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A multi-period analysis of a carbon tax including local health feedback: an application to Thailand

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ABSTRACT. An ancillary benefit of Greenhouse Gas (GHG) mitigation refers to a benefit derived from GHG mitigation that is in addition to the reduction in adverse impacts of global climate change. One type of ancillary benefits of GHG mitigation is reduced local conventional pollutants, which is associated with improved health. Middle-income countries like Thailand are in unique positions to obtain large ancillary health gains from reduced local conventional pollutants when GHG is mitigated by curbing fossil fuel consumption.

This paper assesses whether by capturing the local health effects of reduced conventional pollutants as an ancillary effect of GHG mitigation, and by allowing this benefit to feed back into the economy, the desirability of policies aimed at GHG mitigation will change, from the standpoint of macroeconomic and welfare indicators. The author uses a multi-period cost/benefit framework – a Dynamic Recursive Computable General Equilibrium (CGE) model – for the assessment. A health effects sub-model takes the PM_{10} emissions (volume) from the CGE model to assess its implications for ambient PM_{10} concentration, local health, labor supply and medical expenditures. The saved labor is exogenously fed back into the CGE model to find the economy-wide repercussions, whereas the adjustment of medical expenditures due to improved environmental quality is endogenized in the model. The methodology is illustrated through an application to the country of Thailand.

Findings include: (1) average GDP growth with the carbon tax relative to the no policy scenario turns positive when the health feedback is included, and (2) the negative welfare impact for households is reduced by a factor of two when the feedback is incorporated. An extensive sensitivity analysis over these results was then carried out, using upper and lower bound values instead for 11 key parameters. Three parameters were identified as the most influential parameters.

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1. Introduction

An ancillary benefit of Greenhouse Gas (GHG) mitigation refers to a benefit derived from GHG mitigation that is in addition to the reduction in adverse impacts of global climate change. One type of ancillary benefit of GHG mitigation is reduced local conventional pollutants, which is associated with improved health. Ancillary benefit analysis is also seen by many as an important way to engage those who may not otherwise be interested in taking actions to curb their GHGs. For example, the US Environmental Protection Agency (EPA) has a program (the International Environmental Strategies Program or IES, formerly known as ICAP) to engage developing countries on the climate issue by helping them conduct ancillary benefits analysis.[1]

This study contributes to developing methodology for capturing the labor effects of reducing local air pollution or integrated strategies for greenhouse gas mitigation and local environmental improvement in developing countries. The author assesses whether by capturing the local health effects of reduced conventional pollutants as an ancillary effect of GHG mitigation, and by allowing this benefit to feed back into the economy, the desirability of policies aimed at GHG mitigation will change from the standpoint of Social Welfare.

2. Previous studies

The IES program referred to earlier has produced initial results from country assessments in Chile, China, and Korea. These results indicate that relatively modest energy sector mitigation measures in these countries can significantly reduce greenhouse gas emissions, improve local air quality, and produce considerable public health and economic benefits.

Other studies that explicitly considered the ancillary benefits of GHG abatement are well summarized in Chapter 8 of the IPCC Third Assessment report.[2] A review of the literature shows that most of these studies have focused on public health, the largest quantifiable impact, dealing with short-term and 'local' impacts mostly. The net ancillary benefits range from a small fraction of GHG mitigation costs to more than offsetting them (see Burtraw *et al.*, 2001, and reviews by Pearce, 1996, 2000; Burtraw and Toman, 1997, 2000; and Ekins, 1996). Such variation in estimates is not surprising as the underlying features differ by sectors considered and the geographic area being studied. Other differences in estimates are due to different assumptions and/or methodologies used to estimate them.

Most of these studies use static or dynamic CGE models that provide sector-specific estimates of ancillary benefits and/or costs. The majority of the studies were done on OECD countries except for two, one on Chile and the other on Hungary. Several studies do not use an economic model and therefore do account for behavioral adjustments, such as

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[1] For more information on the EPA Integrated Environmental Strategies program, contact ies@epa.gov

[2] The report relied on three earlier surveys of the literature (Ekins, 1996; Burtraw *et al.*, 2001; and Kverndokk and Rosendahl, 2000).

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energy substitutions, which could affect the estimates of ancillary benefits considerably.

A few studies have captured the feedback from improved health back to the general economy. Vennemo (1997) used a general equilibrium model to study environmental feedbacks, including health, for Norway. The pollutants considered (with different ones relevant for different feedbacks) included SO_2, NO_X, CO, and particulates. The health feedback loop was captured exogenously using existing associations between pollution and health effects with no air dispersion modeling used. A separate feedback loop that captures non-health-related welfare effects (including noise, road depreciation, and freshwater acidification due to acid rain) was endogenous. The results showed that the non-health-related feedback was more significant than the health-related feedback on welfare for Norway. For China, Garbaccio *et al.* (2000) used the outputs from an air diffusion model and an exposure–response model provided by Lvovsky and Hughes (1997) to capture health feedbacks from an ancillary drop in local SO_2 and particulates when CO_2 emission is reduced. They discovered that a carbon tax reducing carbon emissions by 10 per cent from the concurrent baseline level in each year for 30 years would also reduce premature deaths by 7–8 per cent per year.

Mayres and Van Regemorter (2002) capture health feedback on consumption through the health production function approach which relates a continuous health variable to exogenous (pollution) and choice variables (averting and mitigating behavior).[3] Their study shows that the health production approach generates different and more accurate results than an approach that includes environmental quality as a separable term in the utility function. This way of capturing labor effects through time allocation decisions made by individuals can be termed the demand-side modeling of labor change as a result of change in environmental quality.

3. Methodology

Conceptual framework

In order to curb GHG emissions, a country has to reduce its fossil fuel consumption. In this study we examine an economy-wide carbon tax policy. We employ seven methodological steps to simulate the feedback of health effects and assess the influence of this feedback on measures of social welfare used in policy analysis. These methodological steps are:

1. specify the policy measure and how it alters specific parameters in subsequent methodological steps used in the assessment;
2. alter these parameters in the economic model to determine effects on economic indicators of social welfare and on the emissions from economic activity;
3. from the projected emissions, determine the ambient air concentrations and exposures to the resident population;

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[3] For an overview of literature relevant to the health production approach, see Freeman (1993).

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4. from these exposures and assumed exposure–response relationships, determine morbidity and mortality effects in the resident population;
5. assess the impact of these morbidity and mortality effects on labor and on health care expenditures;
6. apply the economic model again, now including the labor and health care feedbacks; therefore a full equilibrium with the feedbacks is obtained after accounting for changes in PM_{10} as well as CO_2.
7. assess the overall economic as well as welfare distribution impacts of the policy scenario with and without incorporating health feedbacks (labor and medical expenditures).

The following sections describe the methodology to be used in each of these steps.

Within- and between-period CGE

The study employs a Computable General Equilibrium model as the analytical framework. Before building a CGE model, one needs a set of data in the form of a Social Accounting Matrix (SAM). A SAM is a square matrix consisting of row and column accounts that represent the different sectors, agents, and institutions of an economy at the desired level of disaggregation. In the case of Thailand, the author obtained a balanced SAM for Thailand from the Thai Development Research Institute (TDRI) and no balancing procedure was necessary, even after multiple aggregation and disaggregation changes. A limitation of the study is carried over from this stage where only one type of labor is used due to the asymmetrical data availability on the supply side versus the demand side.[4]

The complete model used is a recursive dynamic model consisting of a static within-period model and the dynamic transition or between-period components. The within-period model is a variation from the 'standard model' built by the Trade and Macroeconomics Division of the International Food Policy Research Institute (Lofgren *et al.*, 2001). The between-period component links the static (within-period) models through the updating of factors of production and total factor productivity (TFP) from one period to the next.

The model was 'calibrated' to the base year of 1998 and a multi-period baseline is established by using projected values for several key parameters.

Due to space constraints, for the static model we only cover description of emissions inventory and linkages between medical expenditures and local emissions. For a complete description of the static model (including

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[4] By not differentiating labor by skill level and lumping them into one urban labor category and applying the same DRFs in getting labor productivity changes as PM_{10} concentration shifts, we may over- or underestimate the labor impacts. As part of the sensitivity analysis we test the alternative assumption that rural labor is also affected by the change in ambient PM_{10}. However, we do this by using the same DRFs for the urban and rural labor which would most probably overestimate the effect on rural labor. One of the reasons why rural labor may experience a smaller health gain than urban labor is from worse access to health care. Adopting this alternative assumption, however, does not seem to alter the main findings of the study.

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production technologies, consumption behavior, and model closures), please refer to Li (2003).[5] The description for the between-period component is provided in full in this paper.

Emissions inventory

Two pollutants are tracked in the model: CO_2 and PM_{10}. Industries that burn fossil fuels emit CO_2 as well as PM_{10}. PM_{10} is also generated during what is called "process emissions" (as opposed to combustion emissions), especially in cement production and construction work where a great deal of dust is generated. Process emissions are not related to the amount of fuel used but are related to the total output produced. Another major source of PM_{10} is vehicles. Particulate emissions occur from all types of vehicles, not only from exhausts, but also from tire and brake wear. Exhaust emissions are considerably higher from diesel-engined vehicles than vehicles with petrol engines. Nevertheless, the much greater number of petrol vehicles on the road means their contribution to the road transport inventory for PM_{10} is still significant.[6]

CO_2 emissions on the other hand are predominantly considered as emission through combustion process only, both from industrial production and vehicle use. The following is a summary of the sources of emissions for PM_{10} and CO_2 considered here.

CO_2: production-generated combustion emission,
consumption-generated combustion emission

PM_{10}: production-generated combustion emission,
production-generated process emission,
consumption-generated combustion emission

CO_2 emissions coefficients associated with different intermediate and final consumption of fossil fuels were obtained from the US Energy Information Administration (EIA) (EIA 2001a, 2001b). Industry-specific emissions coefficients for PM_{10} (for combustion and process-generated emissions) were assumed to follow similar distributions as those in Garbaccio *et al.* (2000) applied to China. The use of EIA and Garbaccio

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[5] One important note about the model closures for the labor market: the assumption is a standard one of full employment even though unemployment is present in every economy. In the case of Thailand, the unemployment rate in 1999 was around 3.9 per cent (source: Ministry of Finance of Thailand: http://www.mof.go.th/emof/emof_dec99.htm). With this setting, productivity gains would not be realized completely amongst the 15–59 population with the health gain, as some of these people were unemployed to begin with.

[6] There are certainly also secondary sources of particulate matter. These include photochemical and cloud oxidation of SO_2, conversion of NOx emissions from motor vehicle exhausts, industrial combustion, and power stations into nitric acid, ammonium nitrate, and nitrogen pentoxide, as well as secondary organic aerosol. However, our focus here is primary sources of emissions for PM_{10}. Secondary sources of emissions are taken into account in the 'background' concentration of particulate matter (http://www.defra.gov.uk/environment/airquality/airbornepm/).

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et al. emissions coefficients lead to base year (1998) CO_2 and PM_{10} emissions similar to the emissions for Thailand reported by its Pollution Control Division.[7]

Formally, the total emission for CO_2 takes the form

$$E_{CO_2} = \sum_{A} \sum_{EINP} \alpha_{EINP}\, QINP_{A,EINP} + \sum_{INST} \tau_{INST}\, C_{INST} \qquad (1)$$

E = total emissions
A = 61 activity sectors using energy as input
$EINP$ = eight energy input categories
α = emissions coefficients for combustion emitted CO_2 by sector
$QINP_{A,\,EINP}$ = quantity of each energy input consumed by each sector
τ = emissions coefficients for consumption-generated CO_2 emissions from a consumer group (institution, households, or government)
$INST$ = different institutions
C_{INST} = quantity of polluting good consumed by each institution

For PM_{10}, the total emission takes the following form

$$E_{PM10} = \sum_{A} \sum_{EINP} \alpha_{2,EINP}\, QINP_{A,EINP} + \sum_{A} \beta_A\, QD_A + \sum_{INST} \tau_{2,INST}\, C_{INST} \qquad (2)$$

α_2 = combustion-generated emissions coefficients for PM_{10} by sector
β = process-generated emissions coefficients for PM_{10} by sector
τ_2 = consumption-generated emissions coefficients for PM_{10} by consumer group
QD_A = total domestic output by sector

Emissions from production can be reduced in three ways: through a lower aggregate output (the *scale* effect), a change in the commodity composition (more or less of dirty goods produced, the *composition* effect), or through the adoption of cleaner technologies (rebalancing the input mix in favor of less-polluting inputs, the *technology* effect). Here the third effect, effect of production technology improvement over time, is captured by assuming an increase in TFP from one period to the next. No explicit modeling of production technology and change in production technology composition, however, is done.

An emission abatement policy such as a carbon tax will have several indirect effects on household utility, from price effects to production and therefore employment effects. Household utility is directly linked to environmental quality in the following way. The consumption of the medical/hospital commodity is directly linked to environmental quality (as the next section explains).

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[7] The emissions coefficient data are available upon request.

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Within the CGE model, the emissions inventory provides total emissions of CO_2 and PM_{10} before and after a policy change. The PM_{10} emissions change will have implications for the ambient concentration of PM_{10}. This will in turn affect the health of the mainly urban population in multiple ways. By linking the consumption of medical goods to environmental quality, one can capture the effect of environmental quality change on medical expenditures endogenously.

In addition to endogenized medical expenditure behavior, this study captures the link between environmental quality and labor productivity. This is done through an exogenous estimation of labor productivity change, given what happens to the pollution level that the labor is exposed to. The exogenous labor feedback to the CGE model will capture healthier households, as a result of improved local air quality, which would then work more and earn greater income.

On the production side, environmental degradation does not directly enter production maximization. The labor feedback will affect it through greater labor supply and therefore lower wages and more production. This however will be weighed against the effect of more expensive fossil fuels, as a result of the fossil fuel tax. The net effect on an industry will depend on how energy (carbon-based fuel) intensive that industry is.

Linking expenditures on health/medical treatment to pollution

Depending on the country of focus, the share of public versus private medical expenditures will differ. In Thailand, the government and private institutions (insurance and households) are each responsible for about half of the total medical costs (TDRI, 2000). In the event of improved local environmental quality, some of these hospital costs will be avoided. Here we assume that both the government and the household will cut back on medical expenditures as a result, and the use of this incremental income will follow the same spending pattern (allocation shares) as that of existing government and household accounts.

The change in medical expenditures is taken out of the health and medical care sector (CHLTHMD) in the manner proportionate to the general allocation of input factors in this sector.

Household consumption behavior is assumed to follow a Linear Expenditure System (LES). Linking medical expenditures on CHLTHMD by household and government will take the following specific steps:

- Having a separate definition for the 'subsistence' level of demand for CHLTHMD as a function of total PM_{10} emission and an estimated elasticity of demand (ε) for CHLTHMD with respect to the PM_{10} emission level.
- Allocating disposable income to the consumption of 'all' commodities, including CHLTHMD.
- By these specifications, we allow the subsistence consumption of CHLTHMD to drop when pollution is lessened (price effect), while allowing the income freed up to be spent on all types of goods (income effect).

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With respect to government demand for CHLTHMD, it is separated from government demand for all other commodities. Instead, it is tied to private demand (household demand) for CHLTHMD via the ratio of total government to private consumption of CHLTHMD.

Between-period CGE

From static to recursive dynamic we need to link up the static, one-period model runs, through the updating of key exogenous variables. Specifically, the updating applies to the factors of production, capital and labor, and TFP growth for 1999 through 2010.

The labor force growth rate is drawn from the projection made by the National Statistics Office of Thailand. Capital stock in each one-year simulation period is set equal to the last period's capital stock plus total investment minus depreciation. No optimal behavior is assumed for investment capital accumulation.

When capital stock is updated, two problems that cannot be solved by using SAM alone are as follows. First, for investment to be added to capital stock, both variables need to be in the same unit. However the SAM does not give such information. This is solved by obtaining the output-to-capital ratio, *kscale* below, which provides the unit of capital required to produce one unit of output. This ratio is then used as a 'converter'. Total investment then equals the first term on the right-hand side of the equation. Here *capgrw* stands for the rate of capital growth from one period to the next; *depr* stands for depreciation rate; *oldstk* stands for old stock; the value of investment is the product of price (P^c_{inv}) and quantity (Q^c_{inv}).

$$capgrw = \frac{\left[kscale \cdot \left(P^c_{inv} \cdot Q^c_{inv}\right) + (1 - depr) \cdot oldstk\right]}{oldstk}. \tag{3}$$

Second, there is a need to know how investment is allocated by destination in the benchmark period. This is solvable by assuming that the capital allocation is market driven by the capital rate of return differentials. Capital (again defined as non-depreciated old stock plus new stock) is assumed perfectly mobile within each period. In three sectors, perfect market adjustment within each period shows a negative demand for capital; the negative rate exceeds the depreciation rate in the case of one sector, ocean transportation. It may be unrealistic to assume perfect capital mobility within each year with the possible result of having a sector completely run out of business, as a substantial (>30 per cent) share of its capital is transferred to other sectors. However, if not market-driven allocation, the alternative, such as sector-specific allocation of new capital, requires an *ad hoc* assumption about how such allocation is done given no econometric data are available to inform such a set-up. In addition, this removes any endogenous market allocation effects, since sector-specific capital allocation implies capital allocation determined completely exogenously. The within-period market-driven allocation coupled with sectoral growth rates allow

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sectoral investment shares to change over time as a result of differences in sectoral profit rates.[8]

Here we turn to the updating of TFP. TFP can be influenced by openness to trade (technological spillovers), technological improvement, learning by doing, and quality of labor improvement, among other factors. TFP can be set sector specifically or assumed uniform across sectors. Researchers have estimated that for Thailand the historical average TFP is around 2 per cent; some contend a higher average TFP for non-agricutural sectors and a very small (sometimes negative) average TFP for agricultural sectors (Sussangkarn and Tinakorn, 1994; Diao *et al.*, 2002). Here, a small but positive average TFP growth rate for all sectors is assumed. The TFP growth rate serves as the residual among the sources of growth to target a projected 3–4 per cent GDP growth rate for Thailand in the modeling period of 1999–2010. Using TFP as the residual is consistent with other work on Thailand (Sussangkarn and Tinakorn, 1994).

Policy specification and imposition

A carbon tax proportional to the carbon emissions coefficient is imposed on each of the eight energy commodities from 2003 to 2010. All taxes are raised by the same rate from one year to the next to result in monotonically higher carbon emission reductions in later years. The policy goal is to reduce the 2010 total carbon emission to 90 per cent that of 2000. Aside from the 10 per cent reduction, the author also explored a 5 per cent and a 20 per cent reduction of total CO_2 emission to check whether the results were consistent.

4. From the CGE model to the health module

The dynamic recursive CGE model results show that the carbon tax policy aimed at reducing the 2010 total carbon emission to 90 per cent that of 2000 has minor costs in terms of output. The annual GDP on average is lower by less than 1 per cent (0.25 per cent to be exact) with respect to the benchmark.[9] The reduction in CO_2 emission is primarily due to reductions in production-generated emissions, as most of the carbon tax burden is on enterprises which are the main polluters through their production activities. Production-generated emission was lowered by around 14 per cent as a result of the carbon tax. With the 10 per cent reduction of CO_2 comes an ancillary (unintended) benefit of reduction in PM_{10} by 3.38 per cent. This leads to a lowering of the ambient concentration of PM_{10}, which is

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[8] Some researchers favor an intertemporal dynamic model largely for the reason that it assumes each firm chooses a time path of investment that maximizes the value of the firm defined as the present value of net income. Others find this assumption along with the perfect foresight on the part of both producers and consumers with respect to prices somewhat *ad hoc* as well.

[9] A 10 per cent reduction in CO_2 for a 0.25 per cent reduction in GDP is reasonable. The reference data show a range of 0.1 per cent to 3.01 per cent for stabilizing CO_2 emissions by 2010 (Hoeller *et al.*, 1990). If we exclude the value applied to developed countries, the range narrows down to 0.1 per cent (former USSR) to 2.01 per cent (China).

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beneficial to the health of the urban population. We also run alternative carbon reduction scenarios of reducing 2010 total carbon emissions to 95 per cent and 80 per cent of that in 2000. The results are consistent with the case of 10 per cent reduction.

The following section on Health Module further explores the links between total emissions and the ambient concentration of PM_{10}, and assesses the implications of the change in the ambient concentration of PM_{10} for labor productivity and medical expenditures.

Linking CGE outputs to the health module: from PM_{10} emissions to PM_{10} concentration exposed, the conversion links

Empirical air dispersion model

In order to translate the actual emissions at multiple origins into the ambient concentration level of the respective pollutant, we need what are called 'dispersion coefficients'. Here an 'empirical' air dispersion model is used in calculating the dispersion coefficients. This is based on the assumption that the spatial pattern of emissions resulting from changes in the energy infrastructure does not change with time; only the source terms change. This assumption is adopted in the absence of a reliable method to predict how the spatial pattern might change.

From the Pollution Control Division (PCD) in Thailand we obtained information on emission contributed by three sources: industrial, transportation, and background emissions. The respective shares of total emissions emitted at origin, and shares contributing to mean ambient air concentration, were reported in 1998 as 9.78 per cent, 53.94 per cent, and 36.28 per cent.

The following terms appear in the methodological steps of the empirical air dispersion model used:

Source Term PM_{10} from industries before policy = ST_N^I
Source Term PM_{10} from transportation before policy = ST_N^T
Source term PM_{10} from industries after policy = ST_P^I
Source term PM_{10} from transportation after policy = ST_P^T
Background pollution concentration = C_B
Fraction of ambient PM_{10} contributed by industries = F_I
Fraction of ambient PM_{10} contributed by transportation = F_T
Fraction of time spent indoors by an average adult = Fin^A
Fraction of time spent outdoors by an average adult = Fou^A
Fraction of time spent indoors by an average child = Fin^C
Fraction of time spent outdoors by an average child = Fou^C
Fraction of time spent indoors by an average elderly = Fin^E
Fraction of time spent outdoors by an average elderly = Fou^E
Ratio of ambient air PM_{10} concentration over emissions rate contributed by industries = K_I
Ratio of ambient air PM_{10} concentration over emissions rate contributed by transportation/construction = K_T
Ambient air concentration of PM_{10} without policy = Cn
Ambient air concentration of PM_{10} with policy = Cp

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Assuming a uniform emission density across the study region for the three source categories, we use 9.78 per cent, 53.94 per cent, and 36.28 per cent for F_I, F_T, and C_B, respectively. The source terms, ST_N^T and ST_N^I, correspond to total PM_{10} emissions from the transportation and industrial sectors. Note that the 'controllable' share of PM_{10} emissions is therefore only around 64 per cent of total PM_{10} emissions, assuming background contribution to the ambient air concentration, C_B, is relatively unaffected by policies.[10] ST_N^T and ST_N^I are part of the CGE model outputs from the baseline scenario.

$$F_I = \frac{K_I ST_N^I}{\left(K_I ST_N^I + K_T ST_N^T + C_B\right)} \tag{4}$$

$$F_T = \frac{K_T ST_N^T}{\left(K_I ST_N^I + K_T ST_N^T + C_B\right)}. \tag{5}$$

After substituting in C_B (product of 0.3628 and 68 $\mu g/m^3$, where the latter is the mean ambient air concentration in the study region) and moving the unknowns to the left, we have the following expressions:

$$K_T = \frac{24.67 F_T}{ST_N^T(1 - F_I - F_T)} \tag{6}$$

$$K_I = \frac{24.67 F_I}{ST_N^T(1 - F_I - F_T)}. \tag{7}$$

The units of K are unit ambient air concentration per unit source term. The numerical value of K is unaffected by policy, and therefore invariant in time, given the assumption employed in this study that changes in the economy affect the source terms but not locations of emitting sources. The calculated K values were approximately 0.004 for transportation and 0.000007 for industrial sources. Note the much larger value of K for transportation, as these sources are located closer to housing and workplaces than are the industrial sources.

With these derived dispersion coefficients, we then assess the ambient concentration of PM_{10} for each time period by setting:

$$C_P = C_N \times \left[\left(K_I\, ST_P^I + K_T\, ST_P^T + C_B\right) / \left(K_I\, ST_N^I + K_T\, ST_N^T + C_B\right)\right]. \tag{8}$$

Cn is the level of original ambient concentration, and Cp the ambient concentration of PM_{10} under the carbon tax.

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[10] A carbon tax that influences emissions by industry and transportation as well as by residential sectors would indirectly also influence secondary emissions, which are a component of the background pollution or 36 per cent. However, as the current data do not allow for dividing background exposures into their separate causes, we decided to adopt the conservative assumption that background pollution is not affected by the carbon tax policy. This assumption is likely to cause a slight underestimate of the effectiveness of policies.

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The baseline ambient PM_{10} concentration of around 68 $\mu g/m^3$ for Thailand in 1998 is assumed fixed throughout the modeling period for the baseline. This is a crucial assumption and the reasoning is that the Thai government is aware of the PM_{10} issue and is likely to maintain the current level or prevent it from worsening through measures such as the street sweeping program. Another important note is that the costs of such likely measures in maintaining present PM_{10} concentration in the baseline are *not* captured in the model. What this implies is that the baseline GDP is likely to be overestimated.

Under the carbon tax policy scenario where the tax is implemented from 2003 through 2010, the PM_{10} concentration, Cp, for these years naturally declines.

Medical expenditures and labor impact analysis

With a change in the ambient concentration of PM_{10}, this will impact medical treatment savings/costs and labor productivity, due to the health status change. As mentioned before, change in medical expenditures is captured endogenously by the CGE model, with an assumed relationship between the change in total PM_{10} emissions and change in medical expenditures. In order to cross-check the amount of reduced medical expenditures captured endogenously by the model, we also calculate this using hospital admission exposure–response rate (ERRs) and the average health costs information for the common types of hospital admission affected.

The labor supply change as a result of reduced local particulate matter emission is captured exogenously and then fed back into the CGE model. The change includes change in premature mortality and change in productivity or what are called "reduced activity days" (RADs) (Rosendahl, 1998).

Medical cost analysis: cross checks for changes in medical expenditures

Health impairments, due to exposures to ambient air, demand resources through medical treatment. When the incidence of health impairments caused by exposures to ambient air declines, some resources originally spent for health treatment are reduced and used for other purposes. This effect has been endogenized in the model used here. Here in this section we cross-check the change in medical expenditures estimated by the CGE model, based on the assumed relationship between pollution emission and consumption of medical/hospital goods and services using existing data on medical expenditures and air pollution in Thailand.

A caveat about the study is warranted. The study does not consider medical treatment for long-term chronic effects caused by exposure to particulate matter, e.g. permanent impairment of lung function and the development of diseases such as asthma and chronic obstructive pulmonary disease. It considers only acute effects.

One way to verify the base data is to compare them with the findings of Hagler Bailly Services in a study conducted for the Pollution Control Dept of Thailand (Hagler Bailly, 1995). They estimated that on average a Thai family paid about 131 baht (13 per cent of total medical expenses) monthly

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Table 1. *Exposure–response functions for hospital admissions associated with PM_{10} in Thailand (central value, and 95 per cent lower and upper confidence limits, are shown)*

Health effect category	*Annual number of cases per person per 1 $\mu g/m^3$ change in annual average PM_{10}*
Respiratory hospital admissions	Low: 2.8×10^{-6} Central: 5.7×10^{-6} High: 8.5×10^{-6}
Cardiac hospital admissions	Low: 2.8×10^{-6} Central: 5.0×10^{-6} High: 7.2×10^{-6}

Source: Chestnut *et al*. (1998).

for dust-related illness. This was about 1.6 per cent of the average Thai monthly income.[11]

According to our base-year data, 13 per cent of total monthly medical expenditures translate into 1,237, 1,291, and 24,624 Thai baht for agricultural, government-employed, and non-agricultural households, respectively. The average medical expenditure is then around 3,580 Thai baht per year, or 298 baht per month. After adjusting for inflation, this is roughly equal to the reference information from the Hagler Bailly study.[12]

When the carbon tax schedule was imposed, we observed a total household reduction in medical expenditures in 2003. In order to check whether this value is reasonable, we relied on ERRs estimated for Thailand for PM_{10}-related hospital admissions in relation to ambient PM_{10} concentration (see table 1 below). Since we could not find the Mean Length of Stay (MLOS) and Mean Total Charge data for Thailand, we decided to use the US figures and then scale the result (cost per day of stay) by the purchasing power parity (PPP) ratio between the US and Thailand to obtain similar information for Thailand.[13]

$$\begin{aligned}\Delta H_{RS} = {} & [(0.0000028 \cdot \Delta \mathrm{PM10}) \cdot 0.333] + [(0.0000057 \cdot \Delta \mathrm{PM10}) \cdot 0.334] \\ & + [(0.0000085 \cdot \Delta \mathrm{PM10}) \cdot 0.333] * POP. \qquad (9)\end{aligned}$$

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[11] http://www.anamai.moph.go.th/factsheet/Matter.htm

[12] The reference figure, 131 baht, for average monthly household expenditure on dust-related illnesses, adjusted for inflation, equals 276 baht in 1998. Inflation rates of 5.8, 5.9, and 5.6 for 1995, 1996, and 1997 respectively are drawn from *E. Thailand Monthly Economic Review*, January 2001, published by Macroeconomic Policy Section, International Economic Policy Division, Ministry of Finance, Thailand. (www.mof.go.th/emof/Jan2001Review.pdf)

[13] Mean length of stay for the US was calculated by dividing the sum of in-patient days by the number of patients within the DRG (diagnosis-related groups). DRGs are a classification of hospital case types into groups expected to have similar hospital resource use). In-patient days were calculated by subtracting day of admission from day of discharge, so persons entering and leaving a hospital on the same day have a length of stay of zero. Mean total charge is calculated by dividing the sum of patient charges by the number of patients

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Given the change in the ambient concentration of PM_{10} and the population for each period, we calculate the probability weighted respiratory and cardiac hospital admission changes associated with a change in PM_{10} concentration using the hospital admission exposure–response relationships for respiratory and cardiac hospital admissions (see equation (9) above).

As the focus of this study is on the working population, we limit our at-risk population to the working age population in Thailand. According to the National Statistical Office of Thailand, the working population in Thailand is defined to be between 15 and 59 years of age.[14] Based on NSO, 44.5 per cent of all reported illnesses in 1998 can be attributed to the 15–59 population. We applied this percentage to derive the number of respiratory and cardiac hospital admissions saved as a result of lowered PM_{10} concentration for the 15–59 age group.

Then we used the average mean length of stay and mean total charge information estimated for the US for the two disease categories – respiratory and cardiovascular – to obtain an estimate of total expenditures saved for Thailand after adjusment using the PPP ratio.

Going through these steps allows us to derive an estimate of the total decrement in medical costs incurred by particulates-induced hospital admissions in 1998 in Thailand, based on the reference DRF for hospital admissions and the MLOS and mean total charge for the two disease categories associated with PM_{10}. The resultant number was consistent with what the model has produced.

Labor impact analysis and feeding back labor supply

Again exposure to particulate matter has multiple effects on health, including short- and long-term effects, but in this study we focus on short-term or acute effects only.

The change in labor supply includes permanent and temporary change in labor supply. The temporary change has two components – days of work lost (due to sick leaves, hospital visits, etc.) and reduced productivity at work. To assess the temporary change in labor supply (both loss of days and productivity), we use an ERR that links changes in PM_{10} concentrations directly to the changes in the reduced activity days or RADs. Premature mortality as a result of short-term local air pollutant exposure on the other hand has a permanent effect on labor supply. For the permanent change, we use an ERR for particulate matter exposure in relation to premature mortality.[15]

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within the DRG category. Total charges represent the dollar amount charged for the hospitalization rather than the amount paid or the actual costs to provide the care. Physician payments are not included. Although capitation and negotiated discounts have made total charges an imprecise measure of reimbursements, charges still represent one of the only ways to approximate costs of hospital care (http://www.ahcpr.gov/data/hcup/94drga.htm).

[14] http://www.nso.go.th/gender/epop.htm

[15] Again since our focus is on labor supply change, we limit our at-risk population to the working age population in Thailand. In addition, the labor supply change

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Table 2. *Dose–response function for exposure to ambient PM10 and premature mortality for the 24–64 age population*

Age	*Exposure–response rate*
24–64	RR = 1.01 per 10 μg/m^3 PM10 (1.0062, 1.013) or per cent $\Delta H_{MT} = 0.1 \cdot \Delta$PM10 where per cent ΔH_{MT} is the percentage change in effect (here, mortality) and where ΔPM10 is the change in PM10 concentration (note the coefficient is 0.1 per cent, rather than 1 per cent because it now reflects the change in fractional mortality per μg/m^3 and not per 10 μg/m^3)

Vajanapoom (1999) studied PM air pollution and daily premature mortality in Bangkok. Her estimation of the ERR for mortality in Bangkok is consistent with previous studies conducted for developed countries. Table 2 presents the results from her study where Dose–Response function refers to the function capturing the exposure–response rate and RR stands for Relative Risk. The equation states that a 10 μg/m^3 change in PM_{10} concentration is associated with a 1 per cent change in mortality.[16] The numbers in the parentheses report the lower and upper bound values for the percentage change.

To translate percentage change in mortality into the actual number of deaths attributable to PM_{10} exposure, we can rewrite the equation as follows:

$$\Delta H_{MT} = b \cdot \Delta \text{PM10} \cdot CMR/100 \tag{10}$$

(Pearce and Crowards, 1996), where ΔH_{MT} stands for the Change in Mortality due to PM_{10} exposures in a population (not the percentage change, as in the table above), and b the slope of the dose–response function which equals 0.1 for the central value.[17] *PM10* stands for the average change in ambient PM_{10} concentration. *CMR* is Crude Mortality Rate for the same geographic region or population. Dividing the right-hand side by 100 converts the slope

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is assumed to occur in the urban work force only, given the predominantly urban nature of particulate matter pollution.

[16] Since the writing of the paper, this figure has dropped to closer to 0.5 per cent per 1 µg/m^3 PM_{10} change. Rather than using 0.5 per cent as the default, we have kept 1 per cent per 1 µg/m^3 PM_{10} as the default but apply the 0.5 per cent per 1 µg/m^3 PM_{10} change value in the sensitivity analysis. No significant change to the main findings was observed under the 0.5 per cent per 1 µg/m^3 assumption.

[17] In the sensitivity analysis, in addition to the upper (0.13) and lower bound (0.062) slopes for *b* provided by Pearce and Crowards (1996), the author sought a wider range of plausible values from similar types of studies in the literature. This is due to the fact that the 0.13 and 0.062 values were from one study, and therefore would be highly influenced by the sample size used in that study. The wider range has upper and lower bound slopes of 0.376 and 0.026. These values are from Pönkä *et al.* (1991) and Hoek *et al.* (2000) respectively.

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from a percentage to a fractional change, which converts the mortality from a percentage change to the absolute change in number of deaths due to exposure.

For this study, we apply the ERR (estimated in Bangkok) to the entire urban population in Thailand. In order to extract incidence of mortality applicable to the 15–59 population only, as opposed to the 24–64 range, we go through two steps: first, for the 24–59 range, we estimate its share out of the 24–64 range (67.9 per cent) with respect to mortality (all causes) for Thailand in 1998 with data from the National Statistics Office of Thailand; second, for the 15–23 range, we assumed the mortality induced by exposure to PM_{10} is the same as its relative share over mortality (all causes) *vis-à-vis* the 24–64 age group (approximately 10 per cent).

When the carbon tax policy is imposed for the years 2003 to 2010 we see a reduction in PM_{10} concentration in these periods. Regarding its implication for premature mortalities, we assume only those experienced by the urban households will be affected. This is due to the assumption that the secondary effects of reduced local air pollution will mostly benefit urban population.[18]

There has not been an ERR estimated for Thailand's RAD from PM_{10} exposure. Instead, the author applied the ERR estimated for the US by Ostro (1994) and again adjusted the outcome using the PPP ratio to obtain the economic outcome for Thailand.[19]

As the calculation for RAD includes that for RAD and so-called Minor RAD, here we present the steps used by Ostro (1994) in calculating them:

- 1 per cent rise in PM_{10} leads to an increase of 0.058 RAD per person per year or 0.00016 RAD per person per day.
- 62 per cent of all RAD are bed-disability days (100 per cent productivity loss).
- The other 38 per cent are minor RAD or MRAD (10 per cent productivity loss).
- Multiplying 0.058 by the average wage of the working population, we can get an estimate of the value of work lost per year per unit rise in PM_{10}.

As a result of reduced ambient concentration of PM_{10}, after imposing our carbon tax, we expect labor to be saved due to avoided premature mortality and avoided RAD and MRAD. Table 3 below presents these figures

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[18] In addition, due to a lack of air dispersion modeling data, we cannot trace location-specific welfare change in terms of health. This applies to both urban and non-urban households. We can only establish 'average' changes.

[19] Pearce and Crowards (1996), when applying the same DRF to the UK, used this scaling procedure to infer the implications of a change in particulate matter and the resultant RAD for the UK. Sick-day/annual leave policies are doubtlessly different between Thailand and the US and therefore this epidemiological 'transfer' is probably not very reliable. The sensitivity analyses over the slopes of the ERR functions help assess the effects of the uncertainties related to 'transferring' the ERR functions.

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Table 3. *Avoided premature mortality and reduced activity days for the urban working population in Thailand under the carbon tax scenario relative to the baseline*

	Total labor saved						
	HH_NAG		*HH_GOV*				
	RAD	*RAD Due to Premature Mortality*	*RAD*	*RAD Due to Premature Mortality*	*Original total number of labor units (# people)*	*RAD saved per person in this year*	*PPP adjusted value of previous column*
2003	933,814	2,092	189,629	2,092	32,258,555	0.026	0.006
2004	2,900,581	7,402	589,019	7,402	32,532,755	0.091	0.02
2005	2,153,939	8,233	137,399	8,233	32,809,285	0.1	0.022
2006	1,228,266	3,964	249,423	3,964	33,088,165	0.048	0.011
2007	1,061,408	3,348	215,539	3,348	33,369,410	0.04	0.009
2008	1,083,058	3,115	219,936	3,115	33,653,050	0.037	0.008
2009	1,066,465	3,292	216,566	3,292	33,939,105	0.039	0.009
2010	1,075,727	3,283	218,447	3,283	34,227,585	0.038	0.008

for the years affected. The households affected include non-agricultural (HH_NAG) and government-employed (HH_GOV) households, but not the agricultural households. In order to aggregate labor saved from avoided premature mortality and saved RAD, labor saved from avoided premature mortality was converted to saved RAD. For total RAD saved per year, this was done by multiplying the former by 300 (the assumed number of days worked per year otherwise).[20] As the DRF for RAD was originally estimated for the US, we adjust total labor saved by the US–Thai PPP ratio of 4.5. The furthest right column in the table below shows the PPP-adjusted estimation of total labor saved due to the carbon tax in Thailand.

The change in labor supply (output from the previous step) will lead to an adjustment in the amount of labor available in the periods the carbon tax is imposed. To assess economy-wide repercussions of the ancillary benefit of saved labor, we feed back this additional labor supply to the total labor supply as a percentage (for instance for an increase of 0.2 per cent, we multiply the original labor supply by 1.02). Thus the labor supply change as a result of the ancillary benefit of the carbon tax is fed back 'exogenously'.

New CO_2 tax schedule to achieve policy goal

With the exogenous labor feedback for the period of 2003–2010, the GDP would be higher but so will emissions. In order to still achieve the original policy goal of reducing total CO_2 emission to 90 per cent of that in 2000 by 2010, we need to raise the carbon tax. This again was done so that taxes on all eight energy goods were raised by the same rate relative to their former levels and the rates grow overtime to lead to monotonically higher carbon emission reductions overtime.

5. Results

It is important to review the purpose behind all the estimations and calculations covered. We are interested in comparing macroeconomic and income distributional outcomes of the carbon tax policy relative to the baseline (no policy, no health feedback). More importantly, we want to compare the results under the 'carbon tax with health feedback' vs. the 'carbon tax without health feedback' scenario. We expect to see that by including more fully the benefit side of GHG mitigation policy, we would see a much more positive effect of GHG mitigating policies on macroeconomic factors and therefore more accurate policy advice to middle-income countries like Thailand. An important note about both policy scenarios is that both use carbon tax revenue collected by the government to re-invest rather than reduce other existing tax(es).[21] Income

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[20] The RAD figures are much greater than RADs from premature mortality. This is due to the fact that the 'base' for RAD is much greater than the 'base' figure to which the premature mortality coefficient/slope was multiplied. In essence, when the ambient concentration of PM_{10} changes, every working individual is assumed affected through the change in RAD, but only a small share of the working population will experience (reduced) premature mortality.

[21] Given that the chosen closure rule keeps government consumption constant, all the extra revenue collected from the carbon tax goes to government saving. This

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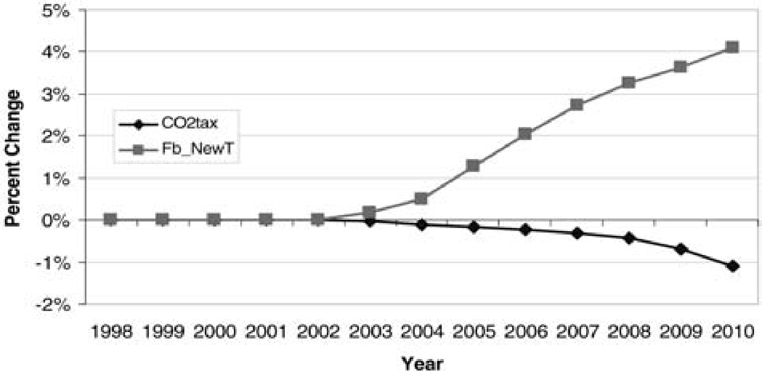

Figure 1. *Projected GDP*
CO2 tax with and without health feedback relative to baseline

distributional change or household welfare change is gauged by real consumption change. The key question is whether the welfare effects of the carbon tax on these and all other sectors are lessened when the health feedback is incorporated.

Based on the model outputs, we observe higher GDP growth with the carbon tax when the feedback is taken into account. *Fb_NewT* (the upper line) reflects the carbon tax with health feedback scenario relative to the baseline. Figure 1 captures these differences under the 'no feedback' and 'with feedback' scenarios relative to the baseline. All effects are in real terms.

The higher GDP with health feedback is a result of higher private consumption. The higher consumption is due primarily to the rise in household income. Household incomes rise as a result of the increase in labor productivity as well as an economy that is experiencing greater growth. The link between the two is that, as labor productivity improves, households work more, which in turn leads the economy to grow more rapidly relative to the baseline. The higher growth experienced by the economy then leads to yet another round of income increase flowing to labor and therefore to the households. Additionally, the rise in investment is another main driver of the higher GDP when health feedback is captured. The additional tax revenue gained from the government from the 'saved' labor gets reinvested (and therefore higher government investment) and over time leads to higher GDP relative to the case when no health feedback is included. At the same time, due to lower reduction in total income, private investment declines by a less amount under the with-health-feedback scenario than under the carbon tax analyzed without health feedback. This latter reason also contributes to the higher total investment under the with-feedback carbon tax scenario relative to the no-feedback carbon tax scenario.

is a form of revenue neutral recycling scheme; this is one of the possible ways of providing a revenue neutral setting in comparing the baseline *vis-à-vis* the carbon tax policy scenarios.

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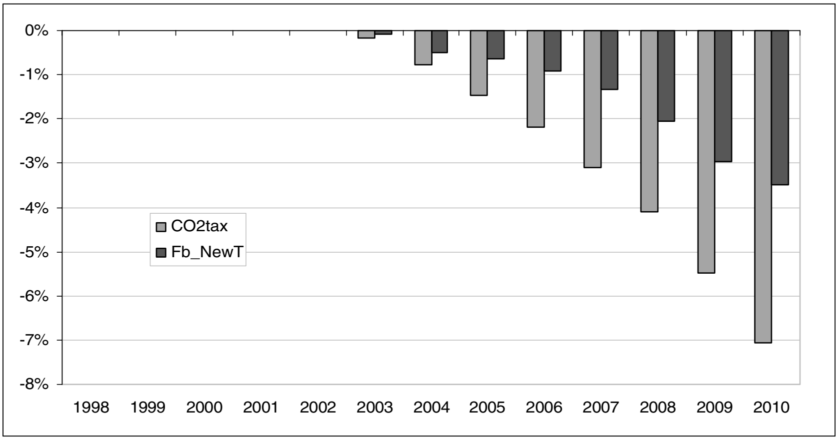

Figure 2. *Projected welfare trends for agricultural households CO2TAX with and without health feedback relative to baseline*

This indicates that when we better capture the benefit side of GHG reduction in the form of ancillary local pollutant reduction and ancillary local health benefits, we find that the cost of a carbon tax (on real private consumption) is actually not as high as when such benefits are not captured.

With respect to household welfare, including health feedback significantly reduces the welfare loss experienced by households compared to without consideration of health feedback. Specifically, the loss of welfare estimated without health feedback is cut almost by half for the lowest- and middle-income households (corresponding with agricultural and non-agricultural households). Including the health feedback does not make as large a difference regarding real consumption of the highest-income household, the government-employed household. This is due to the fact that this household makes up a small share of total population as well as the labor force. Therefore it benefits less from the overall labor supply increase as a result of improved health. Figures 2–4 depict these effects. Based on these comparisons, a carbon tax that would lead to 90 per cent of the projected 2100 GHG emissions has a much lower negative impact on the majority of the households when health feedback is considered.[22]

It is important to point out that household welfare measured in real consumption is largely affected by how the government chooses to use the carbon tax revenue. The assumption we used was that the government makes no transfer to the households. In the event where the households are compensated, private welfare can improve significantly under a carbon tax.

Sensitivity analysis

In a large integrated study like this where assumptions were made about key parameters, it is important to investigate how sensitive the findings

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[22] The results were consistent when the alternative carbon reduction scenarios of 5 per cent and 20 per cent lower than the 2000 level by 2010 were run.

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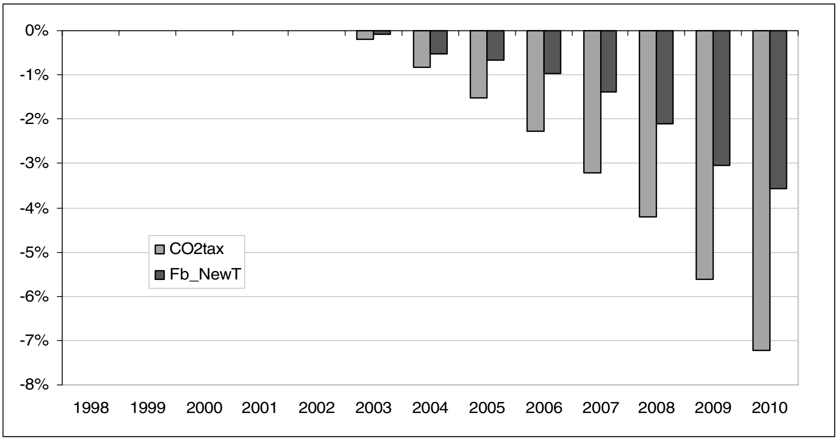

Figure 3. *Projected welfare trends for non-agricultural households CO2TAX with and without health feedback relative to baseline*

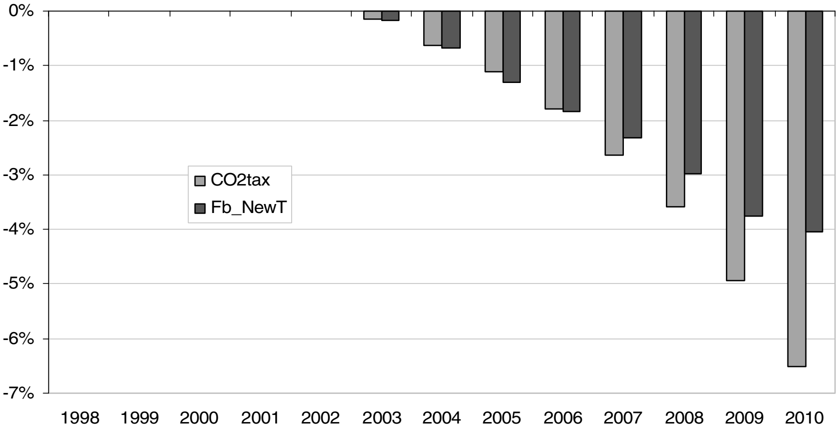

Figure 4. *Projected welfare trends for government-employed households CO2TAX with and without health feedback relative to baseline*

are to varied assumptions about the key parameters. Therefore a sensitivity analysis was performed over eleven key parameters.

The eleven key parameters tested are the following:

- Input elasticity for non-energy inputs (or substitutability among all the non-energy intermediate inputs), *AGGNENG*
- Input elasticity for energy inputs (or substitutability among the eight energy inputs), *AGGENG*
- Input elasticity for value added (or substitutability between labor and capital), *AGGVA*

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- Input elasticity for top level CES aggregation (or substitutability among aggregate energy input, aggregate non-energy input, and aggregate value-added), *AGGINP*
- The share of subsistence level consumption out of total consumption, *Frisch*
- Purchasing power parity ratio between US and Thailand, *PPP ratio*
- PM_{10} emission shares at origin from source types (background, industrial, and transportation), *K coefficients*
- Average GDP growth (by adjusting capital-to-output ratio), *Kscale*
- The slope of exposure–response function for mortality per $\mu g/m^3$ rise in PM_{10}, ***b***, in $\Delta H_{MT} = \boldsymbol{b} \cdot \Delta PM_{10} \cdot CMR \cdot POP/100$
- The slope of exposure–response function for reduced activity days per $\mu g/m^3$ rise in PM_{10}, *RAD*
- The assumption about the inclusion of agricultural household in RAD computation, *RAD_AgHH* s[23]

Table 4 below shows the default values and the plausible alternative values tested for the 11 parameters. The selection of the alternative values was informed by relevant literature.[24]

Improvement in household welfare from the CO2tax scenario to the Fb_NewT scenario is robust when evaluated under alternative parameter values. There is no sign change associated with the welfare increment under all parameter changes for any of the three types of households; i.e. the conclusion that inclusion of health feedback in the analysis reduces the apparent loss in welfare is robust under alternative parameter assumptions.[25]

Three parameters were identified as the most influential parameters – the distribution of source term contributions to ambient PM_{10} (KCOEFF), the capital-to-output ratio (KSCALE), and the elasticity of substitution for top-level CES production technology (AGGINP).

Limitations

The study employs an empirical exposure model that assumes the source locations and relative values of source terms stay constant with and without a policy, so the contribution to ambient air concentration from a source category (except background) scales with the source term for that category. This assumption seems reasonable for modeling periods extending only into the near future. The assumption is also made given very limited data on the exact location of emission sources and the stack heights at which the emissions are released. It was therefore not possible to predict accurately the location-specific concentrations of PM_{10}. As a result, the author considers

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[23] This assumption is tested to see what happens if non-urban or agricultural household labor also benefits from the reduction in PM_{10} concentration. This is in terms of reduced activity days alone, with the assumption that the premature mortality of agricultural households remains unaffected.

[24] For detailed information about the choice of the alternative parameter values, please contact the author.

[25] The sensitivity analysis results are available upon request.

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Table 4. *Default and tested values for key parameters*

	Default values	*Low bound*	*High bound*
AGGNENG	0.5	0.25	0.65
AGGENG	0.7	0.35	0.9
AGGVA	0.6	0.4	0.9
AGGINP	0.5	0.25	0.75
Frisch	–2 (corresponds with 50 per cent subsistence, and 50 per cent disposable)	–1.5 (corresponds with 37.5 per cent subsistence, and 62.5 per cent disposable)	–3 (corresponds with 75 per cent subsistence, and 25 per cent disposable)
PPP	4.5	3.5	5.29
K Coe	Background: 36 per cent Industrial: 10 per cent Transportation: 54 per cent	Kcoeff EQ Background: 33 per cent Industrial: 33 per cent Transportation: 33 per cent Kcoeff B Background: 10 per cent Industrial: 45 per cent Transportation: 45 per cent	Kcoeff A Background: 36 per cent Industrial: 54 per cent Transportation: 10 per cent Kcoeff C Background: 50 per cent Industrial: 25 per cent Transportation: 25 per cent
Kscale	0.355 (for 3–4 per cent average GDP growth)	0.305 (for 2–3 per cent average GDP growth)	0.45 (for 5–6 per cent average GDP growth)
b	0.1	0.062 0.026	0.13 0.376
RAD	0.058	0.0435	0.0720
RAD_AgHH	No assumed change on the part of agricultural households, only assuming change in urban households (non-agricultural & government-employed)	Assume that 25 per cent of this population experience a change in major and minor RAD per $\mu g/m^3$ rise in PM10 concentration	

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a model in which policies affect the overall source magnitude but not the geographic distribution of those sources (in the absence of reliable information to the contrary).

Another limitation of the study is that it has employed emissions coefficients for CO_2 and PM_{10} not specifically calculated for Thailand. When more detailed data for Thailand become available, applying them will improve the study.

In calculating reduced activity days associated with changes in ambient concentration of PM_{10}, the lack of a measured dose–response function for Thailand led to the application of such functions originally estimated for the US. The procedure used to adjust the resultant economic valuation, dividing the valuation by the PPP ratio between US to Thailand, has been applied before by Pearce and Crowards (1996) for adjusting the results from the same DRF for RAD for the UK. The study would improve, however, if a Thailand specific DRF for RAD became available and were applied.

In valuing hospital admission changes as a result of a reduction in the concentration of PM_{10}, we applied the mean length of stay and mean total charge data for the US and scaled the cost per day of stay by the ratio of purchasing power parity per capita between the US and Thailand to obtain similar information for Thailand. Using the US MLOS data introduces another source of uncertainty as MLOS depends on diagnosis, the type of reimbursement system, and treatment prescribed for a diagnosis within that country. In the US, for instance, people now get discharged a lot quicker than they used to. Assuming the same MLOS for Thailand (albeit the scaling of the final results by PPP) introduces some uncertainty about results. Should studies on the MLOS and mean total charge data for the relevant illness categories in Thailand come along, the current study will be improved by using these data instead. One other potential source of uncertainty in estimating hospital admission changes is the assumption that 44.5 per cent of total respiratory and cardiovascular admissions can be attributed to the 15–59 population. This assumed share is derived from the data that 44.5 per cent of total reported illnesses in 1998 can be attributed to this age group. It is quite possible, however, that children and elderly (who are outside of the 15–59 population group) have a higher rate of admission due to air pollution and that the 15–59 range is under-represented in this disease category relative to other disease categories. Therefore, 44.5 per cent can be an overestimate. A sensitivity analysis of this particular share was not conducted because hospital admission represents a very small share out of the valuation of total health benefits (which include those of saved mortality and labor changes as well). But this still represents a source of uncertainty in comparing the savings from avoided hospital admissions and the result from the health and medical expenditure savings endogenously captured by the model.

Finally, the current study does not attempt to include all secondary effects of GHG mitigation. Secondary effects not considered include those on chronic health, ecosystems, visibility and traffic accidents, and related quality of life improvements.

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6. Conclusions

The author has constructed a CGE model and a sub-model on health to study the economic and social welfare implications of capturing the local health benefits of mitigating GHGs. Taking into consideration the limitations of the study design, application of the models to Thailand finds that:

- including health feedback leads to consistently higher projected GDP than not including health feedback;
- including health feedback leads to consistently higher projected private consumption than not including health feedback;
- including health feedback leads to better welfare in the case of all three household types.

These findings are fairly robust with respect to parameter value changes in the elasticities of substitution, share of subsistence consumption over total consumption, slope parameters in the applied DRFs, the average economic growth rate, and the distribution of source contribution to PM_{10} concentration.

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