Accounting for Quality: Issues with Modeling the Impact of R&D on Economic Growth and Carbon Emissions in Developing Economies[†]

Karen Fisher-Vanden[‡]
Dartmouth College

Ian Sue Wing
Boston University

April 25, 2007

ABSTRACT

The literature on climate policy modeling has paid scant attention to the important role that R&D is already playing in industrializing countries such as China, where R&D investments are targeting not only productivity improvements but also enhancements in the quality and variety of products. We focus here on the effects of quality-enhancing innovation on energy use and GHG emissions in developing countries. We construct an analytical model to show that efficiency-improving and quality-enhancing R&D have opposing influences on energy and emission intensities, with the efficiency-improving R&D having an attenuating effect and quality-enhancing R&D having an amplifying effect. We find that the balance of these opposing forces depends on the elasticity of upstream output with respect to efficiency-improving R&D, the elasticity of downstream output with respect to upstream quality-enhancing R&D occurring upstream, and the relative shares of emissions-intensive inputs in the costs of production of upstream versus downstream industries. We employ a computable general equilibrium (CGE) simulation of the Chinese economy to illustrate the difficulties that arise in incorporating these results into models for climate policy analysis, and offer a simple remedy.

JEL Classification: C6, O1, O3, Q5

Keywords: Technological change, product quality, carbon emissions, global climate change, computable general equilibrium.

[†] This work was supported by the U.S. Department of Energy Office of Science (BER), Grant no. DE-FG02-04ER63930 and the National Science Foundation (project/grant #450823) (Fisher-Vanden), and by the U.S. Department of Energy Office of Science (BER), Grants nos. DE-FG02-02ER63484 and DE-FG02-06ER64204 (Sue Wing). We thank Rebecca Terry and an anonymous referee for helpful comments on the original draft.
[‡] Corresponding author: Dartmouth College, 6182 Fairchild Hall, Hanover, NH 03755; phone: 603-646-0213; fax: 603-646-1682; email: kfv@Dartmouth.edu.

1. Introduction

In the few simulation models that explicitly capture innovation's influence on the macroeconomic impacts of climate change mitigation policies, research and development (R&D) either augments the factors of production or reduces the cost of abating emissions of greenhouse gases (GHGs).[1] By contrast, the modeling literature has paid scant attention to the important role that R&D is already playing in key industrializing countries such as China, where firms are making R&D investments not only to improve their productivity, but also to enhance the quality and variety of their products. In this paper we argue that quality-enhancing innovation can have profound effects on energy use and GHG emissions in developing countries.

The conventional wisdom is that the diffusion of advanced technologies from developed countries to developing countries will raise the latter's efficiency, reducing their intensity of energy use and GHG emissions.[2] But while this outcome may well come to pass, it is also likely that increased efficiency will induce an acceleration in the growth of output which increases energy use and emissions in absolute terms (see, e.g., Fisher-Vanden, 2003). Although productivity improvements are an important target of R&D in most developing countries, an increasing share of innovatory activity is being devoted to enhancing product quality and variety. This trend is important because such improvements can affect energy use and emissions by shifting the composition of output and the distribution of value-added among industries, i.e., structural change. Those sectors which experience more rapid improvements in product quality and variety will likely grow faster relative than their less technologically dynamic counterparts, changing the composition of aggregate output. Depending on the energy-using characteristics of

[1] For a review, see Sue Wing (2006).
[2] For an optimistic view, see Grubb, Hope and Fouquet (2002).

these leading industries, the energy and emissions intensities of the aggregate economy may rise or fall.

The accumulation of technological capabilities has two main benefits in developing countries: a reduction in the marginal cost of production—which can be thought of as "process innovation"—and an expansion in the range of commodities to higher-value goods—which can be thought of as "product innovation". The key implication, which we examine here, is that in order to project the future trajectory of GHG emissions from industrializing countries, it is necessary to capture the influence of *both* kinds of innovation on GDP growth and the aggregate demand for fossil fuels.

We first develop a simple analytical model which illustrates that efficiency-improving and quality-enhancing R&D have opposing influences on energy- and emission intensities, with efficiency-improving R&D having an attenuating effect and quality-enhancing R&D having an amplifying effect. We show that the relative magnitude of these forces depends on three factors:

(i) The elasticity of output with respect to efficiency-improving R&D, in industries whose products are consumed by other, "downstream," sectors;

(ii) The elasticity of output with respect to quality-enhancing R&D occurring upstream, in the industries which primarily consume the outputs of the "upstream" sectors in (i); and

(iii) The relative shares of emissions-intensive inputs in the costs of production of upstream versus downstream industries.

These results are subsequently incorporated into a CGE model of the Chinese economy which is calibrated using econometric estimates of the influence of R&D on the cost of manufacturing industries in China. We show that failure to account for the interindustry transmission of quality changes (effect (ii), above) leads to a startlingly counterintutive result: an exogenous increase in the R&D-GDP ratio precipitates reductions in both real GDP and carbon dioxide (CO_2) emissions! The root of the problem is that interindustry demands are not denominated in quality-adjusted units, consequently the model does not differentiate between the opposing effects of efficiency improvements and quality enhancements on the general equilibrium commodity price vector. We offer a method for correcting this problem within the algebraic framework of a CGE model. With this adjustment, a rise in the intensity of R&D induces acceleration in the growth of real GDP, as well as structural changes which lead to a rise in the intensity of energy use and CO_2 emissions per unit output. This result suggests that for China, the amplifying effect of quality-enhancing R&D on energy-intensity will outweigh the attenuating effect of efficiency-improving R&D, leading to higher aggregate emissions.

The paper is organized as follows. Section 2 develops an analytical model of the impact of efficiency-improving and quality-enhancing R&D on structural change and energy intensity. Section 3 summarizes results of our modeling exercise, and develops a method for incorporating the effects of quality-enhancing R&D into CGE simulations. Section 4 provides a summary and concluding remarks.

2. A simple analytical model

Our first task is to develop an analytical framework to assess the implications of quality- and efficiency-enhancing R&D for a country's energy and carbon intensities. We take a deliberately simple approach. We construct a theoretical model in which there are two industries, one upstream (*U*) and the other downstream (*D*), where the latter uses the output of the former as an input to production. The solution gives the elasticities with respect to each type of R&D of the price and quantity of upstream output, the upstream demand for variable inputs, and the quantity of downstream output.

To keep the model simple, we assume that each industry manufactures a homogenous good using Cobb-Douglas production technology. Output of the upstream industry, q_U, is produced from a variable input, v (which we assume represents fossil fuels), and a generic input, x, while output of the downstream industry, q_D, is produced using inputs q_U, v, and the generic input, x. We use p_U and p_D to denote the prices of the upstream and downstream commodities, w to denote price of the variable input, and α and γ to denote the cost shares of v in upstream and downstream production, and β to denote the cost share of q_U in downstream production. We further assume that in each industry x is in perfectly inelastic supply, and normalize its price to one. Doing so guarantees upward sloping supply schedules, and makes the variable x a proxy for each industry's "capacity", which enables us to work directly with their profit functions to compute the output levels and unconditional input demands.

We assume that industries engage in two types of R&D: efficiency-improving and quality-enhancing research, which we denote R^E and R^Q. The first of these corresponds to the way in which research is traditionally modeled—R&D increases the productivity (or, symmetrically, reduces the cost of output) in the industry where it is performed. We assume that both industries conduct efficiency-improving R&D, and therefore specify augmentation functions $\mathrm{E}(R_U^E)$ and $\Omega(R_D^E)$ which act as neutral shift factors in the production functions for U and D.

Research which enhances the quality of output acts in a more subtle way. It does not directly influence the production process in the sector where the R&D is performed, but rather increases the productivity of downstream industries that use the sector's output commodity as an input to production. Our key simplification is to assume that quality-enhancing R&D is conducted only in the upstream sector. Its effect is to reduce the component of *D*'s cost associated with the use of the upstream good and, in so doing, shifts the demand curve for q_U. We therefore specify the function $\Theta(R_U^Q)$ as an augmentation factor which is appended to the input of q_U to the production of *D*:[3]

(1) $$q_U = \mathrm{E}(R_U^E) v_U^{\alpha} x_U^{1-\alpha}$$

(2) $$q_D = \Omega(R_D^E)\left(\Theta(R_U^Q) q_U\right)^{\beta} v_D^{\gamma} x_D^{1-\beta-\gamma}$$

The key implication is that the industries' profits, π_U and π_D, are interdependent. Thus, in order to understand the impact of quality-enhancing R&D we must analyze both industries' profit maximization problems jointly. The profit functions are:

$$\underset{v_U, R_U^E, R_U^Q}{\arg\max} \left\{ \pi_U = p_U q_U - w v_U - x_U - R_U^E - R_U^Q \right\} \text{ s.t. (1), } x_U \text{ given,}$$

$$\underset{q_U, v_D, R_D^E}{\arg\max} \left\{ \pi_D = p_D q_D - p_U q_U - w v_D - x_D - R_D^E \right\} \text{ s.t. (2), } x_D \text{ given.}$$

To facilitate exposition, we parameterize the effects of R&D on productivity using simple iso-elastic functions: $\mathrm{E} = (R_U^E)^{\varepsilon}$, $\Theta = (R_U^Q)^{\theta}$ and $\Omega = (R_D^E)^{\omega}$, where ε, θ and ω are positive parameters ($\varepsilon, \theta, \omega \in (0, 1)$).

To calibrate the reader's expectations, firm-level empirical estimates of the productivity elasticities of private R&D lie in the range 0-0.6, with the majority of estimates being below 0.3

[3] Two points are worth highlighting here. First, quality improvements primarily affect energy use through changes in the structure of economic activity, which suggests that it suffices to examine the neutral effect of R&D. We therefore do not consider the effect of input biased technical change. Second, upstream and downstream R&D are treated in an asymmetric fashion, with both product and technological "spillovers" (in the form of quality enhancements to interindustry commodity streams) flowing unidirectionally from *U* to *D*. We choose this analytical setup for the sake of transparency and tractability rather than realism. Indeed, we note that in the simulation in the following section, every sector is potentially both a downstream and an upstream industry, simultaneously engaging in quality-enhancing R&D that reduces production costs in the "downstream" industries which purchase its product,

(see Congressional Budget Office, 2005, and references therein). As well, inputs of fossil fuels rarely make up more than one third of the total cost of production in energy-supply or energy-intensive industries, so in the analysis below, intensive use of v corresponds to a value of no more than 0.3 for α or γ. In particular, to facilitate interpretation of the results, we impose the relatively mild restriction that $1-\beta-\gamma>\omega$.

We first consider the downstream industry, where we assume that the inputs for the variable factor and the upstream commodity, as well as the investment in efficiency-improving R&D are all chosen optimally. The resulting first-order conditions are:

$$\frac{\partial \pi_D}{\partial v_D} = \gamma p_D \Omega(R_D^E)\left(q_U \Theta(R_U^Q)\right)^{\beta} v_D^{\gamma-1} x_D^{1-\beta-\gamma} - w = 0\,,$$

$$\frac{\partial \pi_D}{\partial q_U} = \beta p_D \Omega(R_D^E) q_U^{\ \beta-1} \Theta(R_U^Q)^{\beta} v_D^{\gamma} x_D^{1-\beta-\gamma} - p_U = 0\,,$$

$$\frac{\partial \pi_D}{\partial R_D^E} = p_D \Omega'(R_D^E)\left(q_U \Theta(R_U^Q)\right)^{\beta} v_D^{\gamma} x_D^{1-\beta-\gamma} - 1 = 0\,.$$

The solution to this system of equations consists of D's conditional demand for the variable input, inverse demand for the upstream commodity, and optimal investment in efficiency-improving research:

(3) $$v_D = \gamma^{\frac{\gamma}{1-\gamma-\omega}} \omega^{\frac{\omega}{1-\gamma-\omega}} w^{\frac{\omega-1}{1-\gamma-\omega}} p_D^{\frac{1}{1-\gamma-\omega}} q_U^{\frac{\beta}{1-\gamma-\omega}} x_D^{\frac{1-\beta-\gamma}{1-\gamma-\omega}} (R_U^Q)^{\frac{\beta\theta}{1-\gamma-\omega}}\,,$$

(4) $$p_U = \beta \gamma^{\frac{\gamma}{1-\gamma-\omega}} \omega^{\frac{\omega}{1-\gamma-\omega}} w^{\frac{-\gamma}{1-\gamma-\omega}} p_D^{\frac{1}{1-\gamma-\omega}} q_U^{-\frac{1-\beta-\gamma-\omega}{1-\gamma-\omega}} x_D^{\frac{1-\beta-\gamma}{1-\gamma-\omega}} (R_U^Q)^{\frac{\beta\theta}{1-\gamma-\omega}}\,,$$

(5) $$R_D^E = \gamma^{\frac{\gamma}{1-\gamma-\omega}} \omega^{\frac{1-\gamma}{1-\gamma-\omega}} w^{\frac{-\gamma}{1-\gamma-\omega}} p_D^{\frac{1}{1-\gamma-\omega}} q_U^{\frac{\beta}{1-\gamma-\omega}} x_D^{\frac{1-\beta-\gamma}{1-\gamma-\omega}} (R_U^Q)^{\frac{\beta\theta}{1-\gamma-\omega}}\,.$$

---

while benefiting from the availability of higher quality intermediate inputs sold to it by "upstream" sectors pursuing improvements in product quality.

We draw particular attention to the fact that $\text{sgn}[\partial p_U / \partial R_U^Q] = \text{sgn}[\beta\theta/(1-\gamma-\omega)] > 0$, which implies that quality-enhancing R&D has the effect of *increasing* the market price of the upstream commodity.[4] As we shall see, this result figures prominently in the empirical and modeling results of the subsequent section. Blindly incorporating this effect into a CGE simulation leads to R&D having a counterintuitive adverse impact on economic growth. Such an outcome would only obtain in the real world if the units of q_U remained unchanged—that is, if the upstream good was of similar quality. But quality improvements have the effect of increasing the quantity of output in "efficiency" units, which is captured by the increased productivity of downstream production due to augmentation of q_U.

We now turn to the upstream industry. As with the downstream industry the system of equations made up of the first-order conditions for the variable input and the levels of efficiency-improving and quality-enhancing R&D may be jointly solved for the optimal values of v_U, R_U^E and R_U^Q. Doing so makes it possible to express R_U^E, R_U^Q, R_D^E, p_U, q_U, q_D, v_U and v_D as functions of the elasticity parameters, the prices of the variable input and *D*'s output, and the levels of the quasi-fixed inputs. Our objective here is different, however: we seek to understand the impact of upstream research on structural change which requires us to elaborate the influence of R_U^E and R_U^Q on the other variables. Accordingly, we assume that *U* only optimizes its use of the variable factor, and treat the two types of upstream R&D parametrically.

The first-order condition with respect to the upstream use of the variable input is:

[4] Also, $\text{sgn}[\partial R_D^E / \partial R_U^Q] = \text{sgn}[\beta\theta/(1-\gamma-\omega)] > 0$, which suggests that if the quantity of efficiency-improving R&D in the downstream industry is chosen optimally, a larger quantity of quality-enhancing R&D in upstream sectors would tend to induce more downstream innovatory effort. We thank a referee for raising this interesting possibility. Nevertheless, we are quick to emphasize that it has little bearing on our subsequent simulation exercises, as R&D is treated as an exogenous forcing variable within our CGE model.

$$\frac{\partial \pi_U}{\partial v_U} = \alpha p_U v_U^{\alpha-1} x_U^{1-\alpha} \mathrm{E}(R_U^E) - w = 0 ,$$

which yields U's optimal conditional demand for the variable input:

(6) $$v_U = \alpha^{\frac{1}{1-\alpha}} p_U^{\frac{1}{1-\alpha}} w^{\frac{-1}{1-\alpha}} (R_U^E)^{\frac{\varepsilon}{1-\alpha}} x_U .$$

We then use this expression to substitute for v_U in (1) to derive the supply function for the upstream commodity

(7) $$p_U = (w/\alpha)(q_U / x_U)^{(1-\alpha)/\alpha} (R_U^E)^{-\varepsilon/\alpha} .$$

By combining eqs. (4) and (7) we can derive the equilibrium quantity of the upstream commodity in terms of exogenous variables:

(8) $$q_U = \kappa_1 \left[p_D^{\alpha} w^{\alpha(\omega-1)} (R_U^E)^{\varepsilon(1-\gamma-\varepsilon)} (R_U^Q)^{\alpha\beta\theta} \right]^{1/\xi} ,$$

where $\xi = 1 - \alpha\,\beta - \gamma - \omega$, and κ_1 is a constant.

Along with (4), this result allows us to eliminate q_U in eqs. (3)-(6):

(9) $$v_D = \kappa_2 \left[p_D w^{\omega-1} (R^E)^{\beta\varepsilon} (R^Q)^{\beta\theta} \right]^{1/\xi} .$$

(10) $$p_U = \kappa_3 \left[w^{\alpha(1-\beta-\omega)-\gamma} p_D^{1-\alpha} (R_U^E)^{-\varepsilon(1-\beta-\gamma-\omega)} (R_U^Q)^{(1-\alpha)\beta\theta} \right]^{1/\xi} .$$

(11) $$R_D^E = \kappa_4 \left[w^{-(\alpha\beta+\gamma)} p_D (R_U^E)^{\beta\varepsilon} (R_U^Q)^{\beta\theta} \right]^{1/\xi} .$$

(12) $$v_U = \kappa_5 \left[p_D w^{\omega-1} (R_U^E)^{\beta\varepsilon} (R_U^Q)^{\beta\theta} \right]^{1/\xi} .$$

Finally, by substituting (8), (9) and (11) into eq. (2) we obtain the effects on the quantity of downstream output:

(13) $$q_D = \kappa_6 \left[w^{-(\alpha\beta+\gamma)} p_D^{\alpha\beta+\gamma+\omega} (R_U^E)^{\beta\varepsilon} (R_U^Q)^{\beta\theta} \right]^{1/\xi} .$$

The terms κ_1-κ_6 in these expressions are all complicated constants in α, β, γ, ε, x_D, and x_U.

Our main findings are summarized in panels A.I and B.I of Table 1. The signs of the elasticities tabulated therein hinge on the sign of ξ, which is positive given the restrictions on the parameters discussed above.[5] We therefore look to the numerators of these expressions to determine the direction of the relevant impacts.

Our focus is on the implications of the two kinds of R&D for upstream production costs, structural change and aggregate energy intensity. We first examine the sensitivity of the price and quantity of upstream output and the quantity of downstream output to efficiency-improving and quality-enhancing R&D. Subject to our restrictions on the variable input's cost shares, R^E will tend to raise the quantity and lower the price of U's output, whereas R^Q will tend to simultaneously increase both the price and quantity. Additionally, efficiency-improving and quality-enhancing R&D both exert positive influences on the upstream demand for v.

Figure 1 shows the simple intuition behind these results. Eq. (4) is indicated by the demand curve, D, while eq. (7) is given by the supply curve, S. Assuming that the sectors are at an initial equilibrium O in which the price and quantity of the upstream good are p_U^* and q_U^* respectively, R^E has the effect of shifting the supply curve downward to S', resulting in a new equilibrium A where q_U expands and p_U declines, while the effect of R^Q is to shift the demand curve outward to D', resulting in a new equilibrium B in which both p_U and q_U increase. In the realistic case where the upstream industry pursues both lines of research simultaneously, we get an equilibrium such as C where the level of output is unambiguously higher, but the price may increase or decrease relative to p_U^* within the bounds $[\underline{p}_U, \overline{p}_U]$.

Both types of research have a positive impact on the downstream industry's output, but their effects operate through distinct channels. The spillover effects of quality-enhancing R&D

[5] For fossil fuel input shares in the range of observations ($\alpha \approx 0.3$), even if $\beta = \gamma = 0.1$, for ξ to approach zero ω

give rise to neutral productivity improvement which raises the level of output, while R&D which makes upstream production more efficient reduces marginal cost, lowering p_U and with it the cost of production downstream, enabling *D* to expand. Since neither kind of R&D has a direct influence on *D*'s use of the variable input, the unconditional demand for *v* simply increases as a consequence of the expansion of the sector.

Our findings thus far have important implications for structural change and aggregate fossil-fuel use. Given that each sector exhibits its own response to each kind of innovation, a key question is whether R&D causes upstream sectors to expand relative to those downstream, or vice versa. To investigate this, we calculate the ratio of the outputs of the upstream and downstream industry, dividing (8) by (13) to obtain our measure of structural change:

$$(14) \qquad q_U / q_D = \kappa_7 \left[w^{\gamma-\alpha(1-\beta-\omega)} p_D^{\alpha(1-\beta)-\gamma-\omega} (R_U^E)^{\varepsilon(1-\beta-\gamma-\omega)} (R_U^Q)^{-(1-\alpha)\beta\theta} \right]^{1/\xi}.$$

In addition, the fossil-fuel intensity of production in each sector indicated by the conditional demand for the variable input:

$$(15) \qquad v_U / q_U = \kappa_8 \left[w^{-(1-\alpha)(1-\omega)} p_D^{1-\alpha} (R_U^E)^{-\varepsilon(1-\beta-\gamma-\omega)} (R_U^Q)^{\beta\theta(1-\alpha)} \right]^{1/\xi}$$

and

$$v_D / q_D = \gamma p_D / w.$$

As before, κ_7 and κ_8 are constants in α, β, γ, ε, x_D, and x_U.

These results are summarized in panels A.II and B.II of Table 1. The impacts of R&D on structural change are both intuitive and consistent with expectations. Because it increases productivity in the upstream sector, efficiency-improving R&D will tend to favor the expansion of *U* relative to *D*. Conversely, the fact that investments in quality-enhancing R&D upstream redound to the downstream sector implies that this type of innovation favors the expansion of *D*

---

would have to exceed 0.7, which is implausibly large.

relative to *U*. Depending upon which effect dominates and which industry (upstream or downstream) is the more energy intensive, aggregate energy intensity can be higher or lower.

Regarding the latter, efficiency-improving R&D in the upstream sector will tend to lower energy intensity while quality-enhancing R&D has the opposite effect. This result is a consequence of the fact that the first kind of innovation saves on *U*'s inputs, while the second induces an outward shift in the demand curve for its product. Neither type of R&D has any impact on the intensity of fossil-fuel use in the downstream sector, which is consistent with the fact each kind of R&D has the same effect on *D*'s variable input demand as it does on output.

Whether the attenuating impact of efficiency-improving R&D on energy intensity is outweighed by the amplifying effects of quality-enhancing R&D depends on the relative energy intensities of the upstream and downstream industries, the elasticities of output with respect to the two types of R&D, and the share of *U*'s output in *D*'s production. Specifically, for given coefficients on energy use in each industry (fixed α and γ), the smaller the elasticity of upstream productivity with respect to R^E (ε), the larger the elasticity of output with respect to R^Q (θ), or the larger the share of *U*'s output in *D*'s production (β), the greater the positive effect of quality-enhancing R&D. In the following section we investigate the implications of these factors for a developing country using the results from an exercise that incorporates econometric estimates of the impacts of R&D into a CGE model for China.

3. Modeling efficiency vs. quality-enhancing R&D: a numerical general equilibrium analysis for China

The key structural difference between our analytical model and the standard representation of innovation in both econometric and simulation models is that the latter almost always resolve only a single stock of R&D capital.[6] It is customary for this stock to be modeled as the accumulation of past investments in research by a particular firm or sector, which in a given period constitutes an intangible input to production that has an efficiency-improving effect.

These modeling choices tend to be driven by data availability and analytical convenience. Data on R&D spending almost never separates investments in efficiency improvement from those intended to improve product quality, consequently we typically observe only the sum of R^E and R^Q. As well, the data used to estimate econometric factor demand models typically represent intermediate inputs only as broad composite goods like “energy” and “materials”, making it virtually impossible to resolve the impact of upstream product quality enhancements on producers’ purchases of individual intermediate commodities.

The upshot is that standard econometric approaches are not capable of distinguishing the effects of the two kinds of R&D. Because a single R&D stock is assumed to drive both efficiency-improving and quality-enhancing innovation, econometric estimates for a given producer will indicate only the *combined* effect of R^E and R^Q. Moreover, such estimates will only reflect the impact of R&D on the price and quantity of output of the firm or sector in which the relevant research is actually undertaken. The aggregate character of the data on intermediate purchases makes it impossible to identify the shift in the downstream demand for the output of a particular producer’s investment in quality-enhancing R&D. The problem is that for an equilibrium such as *C* in Figure 1, econometric estimates of the effect of R&D on the cost of production will reflect the impact of R^Q on the price of the innovating industry’s output but will fail to capture the impact on the quantity of output.

[6] A prominent exception is Popp’s (2006) ENTICE-BR model which incorporates two stocks of R&D capital, one which saves conventional energy that produces CO_2 emissions and the other which increases the productivity of a carbon-free backstop energy supply technology. However, this simulation does not represent the inter-industry structure necessary to distinguish between efficiency improvements and quality enhancements.

We go on to show that when estimates of this kind are naively incorporated into a CGE model's system of inter-industry commodity demands, where every sector is both an upstream and a downstream producer, it is possible to generate results which are completely fallacious.

3.1. Modeling technology development

Fisher-Vanden and Ho (2006)—hereafter, FVH—have developed an econometrically calibrated CGE model of the Chinese economy, which incorporates the effects of innovation on neutral and factor-biased productivity in the industrial sectors. The lynchpin of their approach is a vector of industry-specific stocks of R&D capital, each element of which represents the accumulation of past deliberate investments in new technology development by a given manufacturing industry.

We focus on the representation of innovation within the model and abstract from its other structural details, which is described in Fisher-Vanden and Ho (2006). The model resolves 33 sectors, which include agriculture, 22 manufacturing industries, construction, transportation, and 7 service sectors. Each industry, which we indicate using the index j, produces a unique homogeneous commodity, which we indicate using the index i. In each period of time, t, the production of output ($QO_{j,t}$) requires five types of inputs, capital (K), labor (L), land (T), energy (E) and materials (M), which are denoted by the index $z = \{K, L, T, E, M\}$. Production takes place according to a hierarchical Cobb-Douglas production function, whose associated dual cost function is expressed as a vector of zero profit conditions which equate industries' output prices ($PO_{j,t}$) with their unit costs under the assumption of constant returns to scale (CRTS) and perfect competition:

(16) $$\ln PO_{j,t} = \ln G_{j,t} + \sum_z a_{z,j,t} \ln P_{z,j,t} \ .$$

In this expression, the variable P is a vector of the prices of the inputs to j at time t; a is a vector of parameters which denote the (time varying) shares of the various inputs in the cost of production ($\sum_z a_z = 1$), and G is an industry-specific Hicks-neutral productivity term.

In eq. (16), the composite price indexes of intermediate inputs of energy and materials ($P_{E,j}$ and $P_{M,j}$) are the outputs of Cobb-Douglas unit cost sub-functions denominated over the vectors of output prices of energy-producing sectors (e) and materials-producing sectors (m):

(17a) $$\ln P_{E,j,t} = \sum_{i \in e} \eta_{i,j} \ln[(1+\tau_{i,j}) PO_{i,t}],$$

(17b) $$\ln P_{M,j,t} = \sum_{i \in m} \mu_{i,j} \ln[(1+\tau_{i,j}) PO_{i,t}].$$

The parameters $\tau_{i,j}$ indicate ad-valorem taxes on intermediate inputs, while the technical coefficients η and μ represent the fixed input shares in industry j's E and M sub-cost functions, which also exhibit CRTS ($\sum_{i \in e} \eta_{i,j} = \sum_{i \in m} \mu_{i,j} = 1$). Thus, each sector in the model is both an upstream and a downstream industry, using the outputs of the i upstream industries at prices PO_i (plus input taxes) to produce a commodity with unit cost PO_j, which is in turn employed as an input to downstream sectors.

Autonomous and deliberate technological development affect production in the manufacturing sectors of the economy. Innovation is assumed to alter both the rate of technical change, given here by G, and the bias of technical progress—which is equivalent to the rate of change in the a parameters with prices held constant (Binswanger and Ruttan, 1978). FVH define indices of economy-wide autonomous technology development (represented as a time trend), h_t, and industry-specific deliberate innovation, $R_{j,t}$. Neutral multifactor productivity is given by:

(18) $$\ln G_{j,t}(h_t, R_{j,t}) = g_{A,j}\, h_t + g_{R,j} \ln R_{j,t}, \qquad j \in \text{manufacturing}$$

while biased technical progress is given by the definition of the input share parameters:

(19) $a_{z,j,t}(h_t,R_{j,t}) = a_{z,j,0} + b_{A,z,j}\, h_t + b_{R,z,j} \ln R_{j,t}, \qquad j \in$ manufacturing

The coefficients b_A, b_R, g_A and g_R are econometrically-estimated parameters. The parameters, b_A and b_R capture the effects of autonomous and deliberate technology development on the cost shares of each input, while the parameters, g_A and $g_{R,}$ indicate the effects of autonomous and deliberate technology development on neutral productivity.

This specification enables the implications for the energy- and carbon-intensities of China's industries of an increase in R&D activities to be simulated in the following way. Deliberate technology development in each industry is modeled as the growth rate of the stock of R&D, measured as cumulative R&D expenditures. For simplicity, autonomous technology development is modeled using a time trend. To implement eqs. (18) and (19), the model uses econometric estimates for the parameters b_A, b_R, g_A and g_R. These estimates are based on the work of Fisher-Vanden and Jefferson (2006), who measure the factor bias of autonomous and deliberate technology development activities by estimating a translog cost function along with its corresponding cost share equations on a data set of 1500 industrial enterprises in China over the years 1995-2001.

These estimates are summarized in Table 2. Panel A illustrates that autonomous technology development has only a small impact on the bias of technical change. Its influence on the bias of factor hiring is for the most part not significant, and even where it is (e.g., in the paper, textile or chemical industries) the effect on cost shares is much smaller than that on neutral productivity, and without any discernable trend. On the other hand, autonomous innovation is associated with reductions in unit cost for seven out of the eight sectors in which its influence is significant.[7] Thus, we conclude that autonomous innovation is predominantly efficiency improving in character.

Panel B illustrates that deliberate technology development is capital-using and energy-saving in the majority of industries, but is equivocal in its influence on labor and materials. And out of nine sectors in which deliberate innovation has a significant neutral productivity impact, six exhibit positive responses, which implies that R&D has the effect of increasing the unit cost of production. As discussed above, we interpret this result to mean that the effect of quality-enhancing innovation outweighs that of efficiency-improving innovation. But while the econometric estimates in Table 2 capture the combined effect of R^E and R^Q only on the industries in which research is being performed, they completely miss the corresponding impacts on the downstream users of these sectors' outputs.

The implications of this shortcoming become clear if we substitute the coefficients in Table 2 into eqs. (18) and (19) while ignoring downstream impacts on product quality impacts, and then simulate the CGE model under two sets of assumptions. The first is a business-as-usual (BAU) case in which aggregate R&D is assumed to remain at the initial level of 0.78 percent of GDP. The second is a R&D intensification scenario which assumes that the R&D intensity of the economy increases from 0.78 to 2.5 percent by the year 2050. Figure 2 shows the difference in real GDP and carbon emissions between the two cases. The results suggest that an increase in R&D activities will *lower* both real GDP and emissions. This outcome is not just counterintuitive, it is wrong. The parameterization of the model ensures that R&D drives up the manufacturing sectors' output prices-cum-unit costs, whose apparent effect is to *reduce* sectoral and aggregate productivity, value added and intermediates use of fossil fuels.

[7] The magnitude of the positive and significant estimate is the largest in the table, however the sector in question (other industry) is relatively minor, accounting for 12 percent of manufacturing value added and just five percent of

We would never expect such a result to see the light of day since any competent modeler would immediately reject it as implausible. However, this example serves as a cautionary reminder of the potential magnitude of the problem in developing-country economic simulations where quality enhancements are a significant component of innovation. We now address the issue of how to adjust the model to reflect the fact that the empirical estimates capture both process and product innovations.

The problem arises from the way in which output is measured in the model. The foregoing exercise fails to account for the fact that while quality-enhancing R&D raises production costs, it shifts the composition of output toward higher value commodities for which there is greater demand, and which stimulates an increase in the quantity of output measured in "quality-adjusted" units. For example, in the case of computer manufacturing, we would want to measure output in terms of, say, data processing speed or capacity as opposed to the number of microprocessors. The implication is that quality enhancements lead to a larger quantity of output, which should be reflected in the price of commodity being produced. As we now demonstrate, this suggests a way to correct the estimates so that the model generates more reasonable results.

3.2. Incorporating product quality

In the analytical model of Section 2, quality-enhancing R&D in the upstream industry effectively *increases* the quantity of the upstream good used by the downstream industry. Using a tilde (~) to indicate a quantity measured in quality-adjusted units, it is clear from eq. (1) that from the perspective of the downstream sector, the quantity of the upstream good employed is $\tilde{q}_U = \Theta(R_U^Q) q_U$. The law of one price, however, implies that q_U and $\tilde{q}_U$ cannot have the same

GDP in the benchmark social accounting matrix used to calibrate the model.

price. In particular, market clearing in the upstream commodity means that the quality-adjusted price must satisfy $\tilde{p}_U \tilde{q}_U = p_U q_U$. We therefore have $\tilde{p}_U = p_U / \Theta(R_U^Q)$. This clarifies the problem which gives rise to the results in section 3.1, and also suggests a potential remedy.

Informed by this analysis, we turn once again to the CGE model. We note that in the most general setting, every sector in the model is potentially both a downstream and an upstream industry, simultaneously engaging in quality-enhancing R&D that reduces production costs in the “downstream” industries which purchase its product, while benefiting from the availability of higher quality intermediate inputs sold to it by “upstream” sectors pursuing improvements in product quality. Examining eq. (18), this suggests that by blindly plugging in values for $g_{A,j}$ and $g_{R,j}$ we are effectively treating *all* R&D as if it were efficiency-improving. Therefore, positive values for these coefficients are the equivalent of specifying a negative value for ξ in the analytical model, which would have the effect of *lowering* productivity, output and the demand for fossil fuels—exactly what we observe in the numerical results.

Our problem is a misattribution of the effect of downstream quality-enhancing technical progress which makes it appear to be upstream efficiency-worsening technical retrogression. The root cause is the fact that the separate influences of the two kinds of technology development are not identified. In particular, the estimates in Table 2B represent the combined influence of efficiency improvements and quality enhancements. The implication is that

(18′) $$\ln G_{j,t} = (g_{A,j}^E + g_{A,j}^Q) h_t + g_{R,j}^E \ln R_{j,t}^E + g_{R,j}^Q \ln R_{j,t}^Q ,$$

where the new coefficients g^E and g^Q are the analogues of the ε and θ in the analytical model. We assume that g_A^E and g_R^E are both negative, while g_A^Q and g_R^Q are both positive.

If we could observe the individual terms in (18′), we could partition the neutral productivity term into efficiency and quality components, $\ln G = \ln G^E + \ln G^Q$, where

$$\ln G^E_{j,t} = g^E_{A,j} h_t + g^E_{R,j} \ln R^E_{j,t} \text{ and } \ln G^Q_{j,t} = g^Q_{A,j} h_t + g^Q_{R,j} \ln R^Q_{j,t} .$$

This would allow us to express both the price and quantity of the output of each industry in quality-adjusted units: $\ln \widetilde{QO}_{j,t} = \ln G^Q_{j,t} + \ln QO_{j,t}$. Also, by the law of one price, $\widetilde{PO}_{j,t} \widetilde{QO}_{j,t} = PO_{j,t} QO_{j,t}$. But to be consistent with the theoretical model, the price of output in observed units must be adjusted so as to not be contaminated by the effect of quality-enhancing R&D, and to reflect only the influence of efficiency improvement. This suggests the following modification in the definition of G in eq. (16):

(16′) $$\ln PO_{j,t} = \ln G^E_{j,t} + \sum_z a_{z,j,t} \ln P_{z,j,t} .$$

Together, these expressions imply that

(20) $$\ln \widetilde{PO}_{j,t} = \ln PO_{j,t} - \ln G^Q_{j,t} .$$

Therefore, to account for the influence of upstream increases in product quality on the costs of downstream producers, the final step is to adjust the price of intermediate inputs to reflect quality, as follows:

(17a′) $$\ln P_{E,j,t} = \sum_{i \in e} \eta_{i,j} \ln[(1+\tau_{i,j})\widetilde{PO}_{i,t}],$$

(17b′) $$\ln P_{M,j,t} = \sum_{i \in m} \mu_{i,j} \ln[(1+\tau_{i,j})\widetilde{PO}_{i,t}] .$$

We face the challenge of making this scheme operational, given that neither the data nor the econometric estimates from Fisher-Vanden and Jefferson (2006) permit us to disentangle the effects of efficiency improvements from those of quality improvements. In the absence of alternative information, the best that can be done is to treat the two kinds of R&D in eq. (18′) as one in the same, i.e., setting $R^E_{j,t} = R^Q_{j,t} = R_{j,t}$, and then use their net effect on costs to filter the estimates in Table 2. Under this assumption, if the net effect of either autonomous or deliberate technology development is efficiency improving, then $|g_A^E| > g_A^Q$ or $|g_R^E| > g_R^Q$, which implies that either g_A or g_R will be negative. Conversely, if the net impact of either autonomous or deliberate innovation is quality-enhancing, then $|g_A^E| < g_A^Q$ or $|g_R^E| < g_R^Q$, implying that either g_A or g_R will be positive.

Having established the direction of the net effect, our final, heroic assumption is to attribute g_A and g_R to one or the other type of innovation, depending on their signs. We do this by filtering the estimates of these parameters in the following way. Where an estimate is negative and significant then we assume that it generates a neutral efficiency improvement but does not influence product quality:

$$\text{(21)} \qquad \ln G_{j,t}^E = \min(0, g_{A,j})h_t + \min(0, g_{R,j})\ln R_{j,t}.$$

Where an estimate is positive and significant we assume that it enhances product quality but has no effect on productivity:

$$\text{(22)} \qquad \ln G_{j,t}^Q = \max(0, g_{A,j})h_t + \max(0, g_{R,j})\ln R_{j,t}.$$

Eqs. (16′), (17′) and (20)-(22) make up our adjustment to the model for the representation of quality-enhancing R&D.

The consequences of implementing this adjustment are shown in Figure 2, which illustrates the difference in real GDP and carbon emissions between the S&T takeoff and BAU scenarios. The results are consistent with intuition; i.e., real GDP should rise with increases in industries' R&D intensity. Carbon emissions are higher as well. Although more research leads to greater energy efficiency, its impact on productivity leads to more rapid growth of output and a greater-than-proportional increase in economic activity. Importantly, we find that the growth in real GDP is outweighed by the rise in carbon emissions, implying that the emission intensity of the Chinese economy is rising as well. Drawing on the results of our analytical model, these results may be interpreted as saying that the positive effect of quality-enhancing R&D on energy and carbon intensity outweighs the negative effect of efficiency-enhancing R&D, leading to an overall increase in the economy's carbon intensity.

4. Concluding remarks

This paper has elucidated the channels by which efficiency-improving and quality-enhancing R&D affect an economy's aggregate intensity of energy use and emissions of CO_2. Using an analytical model, we demonstrate that efficiency-improving innovation attenuates energy intensity while quality-enhancing innovation tends to amplify it, and illustrate that the balance of these opposing forces depends on the elasticity of upstream output with respect to efficiency-improving R&D, the elasticity of downstream output with respect to upstream quality-enhancing R&D occurring upstream, and the relative shares of emissions-intensive inputs in the costs of production of upstream versus downstream industries.

We highlight the challenges of incorporating these insights into numerical economic simulations using a CGE model of China's economy which is calibrated based on econometric estimates of the sectoral impacts of efficiency-improving and quality-enhancing R&D. Failure to adjust for the effects of quality-enhancing innovation on interindustry demands leads to flawed results owing to models' inability to resolve their influence on the general equilibrium commodity price vector.

We develop a simple procedure to address this problem; however, our approach suffers from the fundamental limitation that neither kind of innovation can be directly observed, and must inferred from the sign of the relevant empirical estimates used to parameterized the model. In particular, our workaround attributes a positive (negative) neutral R&D elasticity of unit cost to (efficiency) improvements, where in reality such estimates almost surely reflect the combined influence of both types of innovation. Therefore, our model results are biased to an unknown degree. But the fact that our data only allow us to estimate the net effect of homogeneous R&D highlights the need for more research and particularly data gathering on the characteristics of innovation being pursued by industrializing countries.

References

Binswanger, H.P. and V.W. Ruttan (1978). Induced Innovation: Technology, Institutions, and Development, Baltimore MD: The Johns Hopkins University Press.

Congressional Budget Office (2005). Background Paper: R&D and Productivity Growth, Congress of the United States.

Fisher-Vanden, K. (2003). “The Effects of Market Reforms on Structural Change: Implications for Energy Use and Carbon Emissions in China,” The Energy Journal, 24(3), 27-62.

Fisher-Vanden, K., and M.S. Ho (2006). “What Will a Science and Technology Takeoff in China Mean for Energy Use and Carbon Emissions?” Manuscript, Dartmouth College.

Fisher-Vanden, K., and G. Jefferson (2006). “Technology Diversity and Development: Evidence from China’s Industrial Enterprises.” Manuscript, Dartmouth College.

Grubb, M.J., C. Hope and R. Fouquet (2002) Climatic implications of the Kyoto Protocol: the contribution of international spillover, Climatic Change 54(1/2): 11-28

Popp, D.C. (2006). ENTICE-BR: Backstop Technology in the ENTICE Model of Climate Change, Energy Economics, 28: 188-222.

Sue Wing, I. (2006). Representing Induced Technological Change in Models for Climate Policy Analysis, Energy Economics 28: 539-562.

Figure 1.
The Impact of Efficiency-Improving and Quality-Enhancing R&D on Upstream Production

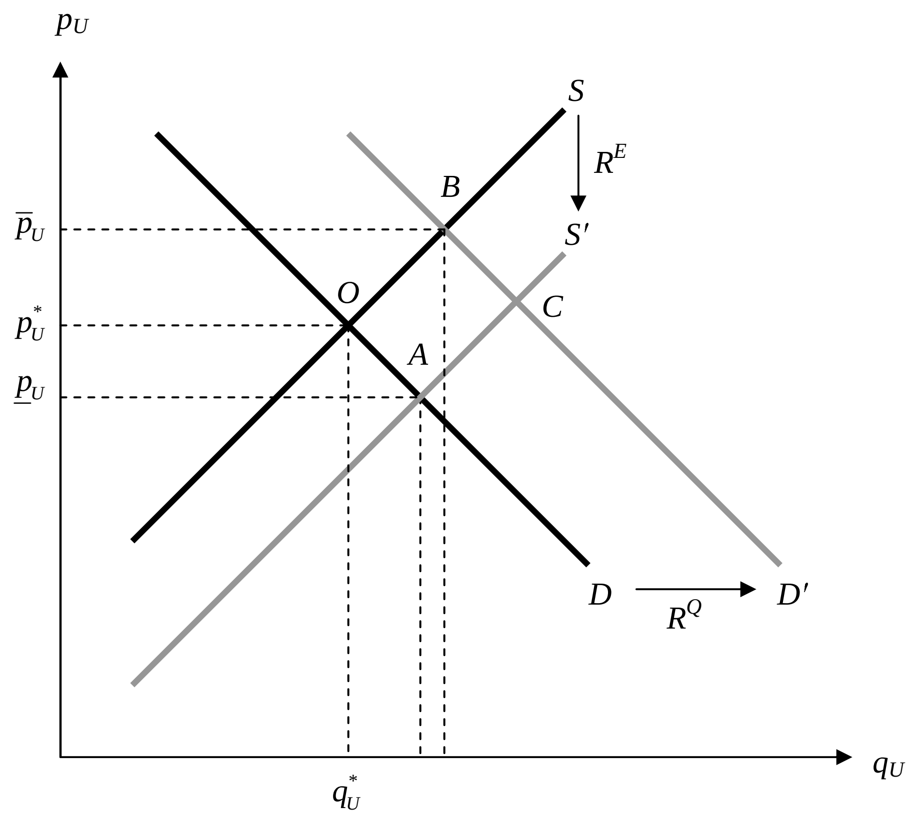

Figure 2. Change in Real GDP and Carbon Emissions:
R&D Intensification Scenario vs. BAU Scenario
Without Adjustment for Quality-Enhancing Impact of R&D

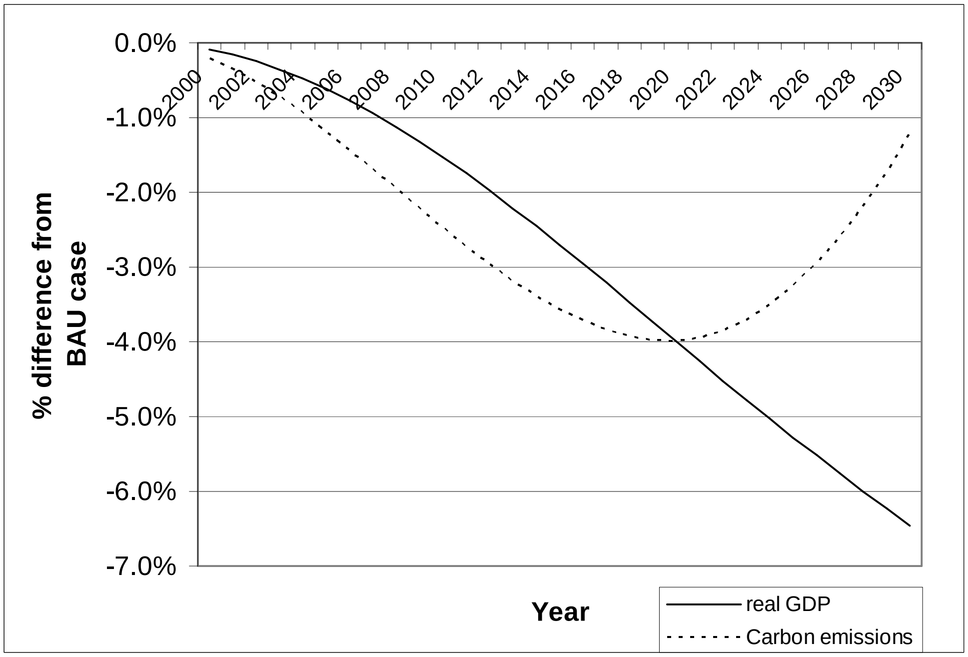

Figure 3. Change in Real GDP and Carbon Emissions:
R&D Intensification Scenario vs. BAU Scenario
With Adjustment for Quality-Enhancing Impact of R&D

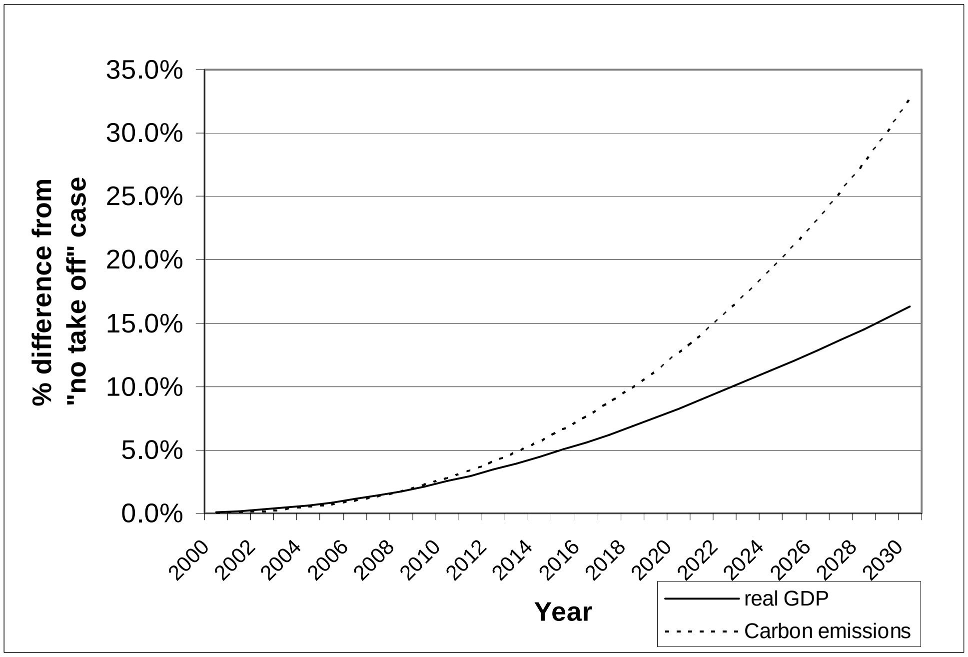

Table 1. Summary of the Results of the Analytical model

	A. Elasticity with respect to:				B. Sign of elasticity w.r.t:			
	R^E	R^Q	w	p_D	R^E	R^Q	w	p_D
	I. Basic variables				I. Basic variables			
p_U	$-\varepsilon\,(1-\beta-\gamma-\omega)\,/\,\xi$	$\beta\theta\,(1-\alpha)\,/\,\xi$	$[\alpha\,(1-\beta-\omega)-\gamma]\,/\,\xi$	$(1-\alpha)\,/\,\xi$	–	+	?	+
q_U	$\varepsilon\,(1-\gamma-\varepsilon)\,/\,\xi$	$\alpha\beta\theta\,/\,\xi$	$\alpha(\omega-1)\,/\,\xi$	$\alpha\,/\,\xi$	+	+	–	+
v_U	$\beta\varepsilon\,/\,\xi$	$\beta\theta\,/\,\xi$	$(\omega-1)\,/\,\xi$	$1\,/\,\xi$	+	+	–	+
v_D	$\beta\varepsilon\,(1-\beta-\gamma)\,/\,\xi$	$\beta\theta\,/\,\xi$	$(\varepsilon\,(1+\alpha\beta)-1)\,/\,\xi$	$1\,/\,\xi$	+	+	–	+
q_D	$\beta\varepsilon\,/\,\xi$	$\beta\theta\,/\,\xi$	$-(\alpha\beta+\gamma)\,/\,\xi$	$(\alpha\beta+\gamma)\,/\,\xi$	+	+	–	+
	II. Derived quantities				II. Derived quantities			
$q_U\,/\,q_D$	$\varepsilon\,(1-\beta-\gamma-\omega)\,/\,\xi$	$-\beta\theta\,(1-\alpha)\,/\,\xi$	$[\gamma-\alpha\,(1-\beta-\omega)]\,/\,\xi$	$[\alpha\,(1-\beta)-\gamma-\omega]\,/\,\xi$	+	–	?	?
$v_U\,/\,q_U$	$-\,\varepsilon\,(1-\beta-\gamma-\omega)\,/\,\xi$	$\beta\theta\,(1-\alpha)\,/\,\xi$	$-\,(1-\alpha)\,(1-\omega)\,/\,\xi$	$(1-\alpha)\,/\,\xi$	–	+	–	+

Notes: α = share of variable input in cost of upstream production; β = share of upstream commodity in cost of downstream production; γ = share of variable input in cost of downstream production; ε = elasticity of upstream output to own efficiency-improving R&D; θ = elasticity of downstream output to upstream quality-enhancing R&D; ω = elasticity of downstream output to own efficiency-enhancing R&D; $\xi = 1-\alpha\beta-\gamma-\omega > 0$; ? indicates that the sign of the relevant elasticity is ambiguous.

Table 2. Neutral and Factor-Biased Effects of Technical Progress by Industry

Sector	Neutral effect on cost	Factor Bias			
		Capital	Labor	Energy	Materials
A. Autonomous technology development					
Mining	-0.001	0.001	-0.003	0.004	-0.002
Food	-0.009*	-0.002	0.001	-0.001	0.003
Textile	-0.018**	0.003	0.004**	0.0004	-0.007**
Paper	0.006	-0.003	-0.007***	-0.001	0.010***
Petroleum	0.002	0.010	-0.004	-0.012	0.006
Chemicals	-0.005	0.006***	-0.001	0.003	-0.007***
Rubber	-0.026**	0.001	0.004	-0.004	-0.0005
Nonmetal	-0.008*	0.0006	-0.003***	0.006***	-0.004
Metal	-0.029***	0.001	0.0008	-0.001	-0.0008
Machinery	-0.026***	0.002	0.002	-0.001	-0.003
Electric power	-0.047***	-0.004	0.0006	-0.007*	0.010**
Other industry	0.054***	0.005	0.006**	0.0003	-0.011**
B. Deliberate technology development					
Mining	0.010**	0.004***	-0.004***	-0.005***	0.005***
Food	0.005**	0.004***	0.001	0.002***	-0.006***
Textile	-0.007***	0.003***	0.005***	-0.001*	-0.006***
Paper	0.012***	0.004***	-0.002***	-0.001	-0.001
Petroleum	0.036***	0.005	-0.003**	0.011**	-0.013***
Chemicals	-0.004*	0.000	0.001***	-0.004***	0.003***
Rubber	0.003	0.001	-0.002	-0.0004	0.001
Nonmetal	-0.003	0.003***	0.001***	-0.005***	0.001
Metal	-0.005	0.003***	-0.0001	-0.009***	0.006***
Machinery	-0.009***	-0.003***	0.002***	-0.002***	0.003***
Electric power	0.028***	0.005***	-0.002***	0.006***	-0.010***
Other industry	0.013**	0.005***	-0.001*	-0.002	-0.002

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