no takeoff” case)**

Terms in Divisia Equation	2010	2020	2040
<b>First term</b> —Year 2000 carbon emissions	-0.04%	-0.04%	-0.04%
<b>Second term</b> —change in output levels	2.92%	6.87%	10.59%
<b>Third term</b> —change in within industry carbon intensity	-2.84%	-5.24%	-6.18%
<b>Fourth term</b> —change in industry composition of total output	2.15%	6.34%	9.97%
Year <i>t</i> emissions	2.11%	7.64%	14.06%

This higher carbon intensity in the “takeoff” case after 2020 can be explained by examining the differences in the composition of industry. As shown in Table 6, higher technology development in the S&T takeoff case results in higher real output in every sector. However, real output is relatively higher in certain sectors; in particular, the primary energy sectors. This can be explained by examining the general equilibrium effects. As shown in Table 6, greater R&D intensity leads to lower prices overall relative to the wage numeraire, with the largest declines in energy prices.

Higher output of energy and lower energy prices may seem counter-intuitive. The energy-saving bias of R&D in most industries shifts the demand curve for energy inward, i.e. the demand for energy conditional on the demand for the particular industry’s output. However, in most sectors, increases in R&D lead to higher total factor productivity (TFP) growth. This TFP growth has two effects. First, higher TFP growth leads to an increase in real incomes and thus a greater demand for goods. This results in an outward shift of the conditional demand curve for

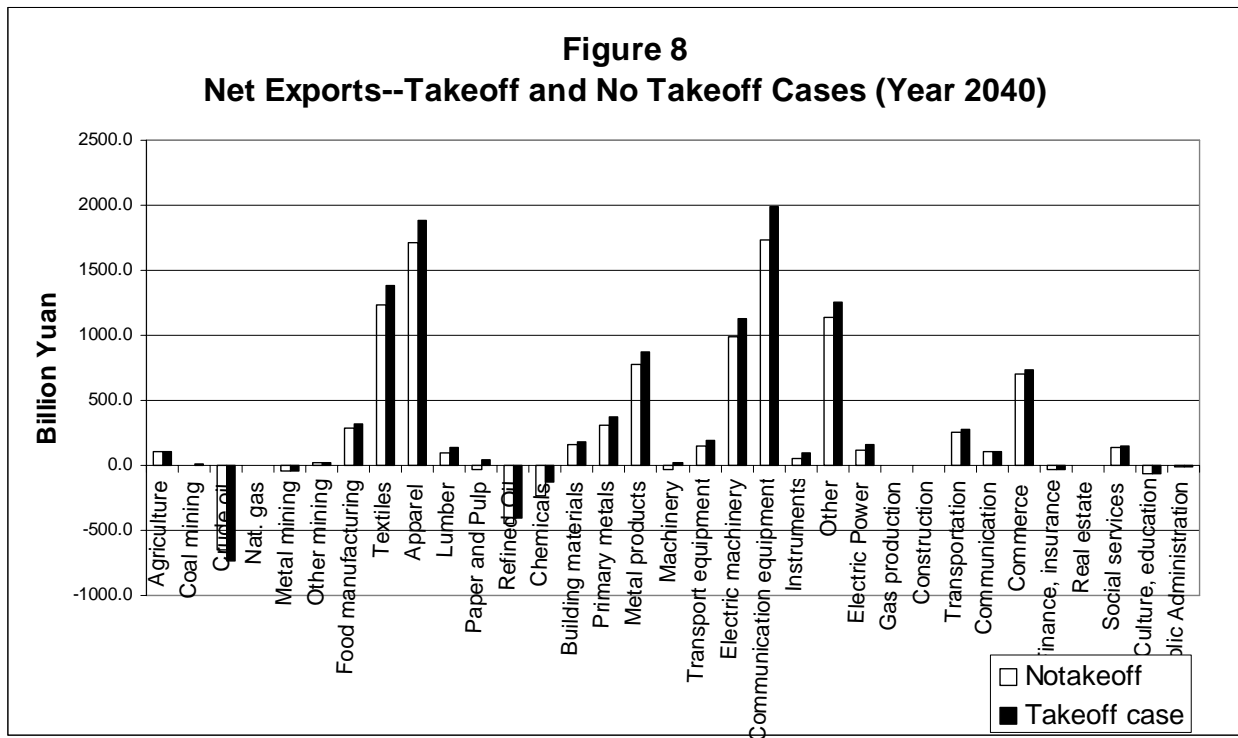
energy by industry, and an outward shift of the direct demand (final demand) curve for energy by households. Second, TFP growth leads to productivity improvements in the energy sectors. This will shift the energy supply curve out, leading to a larger supply of energy and a further drop in energy prices. The general equilibrium results are lower energy prices and higher output of energy-intensive products.

<b>Industry</b>	<b>Output</b>	<b>Price</b>	<b>Industry share</b>	<b>Carbon intensity</b>	<b>Net exports</b>
Agriculture	1%	-3%	-9%	9%	2%
Coal mining	17%	-12%	6%	3%	12%
Crude oil/ Nat. Gas	18%	-5%	7%	10%	14%
Nat. gas	13%	-10%	2%	4%	10%
Metal mining	18%	-10%	7%	-2%	3%
Other mining	11%	-10%	0%	-4%	22%
Food manufacturing	7%	-5%	-3%	31%	11%
Textiles	6%	-11%	-4%	-6%	12%
Apparel	9%	-11%	-2%	-14%	10%
Lumber	20%	-16%	9%	-5%	39%
Paper and Pulp	20%	-17%	8%	-3%	-206%
Refined Oil	64%	-39%	48%	14%	-10%
Chemicals	9%	-11%	-2%	0%	-44%
Building materials	10%	-8%	-1%	0%	10%
Primary metals	15%	-8%	4%	-9%	21%
Metal products	12%	-9%	1%	-33%	13%
Machinery	15%	-8%	4%	-3%	-150%
Transport equipment	15%	-8%	4%	-9%	30%
Electric machinery	14%	-15%	3%	-12%	13%
Communication equipment	13%	-8%	2%	-33%	15%
Instruments	14%	-14%	2%	-12%	80%
Other	11%	-20%	0%	1%	10%
Electric Power	34%	-17%	21%	15%	35%
Gas production	69%	-42%	53%	17%	100%
Construction	8%	-5%	-2%	11%	-98%
Transportation	4%	-5%	-6%	7%	8%
Communication	6%	-7%	-5%	11%	4%
Commerce	5%	-8%	-6%	11%	4%
Finance, insurance	4%	-4%	-6%	12%	3%
Real estate	7%	-5%	-4%	12%	0%
Social services	6%	-8%	-5%	10%	9%
Culture, education	5%	-3%	-5%	10%	2%
Public Administration	6%	-4%	-4%	5%	3%

These results suggest that the energy-intensive industries are gaining in terms of industry share. Table 6 shows the percent difference in industry share (defined as output in industry  $j$  as a share of total output across all industries) for each industry. We see that an S&T takeoff leads to higher output shares in the energy-intensive sectors. Table 6 also provides carbon intensities by industry. We see that the industries with larger energy-saving biases of technology development (as implied by the econometric results in Table 2) have lower carbon intensities with an S&T takeoff.

Figure 8 shows the effects of an S&T takeoff on trade. In most industries, net exports are higher in the “takeoff” case. Higher productivity growth in the “takeoff” case leads to lower prices for domestic goods relative to wages and world prices ( $PE_{i,t}^*$  in equation (A.26) of Appendix A). To maintain the exogenously-set current account, the exchange rate (variable  $e_t$  in equation (A.26)) must appreciate. The net effect of lower domestic prices and appreciated currency is a rise in the landed price of imports in relation to the price of domestic goods, leading to a higher quantity of net exports in the aggregate.

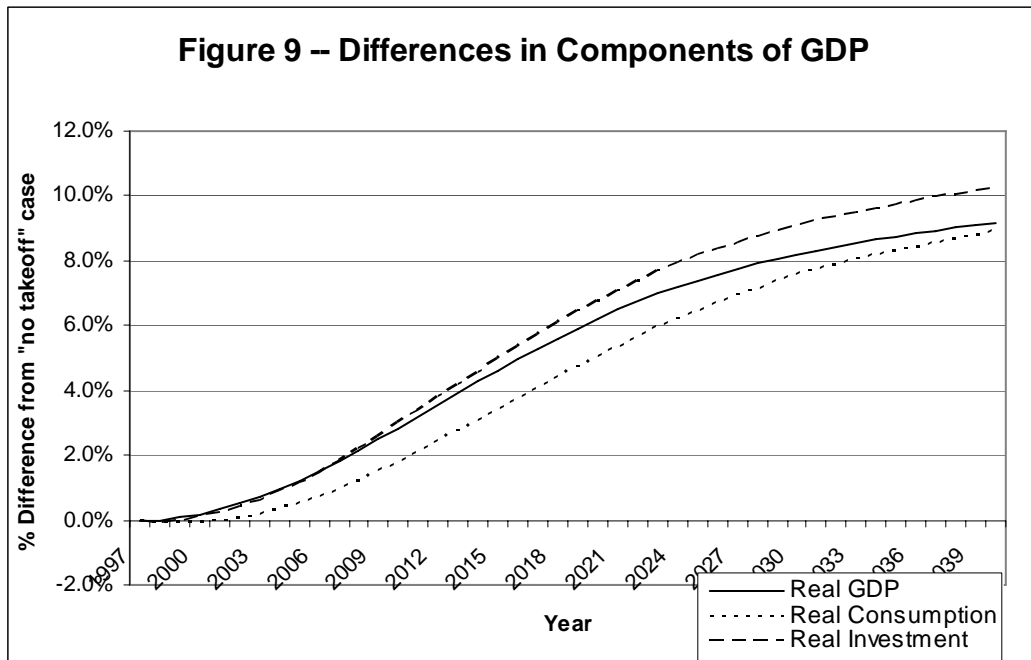
The crude oil sector, however, experiences an increase in net imports with an S&T takeoff. This result is consistent with our previous findings that show a higher consumption of energy in the “takeoff” case. Greater imports of crude oil are needed to meet this increase in domestic energy demand.



What does an S&T takeoff imply for welfare? Figure 9 shows the differences in real GDP, consumption and investment between the “takeoff” and “no takeoff” cases. As discussed previously, additional R&D expenditures are funded by a lump sum tax on household income. Thus, in the earlier years—before the returns to R&D investment are realized—aggregate household consumption is lower. (Household utility in any given period is measured as a composite of consumption goods as shown in equation (A.9) of Appendix A). However, the productivity gains from R&D quickly emerge leading to higher real GDP, investment and consumption. From Figure 9, we see that higher economic growth in the “takeoff” case is being driven by higher real investment in addition to the productivity effect.

These results tell us that increased R&D spending is welfare improving in the later years, which would dominate the short term fall in consumption if one applies a conventional intertemporal utility function. R&D leads to productivity improvements which result in higher

wages. This leads to higher household income and, therefore, higher investment, consumption, and economic growth. Therefore, ignoring any related damages from climate change due to higher emissions in the “takeoff” case, an S&T policy is welfare improving given our estimated coefficients of the neutral and factor-biased effects of R&D.



### 4.3. Sensitivity Analysis

The large effects on output and price in the energy sectors (e.g., refined oil and electricity sectors) in Table 6 raise the question of how sensitive these results are to the estimated coefficients provided in Table 2. In particular, the neutral coefficients associated with refined oil and electricity are significantly larger than the other sectors. As discussed in Section 3.3, we interpret these positive coefficients as technology development used to improve the quality and delivery of energy products (such as electricity). To understand the influence of these coefficients on the results, we conducted a sensitivity analysis where the neutral coefficients associated with refined oil and electricity in Table 2 are reduced from .036 to .01 (a ~70%

reduction) and from .028 to .01, respectively. We find that reducing these coefficients resulted in a reduction in the impacts on these sectors by approximately the same magnitude; for instance, in the case of refined oil, the difference in output levels changed from 64% to 13% (a ~80% reduction). In the aggregate, however, the changes are modest—for instance, the differences in real GDP and carbon emissions between the “takeoff” and “no takeoff” cases follow the same pattern as in Figure 6, with the curves shifted down by approximately 2 percentage points (from 8% to 6% in 2030). Note that the coefficients given in Tables 2 and 3, and these alternative test coefficients, are used in both the “takeoff” and “no takeoff” simulations. Therefore, a large change to a particular coefficient may substantially change both “takeoff” and “no takeoff” projections, but lead to a modest change in the *difference* between the two projections.

In addition to the parameter assumptions, it is important to note that these results could be influenced by the functional form assumed for the relation between the stock of research knowledge (R) and production cost, and biases of technical change. In particular the model’s cost function assumes a log-linear relationship between R and unit cost. Thus, the estimated effects would be smaller if there were strong diminishing returns to research. However, the effects may be larger if there are externalities that are not captured by our constant returns to scale and perfect competition assumptions. For instance, positive R&D spillovers—e.g., benefits from R&D that accrue to other firms or industries—are not captured in our model.

As discussed in Section 3, our data constraints force us to assume that all R&D is productive; i.e., we assume that negative total factor productivity growth implied by the econometric estimation is actually unmeasured quality improvements. If this assumption is too optimistic—and total factor productivity growth in manufacturing can actually be negative—then

the results could be overstated. However, given the well-known deficiencies in Chinese economic data historically (see e.g. Wu (2000)), it may very well be the case that we have made an insufficient adjustment for unmeasured quality improvements.

## 5. Conclusions

Given its vast size and stage of development, China is expected to dominate global energy consumption and carbon emissions in the near future. A key driver of China's recent and future economic growth is the country's emphasis on developing its science and technology capabilities. Previous econometric work has shown that R&D has an energy-saving bias; however, R&D is also likely to lead to higher total factor productivity, income levels, and demand for goods. Therefore, it is not immediately obvious what a science and technology takeoff in China will mean for energy use and carbon emissions.

We employ a computable general equilibrium (CGE) model of China that explicitly takes into account the effects of an S&T takeoff on sectoral total factor productivity and factor intensity by incorporating the industry-level R&D effects econometrically estimated using data from 1500 industrial enterprises in China. We find that an S&T takeoff will lead to higher real GDP and carbon emissions than if no takeoff occurred. Such an increase in R&D expenditures in China will lead to lower goods prices overall, but a larger drop in energy prices due to the large total factor productivity effect on energy producers and the energy-saving bias of R&D. This leads to higher economic growth, a substitution of energy for other factors of production, and greater energy consumption by consumers.

These results have important policy implications. Although the carbon and energy intensities are falling in an S&T takeoff scenario, these intensities are higher than they would be if no S&T takeoff occurred. This is primarily due to the growth in the energy intensive industries as a result of changes in relative prices that occur with an S&T takeoff. Therefore, a policy of increasing R&D to reduce energy use and emissions may not meet its intended goals if general equilibrium effects are ignored. These results depend to some degree on the functional

forms assumed in the model although there is no clear bias in the direction of the estimates. Regardless of whether the estimated effects are over- or understated, however, our findings underscore the importance of considering the economy wide implications of a technology policy, recognizing that better technology does not necessarily imply a cleaner environment.

## Appendix A—Description of the Economic Model

The main features of the model for China and data construction are described in this appendix. A detailed account including data sources is given in Garbaccio, Ho, and Jorgenson (2001). Table A-1 provides a list of the 33 production sectors included in the model. To reduce unnecessary notation, we drop the time subscript,  $t$ , from our equations whenever possible.

### A.1. Production

Each of the 33 industries is assumed to produce its output using a constant returns to scale technology. For each sector  $j$  this can be expressed as:

$$(A.1) \quad QO_j = f(KD_j, LD_j, TD_j, A_{1j}, \dots, A_{nj}, t),$$

where  $KD_j$ ,  $LD_j$ ,  $TD_j$ , and  $A_{ij}$  are capital, labor, land, and intermediate inputs, respectively.<sup>17</sup>

In sectors for which both plan and market allocation exists, output is made up of two

components, the plan quota output ( $\bar{QO}_j$ ) and the output sold on the market ( $\tilde{QO}_j$ ). The plan

quota output is sold at the state-set price ( $\bar{PO}_j$ ) while the output in excess of the quota is sold at

the market price ( $\tilde{PO}_j$ ).

A more detailed discussion of how this plan-market formulation is different from standard market economy models is given in Garbaccio, Ho, and Jorgenson (1999). In summary, if the constraints are not binding, then the “two-tier plan/market” economy operates at the margin as a market economy with lump sum transfers between agents. The before-tax return to the owners of fixed capital in sector  $j$  is:

---

<sup>17</sup>  $QO_j$  denotes the quantity of industry  $j$ 's output. This is to distinguish it from,  $QC_j$ , the quantity of commodity  $j$ . In the actual model each industry may produce more than one commodity and each commodity may be produced by more than one industry. In the language of the input output tables, we make use of both the USE and MAKE matrices. For ease of exposition we ignore this distinction here.

$$(A.2) \quad profit_j = \overline{PO}_j \overline{QO}_j + \tilde{PO}_j \tilde{QO}_j - P_{K,j} \tilde{KD}_j - P_{L,j} LD_j - P_{T,j} TD_j \\ - \sum_i \overline{PS}_i \bar{A}_{ij} - \sum_i \tilde{PS}_i \tilde{A}_{ij} .$$

For each industry, given the capital stock  $\bar{K}_j$  and prices, the first order conditions from maximizing equation A.2, subject to equation A.1, determine the market and total input demands.

Given the lack of reliable time-series data for estimating substitution elasticities, we use simple Cobb-Douglas production functions. Equation A.1 for the output of industry  $j$  at time  $t$  then becomes:

$$(A.3) \quad QO_{jt} = g(t) KD_{jt}^{\alpha_{Kj}} LD_{jt}^{\alpha_{Lj}} TD_{jt}^{\alpha_{Tj}} E_{jt}^{\alpha_{Ej}} M_{jt}^{\alpha_{Mj}} , \quad \text{where}$$

$$\log E_{jt} = \sum_k \alpha_{kj}^E \log A_{kjt} \quad \text{and} \quad k = \text{coal, oil mining, gas mining, petroleum refining,}$$

electricity, gas distribution

$$\log M_{jt} = \sum_k \alpha_{kj}^M \log A_{kjt} \quad \text{and} \quad k = \text{non-energy intermediate goods.}$$

Here  $\alpha_{Ej}$  is the cost share of aggregate energy inputs in the production process and  $\alpha_{kj}^E$  is the share of energy of type  $k$  within the aggregate energy input. Similarly,  $\alpha_{Mj}$  is the cost share of aggregate non-energy intermediate inputs and  $\alpha_{kj}^M$  is the share of intermediate non-energy input of type  $k$  within the aggregate non-energy intermediate input.

In the non-industrial sectors (i.e., agriculture, construction, transportation and seven service sectors), biased technical change, i.e. changes in demand for inputs over time that are independent of price changes, is represented by the  $\alpha_{Zj}$  ( $Z=K,L,T,E,M$ ) coefficients which are indexed by time and are updated exogenously. In these sectors, we set  $\alpha_{Ej}$  to fall gradually over

the next 40 years while the labor coefficient,  $\alpha_{Lj}$ , rises correspondingly. The composition of the aggregate energy input (i.e., the coefficients  $\alpha_{kj}^E$ ) is also allowed to change over time. The coefficient  $g(t)$  in equation A.3 represents technical progress and the change in  $g(t)$  is determined through an exponential function ( $\dot{g}_j(t) = A_j \exp(-\mu_j t)$ ). This implies technical change that is rapid initially, but gradually declines toward zero. As discussed in detail in Section 3, for the industrial sectors these parameters change over time as a function of deliberate and autonomous technical change.

The price to buyers of industry output includes the indirect tax on output, the externality ad-valorem tax, and could include a carbon tax per unit output:

$$(A.4) \quad PO_i^t = (1 + t_i^t + t_i^x)PO_i + t_i^c.$$

## A.2. Households

The household sector derives utility from the consumption of commodities, is assumed to supply labor inelastically, and owns a share of the capital stock. The household sector also receives income transfers and interest on its holdings of public debt. Private income after taxes and the payment of various non-tax fees ( $FEE$ ),  $Y^p$ , can then be written as:

$$(A.5) \quad Y^p = YL + DIV + G\_I + G\_transfer + R\_transfer - FEE,$$

where  $YL$  denotes labor income from supplying  $LS$  units of effective labor, less income taxes.

$YL$  is equal to:

$$(A.6) \quad YL = (1 - t^L)PL LS.$$

The relationship between labor demand and supply is given in equation A.30 below.  $LS$  is a function of the working age population, average annual hours, and an index of labor quality:

$$(A.7) \quad LS_t = POP_t^w hr_t q_t^L.$$

Household income is allocated between consumption ( $VCC_t$ ) and savings. In this model we use a simple Solow growth model formulation with an exogenous savings rate ( $s_t$ ) to determine private savings ( $S_t^p$ ):

$$(A.8) \quad S_t^p = s_t Y_t^p = Y_t^p - VCC_t.$$

Household utility is a function of the consumption of goods such that:

$$(A.9) \quad U_t = U(C_{1t}, \dots, C_{nt}) = \sum_i \alpha_{it}^C \log C_{it}.$$

Assuming that the plan constraints are not binding and given market prices and total expenditures, the first order conditions derived from equation A.9 determine household demand for commodities,  $C_i$ , where  $C_i = \bar{C}_i + \tilde{C}_i$ . Here  $\bar{C}_i$  and  $\tilde{C}_i$  are household purchases of commodities at state-set and market prices. The household budget can be written as:

$$(A.10) \quad VCC = \sum_i (\tilde{P}S_i \tilde{C}_i + \bar{P}S_i \bar{C}_i).$$

A Cobb-Douglas utility function was chosen due to the lack of disaggregated data to estimate an income elastic functional form. However, one would expect demand patterns to change with rising incomes and this is implemented by allowing the  $\alpha_{it}^C$  coefficients to change over time.

### A.3. Government and Taxes

In the model, the government has two major roles. First, it sets plan prices and output quotas and allocates investment funds. Second, it imposes taxes, purchases commodities, and redistributes resources. Public revenue comes from direct taxes on capital, value-added taxes, indirect taxes on output, tariffs on imports, the externality tax, and other non-tax receipts:

$$(A.11) \quad Rev = \sum_j t^k (P_{K,j} KD_j - D_j) + t^V \sum_j (P_{K,j} KD_j + P_{L,j} LD_j + P_{T,j} TD_j) + \sum_j t_j^t PO_j QO_j$$

$$+\sum_j t_j^x PO_j QO_j + \sum_i t_i^r PM_i^* M_i + \sum_i t_i^c (QO_i - X_i + M_i) + FEE$$

where  $D_j$  is the depreciation allowance and  $X_i$  and  $M_i$  are the exports and imports of good  $i$ .

Total government expenditure is the sum of commodity purchases and other payments:

$$(A.12) \text{ Expend} = VGG + G\_INV + \sum s_i^e PO_i X_i + G\_I + G\_IR + G\_transfer .$$

Government purchases of specific commodities are allocated as shares of the total value of government expenditures,  $VGG$ . For good  $i$ :

$$(A.13) PS_i G_i = \alpha_i^G VGG .$$

We construct a price index for government purchases as  $\log PGG = \sum_i \alpha_i^G \log PS_i$ . The real quantity of government purchases is then:

$$(A.14) GG = \frac{VGG}{PGG} .$$

The difference between revenue and expenditure is the deficit,  $\Delta G$ , which is covered by increases in the public debt, both domestic ( $B$ ) and foreign ( $B^{G*}$ ):

$$(A.15) \Delta G_t = \text{Expend}_t - \text{Rev}_t ,$$

$$(A.16) B_t + B_t^{G*} = B_{t-1} + B_{t-1}^{G*} + \Delta G_t .$$

The deficit and interest payments are set exogenously and equation A.15 is satisfied by making the level of total government expenditure on goods,  $VGG$ , endogenous.

#### A.4. Capital, Investment, and the Financial System

We model the structure of investment in a fairly simple manner. In the Chinese economy, some state-owned enterprises receive investment funds directly from the state budget and are allocated credit on favorable terms through the state-owned banking system. Non-state enterprises get a negligible share of state investment funds and must borrow at competitive

interest rates. There is also a small but growing stock market that provides an alternative channel for private savings. We abstract from these features and define the capital stock in each sector  $j$  as the sum of two parts, which we call plan and market capital:

$$(A.17) \quad K_{jt} = \bar{K}_{jt} + \tilde{K}_{jt}.$$

The plan portion evolves with plan investment and depreciation:

$$(A.18) \quad \bar{K}_{jt} = (1 - \delta)\bar{K}_{j,t-1} + \bar{I}_{jt}, \quad t = 1, 2, \dots, T.$$

In this formulation,  $\bar{K}_{j0}$  is the capital stock in sector  $j$  at the beginning of the simulation. This portion is assumed to be immobile across sectors. Over time, with depreciation and limited government investment, it will decline in importance. Each sector may also rent capital from the total stock of market capital,  $\tilde{K}_t$ :

$$(A.19) \quad \tilde{K}_t = \sum_j \tilde{K}_{jt}, \text{ where } \tilde{K}_{jt} > 0.$$

The allocation of market capital to individual sectors,  $\tilde{K}_{jt}$ , is based on sector rates of return. As in equation A.2, the rental price of market capital by sector is  $\tilde{P}_{K,j}$ . The supply of  $\tilde{K}_{jt}$ , subject to equation A.19, is written as a translog function of all of the market capital rental prices,

$$\tilde{K}_{jt} = K_j(\tilde{P}_{K,1}, \dots, \tilde{P}_{K,n}).$$

In three sectors—agriculture, crude petroleum and gas mining—“land” is a factor of production. We have assumed that agricultural land and oil fields are supplied inelastically, abstracting from the complex property rights issues regarding land in China. After taxes, income derived from plan capital, market capital, and land is either kept as retained earnings by the enterprises, distributed as dividends, or paid to foreign owners:

$$(A.20) \quad \sum_j profits_j + \sum_j \tilde{P}_{K,j} \tilde{K}_j + \sum_j P_{T,j} T_j = tax(k) + RE + DIV + r(B^*),$$

where  $tax(k)$  is total tax on capital and value added (the first two terms on the right hand side of equation A.11).<sup>18</sup>

As discussed below, total investment in the model is determined by savings. This total,  $VII_t$ , is then distributed to the individual investment goods sectors through fixed shares,  $\alpha_{it}^I$ :

$$(A.21) \quad PS_{it} I_{it} = \alpha_{it}^I VII_t.$$

A portion of sector investment,  $\bar{I}_t$ , is allocated directly by the government, while the remainder,  $\tilde{I}_t$ , is allocated through other channels.<sup>19</sup> The total,  $I_t$ , can be written as:

$$(A.22) \quad I_t = \tilde{I}_t + \bar{I}_t = I_{1t}^{\alpha_1^I} I_{2t}^{\alpha_2^I} \dots I_{nt}^{\alpha_n^I}.$$

As in equation A.18 for the plan capital stock, the market capital stock,  $\tilde{K}_{jt}$ , evolves with new market investment:

$$(A.23) \quad \tilde{K}_{jt} = (1 - \delta) \tilde{K}_{jt-1} + \tilde{I}_{jt}.$$

### A.5. The Foreign Sector

Trade flows are modeled using the method followed in most single-country models. Imports are considered to be imperfect substitutes for domestic commodities and exports face a downward sloping demand curve. We write the total supply of commodity  $i$  as a CES function of the domestic ( $QO_i$ ) and imported good ( $M_i$ ):

$$(A.24) \quad QS_i = A_0 \left[ \alpha^d QO_i^\rho + \alpha^m M_i^\rho \right]^{\frac{1}{\rho}},$$

<sup>18</sup> In China, most of income from “dividends” is income derived from agricultural land.

<sup>19</sup> It should be noted that the industries in the Chinese accounts include many sectors that would be considered public goods in other countries. Examples include local transit, education, and health.

where  $PS_i QS_i = PO_i^t QO_i + PM_i M_i$  is the value of total supply. The purchaser's price for domestic goods,  $PO_i^t$ , is discussed in the producer section above. The price of imports to buyers is the foreign price plus tariffs (less export subsidies), multiplied by a world relative price,  $e$ :

$$(A.25) \quad PM_i = e(1 + t_i^r) PM_i^*.$$

Exports are written as a simple function of the domestic price relative to world prices adjusted for export subsidies ( $s_{it}^e$ ):

$$(A.26) \quad X_{it} = EX_{it} \left( \frac{\tilde{PO}_{it}}{e_t(1 + s_{it}^e) PE_{it}^*} \right)^{\eta_i},$$

where  $EX_{it}$  is base case exports that are projected exogenously.

The current account balance is equal to exports minus imports, less net factor payments, plus transfers:

$$(A.27) \quad CA = \sum_i \frac{PO_i X_i}{(1 + s_i^e)} - \sum_i PM_i M_i - r(B^*) - G\_IR + R\_transfer,$$

Like the government deficits, the current account balances are set exogenously and accumulate into stocks of net foreign debt, both private ( $B_t^*$ ) and public ( $B_t^{G*}$ ):

$$(A.28) \quad B_t^* + B_t^{G*} = B_{t-1}^* + B_{t-1}^{G*} - CA_t.$$

## A.6. Markets

The economy is in equilibrium in period  $t$  when the market prices clear the markets for the 33 commodities and the three factors. The supply of commodity  $i$  must satisfy the total of intermediate and final demands:

$$(A.29) \quad QS_i = \sum_j A_{ij} + C_i + I_i + G_i + X_i, \quad i = 1, 2, \dots, 33.$$

For the labor market, we assume that labor is perfectly mobile across sectors so there is one average market wage, which balances supply and demand. As is standard in models of this type, we reconcile this wage with the observed spread of sector wages using wage distribution coefficients,  $\psi_{jt}^L$ . Each industry pays  $P_{L,j,t} = \psi_{jt}^L P_{L,t} / (1 - t_j^V)$  for a unit of labor. The labor market equilibrium is then given as:

$$(A.30) \quad \sum_j \psi_{jt}^L LD_{jt} = LS_t.$$

For the non-plan portion of the capital market, adjustments in the market price of capital,  $\tilde{P}_{K,j}$ , clears the market in sector  $j$ :

$$(A.31) \quad KD_{jt} = \psi_{jt}^K K_{jt},$$

where  $\psi_{jt}^K$  converts the units of capital stock into the units used in the production function. The rental price  $P_{T,j}$  adjusts to clear the market for “land”:

$$(A.32) \quad TD_j = T_j, \quad \text{where } j = \text{“agriculture”, “crude petroleum”, “gas mining”}.$$

In this model without foresight, investment equals savings. There is no market where the supply of savings is equated to the demand for investment. The sum of savings by households, businesses (as retained earnings), and the government is equal to the total value of investment plus the budget deficit and net foreign investment:

$$(A.33) \quad S^p + RE + G\_INV = VII + \Delta G + CA.$$

The budget deficit and current account balance are fixed exogenously in each period. The world relative price ( $e$ ) adjusts to hold the current account balance at its exogenously determined level.

## A.6. Energy Use and Carbon Emissions

Emissions of carbon dioxide are calculated based on domestic primary energy (i.e., coal, natural gas, and oil) consumption. Output in each of the primary energy sectors is converted to energy units (standard tons of coal equivalent (SCE)) using fixed coefficients,  $\beta$ :

$$coal_t = \beta_{coal} QO_{coal,t}$$

$$gas_t = \beta_{gas} QO_{gas,t}$$

$$oil_t = \beta_{oil} QO_{oil,t}$$

Total domestic primary energy consumption is equal to output in each of the primary energy sectors less net exports in these sectors and in the refined oil sector:

$$(A.34) \quad \begin{aligned} Energy_{total,t} = & coal_t + gas_t + oil_t - \beta_{coal}(X_{coal,t} - M_{coal,t}) - \beta_{gas}(X_{gas,t} - M_{gas,t}) \\ & - \beta_{oil}(X_{oil,t} - M_{oil,t} + X_{refoil,t} - M_{refoil,t}) \end{aligned}$$

Carbon dioxide emissions are calculated by applying coefficients,  $c$ , (representing the ratio of carbon dioxide to energy) to domestic primary energy consumption:

$$(A.35) \quad \begin{aligned} C_{total,t} = & c_{coal} coal_t + c_{gas} gas_t + c_{oil} oil_t - c_{coal} \beta_{coal} (X_{coal,t} - M_{coal,t}) \\ & - c_{gas} \beta_{gas} (X_{gas,t} - M_{gas,t}) - c_{oil} \beta_{oil} (X_{oil,t} - M_{oil,t} + X_{refoil,t} - M_{refoil,t}) \end{aligned}$$

#### A.7. Parameters, Exogenous Variables, and Data Sources

The key source of data for the model is China's Social Accounting Matrix (SAM) for 1997. The SAM traces the flow of commodities and payments among the producers, household, government and rest of the world. The SAM is assembled from the official 1997 input-output table (NBS 1999b). From this we derive the labor and capital incomes, the tax revenues for each type of tax, the expenditures on specific commodities by the household, government and foreign sectors, and government payments of all types, as given in equation (A.12).

These payments are combined with employment and capital input data to construct the compensation rates for labor and capital for each sector. The estimates for employment and

capital stocks by sector are taken from a productivity study of China by Ho and Jorgenson (2001) that supplements the official data with labor force surveys. The various tax and subsidy rates are not statutory rates but derived by dividing revenues by the related denominator—i.e., value of industry output, capital income, total value added, and imports.

The exogenous variables in the model include total population, working age population, saving rates, dividend payout rates, government taxes and deficits, world prices for traded goods, current account deficits, rate of productivity growth, rate of improvement in capital and labor quality, and work force participation. These variables may of course be endogenous (since there are interactions among these variables) but for our purposes we assume that these variables are exogenous.

An important parameter affecting the growth rate of the economy is the household savings rate,  $s_t$ . We assume the household savings rate starts at the observed rate of 30 percent in 1997 and gradually falls to 20 percent by the end of the modeling period. National private savings is household savings plus the retained earnings of enterprises. The share of retained earnings is assumed to fall, and dividend payouts are assumed to rise. These two assumptions produce a national savings rate close to the 37 percent found in recent data. We note that national savings and investment in the Chinese data includes public capital such as roads and other public infrastructure, items that are usually excluded in the national accounts of other countries.

Labor supply in the model (equation (A.7)) is the product of population, annual average hours, and quality. Population projections by age groups are provided by the World Bank's Human Development Network.<sup>20</sup> The composition of the work force changes over time with a

---

<sup>20</sup> See World Bank Human Development Network (2002). The demographic projections were downloaded from the World Bank web site [http://devdata.worldbank.org/hnpstats/files/CHN\\_pop.xls](http://devdata.worldbank.org/hnpstats/files/CHN_pop.xls), January 2002.

larger proportion of educated workers, larger or smaller proportion of more experienced workers, and an older average age. We capture such changes in the model with the  $q_t^L$  index (referred to as the quality of labor input in Ho and Jorgenson (2001)). Given the expectation of higher educational attainment in the future, we assume that China's labor quality rises at 0.8 percent per year initially, compared to 0.5 percent during the peak in the U.S in the 1960's. Total labor hours depend also on the participation rate and annual working hours. Since data on the number of hours worked do not exist, we project working hours to rise over time with improvements in the functioning of the labor market—lower underemployment, seasonal unemployment, and other labor market frictions. We assume that hours worked per capita rises at 0.5 percent per year initially and slows over time.

An adjustment for improvements in future capital quality is also made in the model. This quality change refers to the shift in the composition of capital towards assets with shorter life, as documented in Ho and Jorgenson (2001). We assume that capital quality rises by 2 percent per year initially. In the case of land, the supply of land for agriculture, oil mining and gas mining is simply fixed for all periods to the base year value.

The government deficit,  $\Delta G$ , is set to the base year value of 3.2 percent of GDP initially, declining steadily towards zero in the long run. These deficits are cumulated into the stocks of debt,  $B_t$  and  $B_t^{G*}$ , assuming a constant division between domestic and foreign borrowing. Data for the stock of debt and interest paid was taken from the World Bank (1995, 1996) and Social Accounting Matrix. Government transfers,  $G\_transfer$ , are set to rise in proportion with population and average wage. The nontax fees paid by households are set to a fixed share of GDP equal to the base year's share.

The current account balance in China has been in a surplus in recent years after a period of large deficits in the early 1990s. We set the current account surplus equal to the share of GDP observed in 1997 for the base year, declining rapidly to zero over time. This  $CA_t$  is also the assumed rate of borrowing from the world. Import prices,  $PM_t^*$ , are assumed fixed for every period. The model also requires estimates of world demand for Chinese exports,  $EX_{it}$ . Consistent with the recent Chinese experience, we project a high rate of growth of exports, starting at 7 percent annually and falling gradually.

### *Parameters*

The value share parameters of the production functions ( $\alpha_{Kj}$ ,  $\alpha_{Lj}$ , etc.) are set to the values in the 1997 input-output table in the first year of the simulation. For the industrial sectors, these parameters change over time as a function of deliberate and autonomous technical change. (See Section 3 for a detailed description). For the non-industrial sectors, we change most of these parameters over time so that they gradually resemble the shares found in the U.S. input-output table for 1982. The exceptions to this are the coal inputs for all the sectors which are set to converge to a value between current Chinese shares and U.S. shares in 1982.<sup>21</sup> The rate of reduction in energy use is set at a modest level relative to the rapid improvements in recent Chinese history. We assume that the share of energy in industry output is reduced gradually to 70% of the 1997 level in 50 years. This is a conservative estimate compared to, for example, the performance in the electric power industry during the 1990-99 period. During this time thermal

---

<sup>21</sup> We have chosen to use U.S. patterns in our projections of these exogenous parameters because they seem to be a reasonable anchor. While it is unlikely that China's economy in 40 years time will mirror the U.S. economy of 1982, it is also unlikely to closely resemble any other economy. Other projections, such as those by the World Bank (1994), use the input-output tables of developed countries including the U.S.

output grew 88% whereas coal input only rose 61%, a rate of improvement of approximately 1.5% per year.<sup>22</sup>

The  $\alpha_{it}^C$  parameters of the consumption function are set in a similar way. In the first period these parameters are set to the shares found in the 1997 Social Accounting Matrix. In future periods these parameters are assumed to gradually approach U.S. shares in 1982, except for coal. This implies a higher projected demand for private vehicles and gasoline than what is assumed in most other models of China. The coefficients determining demand for different types of investment goods ( $\alpha_{it}^I$ ), and different types of government purchases ( $\alpha_{it}^G$ ), are projected in a similar manner.

Given the lack of estimates for trade elasticities for China, these elasticities are simply set at conservative values; i.e., the  $\rho$  coefficients in the import demand functions are set at 0.2, while the  $\eta$  coefficients in the export function set to -1.2. The base share of exports and imports are taken from the SAM.

---

<sup>22</sup> China Energy Statistical Yearbook 1997-1999, Tables 4-5 and 4-15 (NBS 2001).

**Table A-1. Production sectors included in the model**

---

Agriculture  
Coal mining  
Crude oil  
Natural gas  
Metal mining  
Other mining  
Food manufacturing  
Textiles  
Apparel  
Lumber  
Paper and Pulp  
Refined Oil  
Chemicals  
Building materials  
Primary metals  
Metal products  
Machinery  
Transport equipment  
Electric machinery  
Communication equipment  
Instruments  
Other industry  
Electric Power  
Gas production  
Construction  
Transportation  
Communication  
Commerce  
Finance, insurance  
Real estate  
Social services  
Culture, education  
Public Administration

---

## References

- Acemoglu, D. 2002. "Directed Technical Change." *Review of Economic Studies*, 69, 781-809.
- Ang, B.W. and F.W. Zhang. 2000. "A Survey of Index Decomposition Analysis in Energy and Environmental Studies." *Energy*, 25 (2000), 1149-1176.
- Dahlman C. and J.E. Aubert. 2001. *China and the Knowledge Economy: Seizing the 21<sup>st</sup> Century*, World Bank Institute, Beijing.
- The Economist. 2006. "Something New." Volume 380, Issue 8489, p. 38-39, August 5<sup>th</sup>.
- Fisher-Vanden, K., and G. Jefferson. 2006. "Technology Diversity and Development: Evidence from China's Industrial Enterprises." Manuscript, Dartmouth College.
- Fisher-Vanden, K., and I. Sue Wing. 2006. "Bringing Quality Back In: Issues with Modeling R&D, Economic Growth, and Carbon Emissions in Developing Economies." Manuscript, Dartmouth College.
- Gao, J. and G.H. Jefferson. 2005. "Science and Technology Takeoff in Theoretical and Empirical Perspective." Manuscript, Brandeis University, Waltham, MA.
- Garbaccio, R.F., M.S. Ho, and D.W. Jorgenson. 1999. Controlling carbon emissions in China. *Environment and Development Economics* 4(4): 493-518.
- Garbaccio, R.F., M.S. Ho, and D.W. Jorgenson. 2001. A dynamic economy-energy-environment model of China, version 2. Unpublished manuscript. Harvard University.
- Ho, M.S. and D.W. Jorgenson. 2001. "Productivity Growth in China, 1981-95." Mimeo. John F. Kennedy School of Government, Harvard University, Cambridge, MA.
- Hu A.G.Z. and G.H. Jefferson. 2004. "Returns to Research and Development in Chinese Industry. Evidence from State-Owned Enterprises in Beijing." *China Economic Review*, 15(1), 86-107.
- Hu A.G.Z, G.H. Jefferson, and J. Qian. Forthcoming. "R&D and Technology Transfer in Chinese Industry." *Review of Economics and Statistics*.
- Jefferson, G.H. 2005. "R&D and Innovation in China: Has China begun Its S&T Takeoff?" *Harvard China Review*, 5(2), 44-50.
- National Bureau of Statistics. 1999b. *China input output table, 1997*. Beijing: China Statistics Press.

- National Bureau of Statistics. 2001. *China Energy Statistical Yearbook (1997-1999)*. Beijing: China Statistics Press.
- Organization of Economic Cooperation and Development (OECD). 2002. *OECD Science, Technology and Industry Outlook, 2002*. OECD, Paris.
- United Nations Development Program (UNDP). 2002. *Human Development Report 2001: Making New Technologies Work for Human Development*, Oxford University Press, New York.
- U.S. Department of Energy, Energy Information Administration. 2006. "International Carbon Emissions and Carbon Intensity."  
<http://www.eia.doe.gov/emeu/international/carbondioxide.html>
- World Bank. 1994. *China: Issues and options in greenhouse gas emissions control*. Washington, DC: World Bank.
- World Bank. 1995. *Macroeconomic stability in a decentralized economy*. Washington, DC: World Bank.
- World Bank. 1996. *The Chinese economy: Fighting inflation, deepening reforms*. Washington, DC: World Bank.
- World Bank. 2006. *World Development Indicators (WDI) Online*. World Bank, Washington, DC.
- World Bank Human Development Network. 2002. *Health, nutrition and population statistics*. Available at <http://devdata.worldbank.org/hnpstats/>, last accessed on January, 2002.
- Wu, Harry X. 2000. "China's GDP level and growth performance: Alternate estimates and the implications", *Review of Income and Wealth Series* 46(4), Dec 475-499.