A Dynamic Recursive Analysis of A Carbon Tax Including Local Health Feedback

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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 benefit of GHG mitigation is reduced local air toxics, which is associated with improved health. Middle-income countries, as defined by the World Bank, like Thailand are in a unique position to obtain large ancillary health gains from reduced local air toxics when GHG is mitigated by curbing fossil fuel consumption.

The author assesses whether by capturing the local health effects of reduced air toxics 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 comprehensive 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) information from the CGE model to assess the implications for ambient PM_{10} concentration, local health, labor supply and medical expenditures. The saved labor is exogenously fed back to 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. To illustrate this methodology, the methodology is applied to the country of Thailand, a middle-income country, for the period of 1998-2010. The base year was calibrated to a 1998 Social Accounting Matrix originally obtained from the Thai Development Research Institute.

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 welfare of households with the carbon tax relative to the no policy scenario improve by a factor of two when health feedback in incorporated. An extensive sensitivity analysis over these results was then carried out, using upper and lower bound values instead of the central or default values for 11 key parameters. A tornado diagram was used to identify the parameters whose uncertainties influence key results the most. 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). The key results corresponding with alternative assumptions about these three parameters were then evaluated more closely. Under three alternative scenarios - low bound KCOEFF, low bound KSCALE, and high bound AGGINP - the key results or findings alluded to earlier no longer hold. Although the author does not have the information about the probability

* The author would like to thank Sherman Robinson, Hans Lofgren, and Xinshen Diao at IFPRI for their helpful feedback, as well as Professors Douglas Crawford-Brown and Mort Webster at the University of North Carolina at Chapel Hill for their feedback.

distributions of the occurrence of alternative values for these parameters, she assesses the likelihoods of these alternative values' being closer to reality than their default values.

1. Introduction

Emerging economies like Thailand have a unique set of features. First, they have achieved a certain degree of economic development and passed the level of only caring about economic growth. In particular, local health and its relationship to environmental quality have gained a greater emphasis. Second, these countries have experienced pressure from the international community to do something about GHG emissions, and have expressed at least an interest in participating in efforts to curb GHG emissions, as their economies have benefited to some extent from technologies rooted in fossil fuel use. Third, there is a link between GHG emission reduction and local health improvement in those countries since fossil fuel use is producing both GHGs and air toxics. Hence reducing GHG emissions by controlling fossil fuel consumption will lower local health pollutants also.

2. Methodology

2.1 Conceptual Framework

This study employs nine distinct methodologies to simulate the feedback of health effects and to assess the influence of this feedback on measures of Social Welfare. These methodological steps, shown in Figure 1 on the next page as the boxes and arrows, are:

1. Obtain a 1998 Social Accounting Matrix for Thailand and modify it to fit the purpose of the current policy analysis.
2. Build a baseline scenario for the period of 1998 through 2010 using a recursive dynamic CGE model, which has two components: within-period model and between-period specifications. Figure 2 illustrates the link between within-period and between-period models.
3. Impose a carbon tax schedule that would reduce CO_2 emission to 10% less than the 2000 level by 2010.

4. From the emissions inventory captured within the CGE model, obtain the PM_{10} emissions in volume both before and after the policy imposition. Use an Empirical Air Dispersion Model to determine the ambient air concentrations of PM_{10} after the policy shock.
5. Determine the implications of the reduction in PM_{10} exposures to the health of the resident population. This is done in two steps: (1) cross checking the change in medical expenditure (endogenously captured) using reference data, and (2) estimating labor supply changes (exogenously estimated) using dose-response functions for premature mortality and reduced activity days.
6. Feedback labor supply change exogenously to the recursive dynamic CGE model.
7. Impose a new carbon tax schedule to achieve the same policy goal of reducing CO_2 emission to 10% less than the 2000 level by 2010.
8. Assess the overall economic impact, through the economic model, considering both primary and secondary (feedback) effects; summarize as economic and welfare indicators.
9. Apply a decision model to compare the carbon tax policy scenarios (with and without all health feedbacks) based on a combination of the economic efficiency criterion, income distribution criterion, and the criterion of institutional feasibility.

2.2 Social Accounting Matrix

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. It is a useful framework for preparing consistent, multi-sectoral, economic data that integrates national income, input-output, flow-of-funds, and foreign trade statistics into a comprehensive and consistent dataset. In the case of Thailand, the author obtained a balanced SAM for Thailand and no balancing procedure was necessary even after multiple aggregating and disaggregating changes.

Once the model was 'calibrated' to the base year, the 'benchmark' to which the policy scenarios will be compared was established. In order to create a baseline rather than a benchmark to explore the temporal dimension of the carbon tax policy, a multi-period baseline is created by updating several key parameters from one period to the next. These include the growth of factors of production, capital and labor, and the total factor productivity, given the data sources.

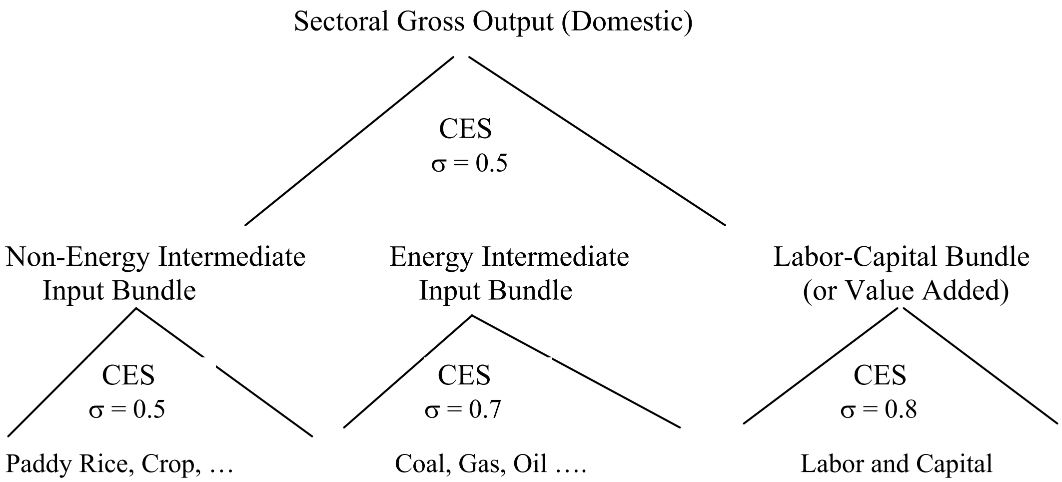
The model used consists of static within-period and dynamic transitional or between-period models. The within-period model is a variation from the “standard model” built by the Trade and Macroeconomics Division of the International Food Policy Research Institute (Lofgren et. al, 2001). The between-period model links the static (within-period) models by updating factors of production and total factor productivity from one period to the next.

2.3 Within-Period CGE

2.3.1 Production

Each producer is assumed to maximize profits, defined by the difference between revenue earned and the costs of factors and intermediate inputs. Profits are maximized subject to a production technology, the structure of which is shown in Figure 1. At the top level, outputs from the three composite goods – non-energy intermediates, energy intermediates, and valued added – are aggregated via the Constant Elasticities of Substitutions (CES) technology. The CES alternative is preferred since no empirical evidence suggests that aggregate mix between the intermediates and value added is non-existent. Value added itself is a CES function of primary factors: labor and capital. The non-energy intermediate aggregate is a CES function of all non-energy intermediate commodities; and the energy intermediate is a CES function of eight energy commodities. The elasticities of substitution, σ’s, reflect the adjustment possibilities in producers’ demand for factors when the relative prices of these factors change. The values are informed by literature and are altered for the sensitivity analyses of the study’s findings.

Figure 1: Sectoral Production Technology Applied in the Within-period CGE Model



2.3.2 Consumption, Income Distribution, and Absorption

On the consumption side, private consumption demand is obtained through maximization of a household-specific utility function following the Stone-Geary Linear Expenditure System or the Extended Linear Expenditure System (LES) (Lluch, 1973). For each household, consumer demand, C, is defined by:

$$C_i = \gamma_i + \frac{\beta_i}{P_i}\left(Y - \sum_j P_j \gamma_j\right) \qquad (1)$$

where Y is total nominal expenditure for the household, γ_i are the committed expenditures or "subsistence minima" in physical terms, P is the price per unit commodity consumed, and β_i are the marginal budget shares that determined the allocation of supernumerary income (i.e., the expenditure above that required for purchasing the subsistence minima) (Dervis et. al., 1982). The parameters of LES are computed for each household using average budget shares from the SAM, assumed income elasticities of demand, and a parameter measuring the elasticity of the marginal utility of income with respect to income (often called the "Frisch parameter"). In the LES, the Frisch parameter (ϕ) is equal to the ratio of total expenditure to supernumerary expenditure:

$$\phi = \frac{-Y}{Y-S} \quad \text{where} \quad S = \sum_j P_j \gamma_j \qquad \text{(2) and (3)}$$

Given the average budget shares and expenditure elasticities, the marginal budget shares are given by

$$\beta_1 = \varepsilon_i \alpha_i \tag{4}$$

where ε_i are the expenditure elasticities and α_i are average budget shares. Note that the marginal budget shares must sum to one, which is equivalent to imposing the condition, known as Engel aggregation, that the sum of the expenditure elasticities weighted by average budget shares must equal one. This condition was met in determining household expenditure schedules (for three different types of household), using given budget share information. Informed by household expenditure elasticity schedule of cross-country studies, the schedule for Thailand was determined. The elasticity values, differentiated by household and product, vary in the range of 0.40 (for basic products consumed) to 2.0 (for services).

The subsistence minima γ_i are related to the other parameters according to the following equation:

$$\gamma_i = \left(\frac{Y}{P_i}\right)\left(\alpha_i + \frac{\beta_i}{\phi}\right) \tag{5}$$

The estimates of Frisch parameters were based on the range Dervis et al. (1982) reported based on a variety of cross-country studies. For countries with per capital GDP of about \$500, the authors found a range of Frisch parameter from –5.0 to –1.6. For the country of Thailand, where the GDP per capita in 1998 was around \$1,300, –2 was chosen as the default value for the Frisch parameter; other values were considered in the sensitivity analysis.

Labor income is allocated to households according to a fixed coefficient distribution matrix derived from the original SAM. Likewise capital revenues are distributed among households, private and public enterprises, and the government. The relative incomes of the three households (Agricultural, Non-agricultural, and Government-employed) are 1:3.38:3.88. On average, government-employed household income is the highest, about 4 times that of agricultural household income and about 1.14 times higher than the average income of non-agricultural households.

The government consumption and investment demands are disaggregated by sector with their shares determined by the base data from SAM.

2.3.3 International Trade

Like most CGE models, the model assumes imperfect substitution among goods originating from different geographical areas or the Armington assumption. Import demand is derived from a CES aggregation of domestic and imported goods. Export supply is symmetrically modeled as a Constant Elasticity of Transformation (CET) function. Producers allocate their output to domestic or foreign markets in response to relative price changes. For Thailand, the Armington elasticities for demand between domestic and imported products are based on Warr (1998) and informed by the base-year shares of imports, exports, and two-way trade. The transformation elasticities for domestic versus export supply are obtained from Methakunavut and Jitsuchon (2000). The small-country assumption is applied; Thailand is assumed to be unable to change world prices. This specification implies that the import and export world prices are exogenous. Balance-of-payments equilibrium assumes a fixed value for the current account.

2.3.4 Emissions Inventory

Two types of polluting substances are included: CO_2 and PM_{10}. An abatement policy targeted at CO_2 has the unintended positive effect of reducing a local pollutant, PM_{10}. We refer to this secondary reduction of PM_{10} as an "ancillary effect" or "ancillary benefit" (Burtraw and Toman, 2000).

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 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 or final consumption-generated. When a carbon tax is imposed to induce less fossil fuel burning, one therefore does not expect the process-generated PM_{10} to drop significantly but should expect the combustion-generated PM_{10} (through industrial production and vehicular combustion through internal combustion engines) to drop more.

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

Emissions coefficients associated with each intermediate and final consumption for CO_2 are derived from the emission coefficients from the U.S. Energy Information Agency. Industry-specific emissions coefficients for PM_{10} (for combustion and process-generated emissions) are assumed similar distributions as those applied by Garbaccio et al. (2000) in their study on China. Thailand-specific data are not available at present. The use of EIA and Garbaccio et al. emissions coefficients lead to base year (1998) CO_2 and PM_{10} emissions similar to the reported emissions from the Pollution Control Division of Thailand.

Formally, the total emission for a given pollutant takes the following form for CO_2:

$$E_{CO2} = \sum_{A} \sum_{EINP} \alpha_{EINP} QINP_{A,EINP} + \sum_{INST} \tau_{INST} C_{INST} \tag{6}$$

E = total emissions.
A = 61 activity sectors which use energy as an input.
$EINP$ = 8 energy input categories.
α = emission coefficients for combustion emitted CO_2 by sector.
$QINP_{A,\ EINP}$ = quantity of each of the 8 energy inputs consumed by each sector.
τ = emission coefficients for consumption originated CO_2 emissions by the final consumer groups or Institutions, households and government.
$INST$ = different institutions.
C_{INST} = amount of each polluting good consumed by each institution.

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

$$E_{PM10} = \sum_{A} \sum_{EINP} \alpha_{2,EINP} QINP_{A,EINP} + \sum_{A} \beta_{A} QD_{A} + \sum_{INST} \tau_{2,INST} C_{INST} \tag{7}$$

α_2 = emissions coefficients for combustion emitted PM_{10} by sector.
β = emissions coefficients for the process emitted PM_{10} by sector.

τ_2 = emission coefficients for consumption originated PM_{10} emissions by final consumer groups

QD_A = total domestic output by activity or 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 Total Factor Productivity from one period to the next. No explicit modeling of production technology and change in production technology composition is carried out.

An emission abatement policy such as a carbon tax will have indirect effects on household utility through multiple channels, from price effects to production and therefore employment effects. Household utility is directly related to environmental quality in one respect. The consumption of the medical/hospital commodity is directly linked to environmental quality (as the next section explains). 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 used in this research in multiple ways. By linking the consumption of medical goods to environmental quality, one can immediately capture the effect of environmental quality change on medical expenditures. In other words, the feedback of medical expenditure change as a result of environmental quality change is "endogenized."

In addition to endogenizing medical expenditure, this study captures the link between environmental quality change and labor productivity change by exogenously estimating labor productivity change given the emissions data from the emissions inventory and the air dispersion effects thereof, and feeding back this change to the CGE model.

This exogenous labor feedback will mean healthier households with more labor to offer and therefore higher income. On the production side, environmental degradation does not directly enter the production maximization function, for instance the productivity of production factors. The labor feedback will mean a larger labor supply and therefore lower wage and more production. This however needs to be weighed against the effect of more expensive fossil fuels as a result of a fossil fuel tax, and the net effect on the industry depends on how energy (carbon-based fuel) intensive that industry is.

2.3.5 Expenditures on Health/Medical Treatment and 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, 1997). In the event of improved local environmental quality, some of these hospital costs will be avoided. Here it is assumed that both the government and the household are able to cut back medical expenditure as a result. The use of this incremental income will follow the spending pattern (allocation shares) of the existing government and household accounts.

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

As alluded to earlier, 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).

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.

2.3.6 Model Closure

2.3.6.1 Factor markets

Labor and capital are assumed fully mobile and fully employed. The economy-wide wage variable is free to vary so that the sum of demands from all activities equals the quantity supplied; the activity-specific wage (distortion) terms are fixed.

2.3.6.2 Macroeconomic balances

The external balance is achieved by a flexible exchange rate, while foreign savings (the current account deficit) is assumed fixed. Given that all other items in the external balance (transfers between the rest of the world and domestic institutions) are fixed, the trade balance is also fixed. If, *ceteris paribus*, foreign savings are below the exogenous level, a depreciation of the real exchange rate would correct this situation by simultaneously (i) reducing spending on imports (a fall in import quantities at fixed world prices); and (ii) increasing earnings from exports (an increase in export quantities at fixed world prices).

The model assumes savings-driven investment on the part of households by having marginal savings propensities of households fixed while letting the investment demand quantity adjust. The quantity of each commodity in the investment bundle is multiplied by a flexible scalar so as to assure that the investment cost will be equal to the savings value.

On the government side, saving is flexible as the residual of total income minus total spending. Direct tax rates and all other taxes (import tax, activity tax, commodity tax, and excise tax) are assumed fixed, set at the carbon tax adjusted level by household categories. Government consumption is fixed.

Among total absorption, private investment has a flexible absorption share; so does government consumption, which leaves the residual household consumption share adjusting as well. Having the components of total absorption change over time is considered a more realistic assumption for multi-period policy modeling.

2.4 Between-Period CGE

The model can be made dynamic by updating the variables that are exogenous in the current year, which, in the case of Thailand is 1998. Here the updating applies to two factors of production: capital and labor, and total factor productivity (TFP) growth for 1999 through 2010.

The labor force growth rate is set by drawing from the projection made by the National Statistics Office of Thailand. Capital stock in each 1-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 encountered. 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 will then be used as a 'converter'. Total investment equals then 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}).

$$capgrw = \frac{\left[kscale \cdot \left(P^c_{inv} \cdot Q^c_{inv}\right) + \left(1 - depr\right) \cdot oldstk\right]}{oldstk} \tag{8}$$

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 capital rate of return differentials. Capital (non-depreciated old stock plus new stock) is assumed perfectly mobile within each period.

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 sector-specific or assumed uniform across sectors. Researchers have estimated that the historical average TFP is around 2% for Thailand; some contend a higher average TFP for non-agricutural sectors and a very small (sometimes negative) average TFP for agricultural sectors (Tinarkon and Sussangkarn; Diao, Rattso, and Stokke). Here, a small positive average TFP growth rate for all sectors is assumed. TFP growth rate serves as the residual among the sources of growth to target a projected 4-5% GDP growth rate for Thailand for the modeling period of 1999-2010. Using TFP as the residual is consistent with other work on Thailand (Tinakorn and Sussangkarn, 1994).

2.5. Policy Specification & Imposition

A carbon tax proportional to the carbon emission coefficient is imposed on each of the eight energy commodities from 2003 to 2010 to simulate the policy shock. All eight tax rates 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% that of 2000. The tax rates for the carbon tax scenario for the application on Thailand are presented here.

Table 1: Difference in Annual GDP under the Carbon Tax Scenario Compared to the Baseline for Thailand

Year	2003	2004	2005	2006	2007	2008	2009	2010
Difference	-0.03%	-0.11%	-0.17%	-0.23%	-0.31%	-0.42%	-0.70%	-1.09%

2.6 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 the "dispersion coefficients." Here an 'empirical air dispersion model' is used in calculating the dispersion coefficient. This is based on the assumption that the spatial pattern of emissions resulting from changes in the energy infrastructure does not change with time; instead only the source term changes. 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 contribution by three sources: point sources, line sources and area sources, corresponding with industrial, transportation, and background emissions. Their respective shares of total emissions emitted at origin (such as at the site of the factories), and the shares of contribution to mean ambient air concentration across the study geographic region, were reported as 9.78%, 53.94% and 36.28% in 1998.

The following terms appearing in the methodological steps of the Empirical Air Dispersion Model used are defined here:

Source Term PM_{10} from Industries before policy $= ST^{I}_{N}$

Source Term PM_{10} from Transportation before policy $= ST^{T}_{N}$

Source Term PM_{10} from Industries after policy = $ST^{I}{}_{P}$

Source Term PM_{10} from Transportation after policy = $ST^{T}{}_{P}$

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 Indoor by an Average Adult = Fin^A

Fraction of Time Spent Outdoors by an Average Adult = Fou^A

Fraction of Time Spent Indoor by an Average Child = Fin^C

Fraction of Time Spent Outdoors by an Average Child = Fou^C

Fraction of Time Spent Indoor 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

Indoor air concentration without policy = Cin

Indoor air concentration with policy = Cip

Assuming a uniform emission density across the study region for the three source categories, we use 9.78%, 53.94%, and 36.28% for F_I, F_T, and C_B, respectively. The Source Terms, $ST^{T}{}_{N}$ and $ST^{I}{}_{N}$, correspond to total PM_{10} emissions from the transportation sectors and the industrial sectors. Note that the only "controllable" share of PM_{10} emissions is therefore about 64% of total PM_{10} emissions, assuming that background contribution to the ambient air concentration, C_B, is relatively unaffected by the policy. The $ST^{T}{}_{N}$ and $ST^{I}{}_{N}$ information is part of the CGE model outputs under the baseline scenario.

$$F_I = \frac{K_I ST_N^I}{\left(K_I ST_N^I + K_T ST_N^T + C_B\right)} \tag{9}$$

$$F_T = \frac{K_T ST_N^T}{\left(K_I ST_N^I + K_T ST_N^T + C_B\right)} \tag{10}$$

After substituting in C_B (product of 0.3628 and 68μg/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 new expressions of:

$$K_T = \frac{24.67 F_T}{ST_N^T (1 - F_I - F_T)} \tag{11}$$

$$K_I = \frac{24.67 F_I}{ST_N^T (1 - F_I - F_T)} \tag{12}$$

The units of K are unit ambient air concentration per unit source term. The numerical value of K will be 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 values of K 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:

$$C_P = C_N \times \left[\left(K_I ST_P^I + K_T ST_P^T + C_B \right) / \left(K_I ST_N^I + K_T ST_N^T + C_B \right) \right] \tag{13}$$

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

The baseline ambient PM_{10} concentration of around 68 μg/m^3 for Thailand in 1998 (ADB, 1999) increases in time in the baseline scenario. After the imposition of a carbon tax from 2003 through 2010, the PM_{10} concentration, Cp, for these years declines as follows:

Table 2: PM_{10} Concentration Estimated Overtime under the Carbon Tax Scenario for Thailand (μg/m^3)

	1998-2002	2003	2004	2005	2006	2007	2008	2009	2010
Estimated Reduction in Ambient PM_{10} Concentration	68	66	64	65	66	66	67	67	67

The indoor air concentration without a policy then is given by Cin = Cn x R, where R is the ratio of indoor to outdoor air concentration. The indoor air concentration with a policy then is given by Cip = Cp x R, where R is the ratio of indoor to outdoor air concentration (R is assumed invariant with policy).

According to Pearce (1996a), an average adult in a developing country spends approximately 70% of his time indoor and 30% outdoors. The author was not able to obtain Thailand specific data and therefore assumed these shares for Thailand.

Based on observations by Dr. Dana Loomis, who is familiar with the PM_{10} issues in Thailand, the indoor-outdoor concentration of PM_{10} in Thailand should not vary significantly for two reasons[1]: (1) the fine size of the particulate matter of concern (less than 10 micrometer in diameter) which is better mixed indoor versus outdoor compared to coarser particulates, and (2) the level of air conditioned housing in Thailand is still relatively low, which makes it more likely that windows will be open, leading to rapid air exchange between indoor and outdoor air. Given these reasons, it is assumed here that R is equal to 1.

The time-weighted average concentration for each period, which equals the weighted sum of the outdoor and indoor concentrations, with weighting by the fraction of time spent daily in those two settings, would therefore remain the same as that reported in Table 1.

2.7 Implications for Health

2.7.1 Cross Checks for Medical Expenditure changes

Health impairments due to ambient air exposures demand resources through medical treatment. When the health effects incidence caused by air toxic exposures 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 expenditure 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.

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[1] Dr. Dana Loomis is a Professor of Epidemiology at the School of Public Health, University of North Carolina at Chapel Hill.

One way to verify the base data is by some existing data from a study by Hagler Bailly Services for the Pollution Control Dept of Thailand (Hagler Bailly, 1995). It was estimated that on average each family paid about 131 baht or 13% of total medical expenses monthly for dust-related illness. This was about 1.6% of the average Thai monthly income (http://www.anamai.moph.go.th/factsheet/Matter.htm)

According to our base data, 13% of total medical expenditures is 1237, 1291, and 24,624 baht for agricultural, government-employed, and non-agricultural households, respectively. An average of the three households is 3580 Thai baht per year, or 298 baht per month. This is roughly equal to the reference data, after adjustment for inflation.[2]

When the carbon tax schedule was imposed, we observed an average household reduction in medical expenditure of 2,182,000 Baht. In order to check whether this value is reasonable, we relied on DRFs for PM_{10} related hospital admissions estimated for Thailand by Chestnut et al. (1998). We did not find the Mean Length of Stay (MLOS) and Mean total charge data for Thailand. Instead we acquired such information for the U.S. and scaled the cost per day of stay by the ratio of purchasing power parity (PPP) per capita between the U.S. and Thailand to obtain similar information for Thailand.[3]

Table 2 below presents the DRFs for PM_{10} and hospital admissions estimated for Thailand by Chestnut et al. (1998).

Table 3: Exposure-Response Functions for Hospital Admissions associated with PM_{10} in Thailand (central value, and 95% lower and upper confidence limits, are shown)

Health effect category	Annual number of **cases per person** per 1 μg/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}

[2] 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)

[3] Mean length of stay (LOS) for the U.S. was calculated by dividing the sum of inpatient days by the number of patients within the DRG category (Diagnosis-related groups (DRGs) are a classification of hospital case types into groups expected to have similar hospital resource use). Inpatient 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 (http://www.ahcpr.gov/data/hcup/94drga.htm)

Source: Chestnut et al. (1998)

$$\Delta H_{RS} = [(0.0000028 \cdot \Delta PM10) \cdot 0.333] + [(0.0000057 \cdot \Delta PM10) \cdot 0.334] + [(0.0000085 \cdot \Delta PM10) \cdot 0.333] * POP \qquad (14)$$

Given the change in the ambient concentration of PM_{10} and the population for each period, we calculated 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.

Given that the focus of this study is on labor supply change, 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 over the range of 15-59 years of age.[4] Based on NSO data, 44.5% of total reported illnesses in 1998 can be attributed to the 15-59 population. We applied this percentage to derive the respiratory and cardiac hospital admissions changes induced by a change in the ambient concentration of PM_{10} to the 15-59 age group. The avoided incidences of respiratory and cardiovascular hospital admissions for this target population were as follows.

Table 4: Estimated Respiratory and Cardiovascular Hospital Admissions Saved Due to PM_{10} Concentration Reduction under the Carbon Tax Scenario in Thailand

	2003	2004	2005	2006	2007	2008	2009	2010
Respiratory	-62	-111	-208	-175	-130	-84	-58	-40
Cardiovascular	-55	-97	-181	-150	-111	-71	-49	-33

With the ERR information, we applied the mean length of stay and mean total charge for the two disease categories: respiratory and cardiovascular estimated for the U.S. and adjusted the total expenditures by the PPP ratio to obtain results for Thailand. .

For instance, for 2003, using DRF information we derived 62 as the total avoided number of annual hospital admissions for respiratory diseases attributable to PM_{10} exposure and 55 as the total avoided number of annual hospital admissions for cardiovascular diseases attributable to PM_{10} exposure. Beginning with Table 5, note that the policy reduced the PM_{10} concentration

[4] (http://www.nso.go.th/gender/epop.htm).

from 68 to 66 μg/m^3, or by 2 μg/m^3. Multiplying this decrement in concentration by equation (14) but ignore the population term for now yields 2.2E-6 for respiratory admissions and 1.9E-6 for cardiovascular admissions per person. Adjusting for the fact that only 44.5% of these admissions are for the age group of interest here, the 15-59 year age group, the previous two values become 9.7E-7 and 8.6E-7, respectively. With a population size of 64 million (as of 2003), this yields a total decrement of 62 respiratory admissions and 55 cardiovascular admissions in that year, as shown in Table 7.

The Mean length of stay associated with each of the two types of hospital admissions is 5.39 days for respiratory admissions and 5.37 days for cardiac admissions. Thus we have 62*5.39 = 334 total decrement in number of bed-days stayed in hospitals for respiratory admissions attributable to PM_{10} exposure and 55*5.37= 295 total decrement in number of bed-days for cardiac hospital admissions attributable to PM_{10} exposure.

Using the Mean total Charge for each of the two types of admissions adjusted by PPP ratio, we get a mean of 366 baht (US$1646 in 1998 divided by 4.5 PPP ratio) per bed day on average for respiratory admissions and a mean of 410 baht (US$1846 in 1998 divided by 4.5) per bed day for cardiovascular admissions. This gives us around 122,244 baht of avoided medical costs for respiratory admissions attributable to PM_{10} exposures and 120,950 baht avoided medical costs for cardiovascular admissions attributable to PM_{10} exposures. The total decrement in medical costs incurred by particulate induced hospital admissions in 1998 in Thailand, according to the reference data in the form of DRF for hospital admissions and the MLOS and mean total charge for the two disease categories associated with PM_{10} concentration, therefore sum to around 243,194 baht. Adjusted by inflation to get a proximate value for 2003, we get around 662,493 Thai baht, which is consistent with the 600,000 Thai baht estimated by the CGE model.[5] The consistency persists for the years beyond 2003.

2.7.2 Labor Supply Change due to Premature Mortality and Reduced Activity Days

Particulate matter has multiple effects on health, both in the short and long term. Again for this study we focus on short-term or acute effects only. The ultimate goal is to estimate the implication of the change in environmental quality for the change in labor supply and medical

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[5] The projected inflation rate of around 2% for Thailand is obtained from the Asian Development Bank. http://www.adb.org/documents/books/ado/2002/tha.asp

expenditures. As mentioned before, medical expenditure change is captured endogenously by the CGE model, with an assumed relationship between the change in total emissions and change in medical expenditures. Thus it is the labor supply change resulting from local, particulate matter, pollutant emission reduction that requires external calculation and ultimately gets fed back exogenously to the CGE model.

The change in labor supply will include permanent change and temporary change in availability of workers at the job. In terms of temporary change, it consists of two components - the days of work lost (due to sick leaves, hospital visits, etc.) and reduced productivity at work, both of which cause a temporary effect on labor supply. Premature mortality as a result of local air pollutant exposure will have a permanent effect on labor supply. A dose-response function (DRF) between particulate matter exposure and premature mortality is used here. To assess the temporary change in labor supply (both days lost and productivity reduction), we will use a DRF that links changes in PM_{10} concentrations directly to the changes in the reduced activity days or RADs.

Again given that the focus is on labor supply change, we limit our at-risk population to the working age population in Thailand. Adjustments are then made to reflect the fact that we focus on the change in labor supply of the pre-defined working population age group. In addition, the labor supply change is assumed to occur in the urban work force only, given the predominantly urban nature of particulate matter pollution.

Vajanapoom(1999) studied PM air pollution and daily premature mortality in Bangkok. Her estimation of the DRF for mortality in Bangkok, which is consistent with previous studies conducted for developed countries, is applied to the urban population in Thailand. Below is the DRF; RR standing for Relative Risk. The equation says that a 10 $\mu g/m^3$ change in PM_{10} concentration is associated with a 1% change in mortality. The numbers in the parentheses are the lower and upper bounds for the coefficient in the equation.

Table 5: 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 $\mu g/m^3$ PM10 (1.0062, 1.013) or

	$\% \Delta H_{MT} = 0.1 \cdot \Delta PM10$ where $\% \Delta H_{MT}$ is the percentage change in effect (here, mortality) and where ΔPM10 is the change in PM10 concentration (note the coefficient is 0.1%, rather than 1% because it now reflects the change in fractional mortality per $\mu g/m^3$ and not per 10 $\mu g/m^3$)

To translate percentage change in mortality into the actual number of deaths attributable to exposure to PM_{10} (rather than fractional or percentage change in deaths), we can write the equation in the following way (for the 24-64 age group, as an example):

$$\Delta H_{MT} = b \cdot \Delta PM10 \cdot CMR / 100 \qquad \text{(Pearce \& Crowards, 1996b)} \quad (14)$$

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); *b* is the slope of the dose-response function and equals 0.062, 0.1, 0.13 respectively for lower, central and upper bounds (remember that the slope is in percentage change per $\mu g/m^3$ and that the central value is used in all calculations here except for the sensitivity analysis described later). *PM10* stands for the average change in ambient PM10 concentration. *CMR* is the Crude Mortality Rate for that same geographic region or population (in this case, it is the total number of *urban* deaths). Dividing the right hand side by 100 converts the slope 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.

In order to extract the incidence of mortality estimated for the 15-59 range from 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%) with respect to mortality (all causes) for Thailand in 1998 with data from the National Statistics Office, Thailand. Then for the 15-23 range, we assumed the mortality induced by exposure to PM_{10} in this age range is the same as its relative share over mortality (all causes) vis-à-vis the 24-64 age group (around 10%).

The current policy simulation results in a reduction in PM_{10} concentration from 2003 through 2010. This leads to the following reduction in premature mortalities. Saved mortality is assumed to be evenly split between the two urban households, non-agricultural household and government-employed household.

Table 6: Avoided Pre-mature Mortality for the Working Population in Thailand by the Central value and the Lower, and Upper Bound Values of the Slope, *b*, of the Exposure Response Function under the Carbon Tax Scenario

	2003	2004	2005	2006	2007	2008	2009	2010
b =0.1	-187	-663	-737	-355	-300	-279	-295	-294
b =0.062	-116	-411	-457	-220	-186	-173	-183	-182
b =0.13	-244	-862	-958	-461	-390	-363	-383	-382

With respect to RAD and particulate matter, there has not been a DRF estimated for Thailand. The author had to apply the DRF developed for the U.S. by Ostro (1994) and scale the resulting expenditures by the ratio of U.S. purchasing per capita to Thai purchasing power per capita to get the adjusted economic outcomes for Thailand. Pearce and Crowards (1996b), 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 UK.

The following lists the steps presented in Ostro (1994).

- 1 unit 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% of all RAD are bed-disability days (100% productivity loss)
- The other 38% are Minor RAD or MRAD (10% 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}.

The current policy simulation results in a reduction in PM_{10} concentration from 2003 through 2010. The following equation was applied to estimate the total RAD saved.

Loss of wages per year per household =

$$\Delta PM10 \cdot 0.58 \cdot (0.062 + (0.38 \cdot 0.1)) \cdot AW_{HH} \qquad (15)$$

Where $\Delta PM10$ stands for the change in PM_{10} concentration under a policy relative to the baseline and AW_{HH} is the average wage by household. This calculation was done for the two urban households, non-agricultural and government-employed. For the sensitivity analysis, we do include 25% of the agricultural or rural households in estimating the RAD to see the effect of this assumed value on the final results (described later).

Applying the formula above leads to the following saved RAD per person per year, shown in Table 6.

Table 7: Avoided Reduced Activity Days and Avoided Minor Reduced Activity Days per Capita for the Urban Working Population in Thailand Under the Carbon Tax Scenario Relative to the Baseline.

	2003	2004	2005	2006	2007	2008	2009	2010
RAD	0.06	0.17	0.13	0.07	0.07	0.06	0.07	0.07
MRAD	0.003	0.011	0.008	0.005	0.004	0.004	0.004	0.004

The total amount of labor saved takes into account the labor saved due to avoided premature mortality as well. The author converts central estimates of the pre-mature mortality avoided into RAD avoided per year by multiplying mortality avoided by 300 (assumed number of days worked per year otherwise). Since the DRF for RAD was originally estimated for the U.S., we adjust the share of labor saved by dividing it by the U.S.-Thai PPP ratio of 4.5. The furthest right column in the table below reflects the PPP adjusted estimation of labor saved for the country of Thailand.

Table 8: Avoided Pre-mature Mortality and Reduced Activity Days for the Urban Working Population in Thailand Under the Carbon Tax Scenario Relative to the Baseline.

	Total labor saved				Original total number of labor units (# people)	RAD saved per person in this year RAD	PPP* adjusted value of previous column RAD Due to Premature Mortality
	HH_NAG		HH_GOV				
	RAD	RAD Due to Premature Mortality	RAD	RAD Due to Premature Mortality			
2003	933,814	2092	189,629	2092	2003	933,814	2092
2004	2,900,581	7402	589,019	7402	2004	2,900,581	7402
2005	2,153,939	8233	137,399	8233	2005	2,153,939	8233
2006	1,228,266	3964	249,423	3964	2006	1,228,266	3964
2007	1,061,408	3348	215,539	3348	2007	1,061,408	3348
2008	1,083,058	3115	219,936	3115	2008	1,083,058	3115
2009	1,066,465	3292	216,566	3292	2009	1,066,465	3292
2010	1,075,727	3283	218,447	3283	2010	1,075,727	3283

*adjustment for PPP made only for non-mortality effects, since loss of work due to mortality is invariant with purchasing power.

2.8 Feeding back labor supply

The change in labor supply (output from the previous step) will lead to an adjustment in the amount of labor in the primary factor sector of labor for the periods that the carbon tax is imposed (2003-2010). From the previous section, we know that the PPP adjusted ratio of labor saved are as follows for the different periods:

Table 9: Labor Supply Increase Fed back to the CGE Model by Time Period

2003	2004	2005	2006	2007	2008	2009	2010
0.6%	2.0%	2.2%	1.1%	0.9%	0.8%	0.9%	0.8%

To assess economy-wide repercussions of the ancillary benefit in the form of labor saved, we add this additional labor supply to the total labor supply in the 2003-2010 period predicted under the baseline. Thus the labor supply change as a result of ancillary benefit of the carbon tax is fed back 'exogenously.'

2.9 New CO_2 tax schedule to achieve policy goal

Given the labor feedback in the form of labor supply increase during the period of 2003-2010, the GDP rises but so do emissions. In order to achieve the policy goal of reducing total CO_2 emission to 90% of that in 2000 by the 2010, we had to raise the carbon tax.

3.0 Comparison of Results With and Without Health Feedback

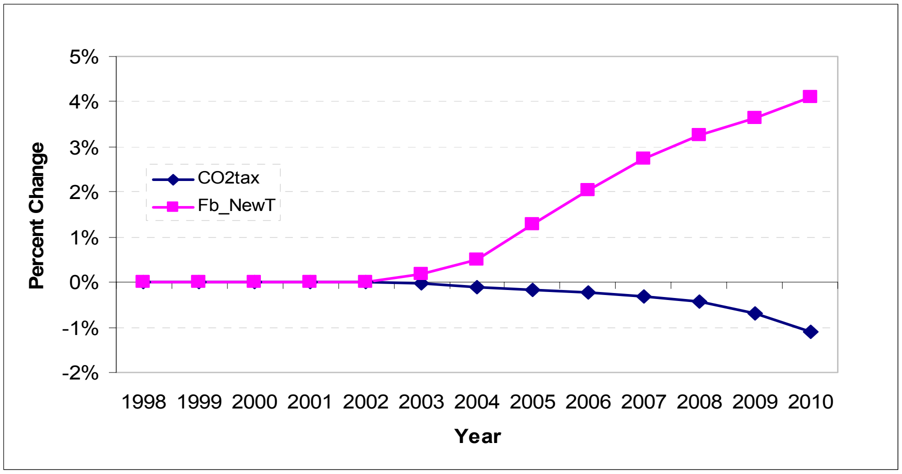
The author has compared the following scenarios: the baseline (no policy, which requires no health feedback), a carbon tax policy analyzed without the incorporation of health feedback (CO2tax), and the same carbon tax analyzed with health feedback (Fb_NewT). Both methods for analyzing the carbon tax policy assume that the carbon tax revenue collected by the government simply gets invested by the government.[6]

[6] Given that the chosen closure rule keeps government consumption constant, all the extra revenue collected from the carbon tax goes to government saving. This is a form of revenue neutral revenue 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.

Chart 1 below demonstrates the difference in projected GDP growth with respect to the baseline under the carbon tax scenario analyzed with and without health feedback. In the chart, *Fb_NewT* (the upper line) represents the carbon tax with health feedback scenario. We can see that, all else being equal, including health feedback leads to higher than baseline GDP over the entire length of the policy (2003-2010); i.e., it leads to a projected positive difference, in contrast to the analysis without health feedback, relative to the baseline.

Chart 1: Projected GDP

CO2tax with and without Health Feedback relative to Baseline



This higher GDP when health feedback is included is reflected in higher private consumption. Chart 2 shows that this leads to consistently higher private consumption than estimated when health feedback is not considered. This is primarily due to the rise in household income. Household incomes rise due to the increase in labor productivity as well as an economy that is experiencing greater growth. Labor productivity improvement means households work more, which in turn leads the economy to grow more rapidly compared to the baseline. The higher growth in the economy as a whole then leads to yet another round of income increase flowing to labor and therefore the households. Hence, 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 effects on trade, capturing health feedback leads to higher than baseline imports and exports during the policy periods (see Charts 2 and 3). Again, the main driver behind the movement in total imports is total demand. When we include the health feedback in analyzing the carbon tax, total demand (sum of investment demand, private consumption, and government consumption) goes up by more than when health feedback is not included. Private consumption decreases by a lesser degree due to the rise in private income. Total investment consumption rises due to a further increase in government investment due to greater carbon tax revenue received from a larger labor force and higher production. Total government consumption is again fixed. The net effect on total demand is a higher rise in the initial periods and a lower drop in the later period. Real imports again reflect the pattern of total demand and indeed rises in the initial periods and drops in the later periods. Total exports again follow the same pattern as total imports due to the current account balance rule. Note that when health feedback is not included, exports and imports show a decline (negative difference) at some point in time, while inclusion of health feedback indicates a positive difference (i.e. improvement in exports and imports) relative to the baseline scenario for all time periods simulated. This implies that the real economic impacts of a carbon tax may actually be a net benefit in trade effects rather than a cost, once the health effects are accounted for.

Chart 2: Projected Real Export Trends
CO2TAX with and without Health Feedback relative to Baseline

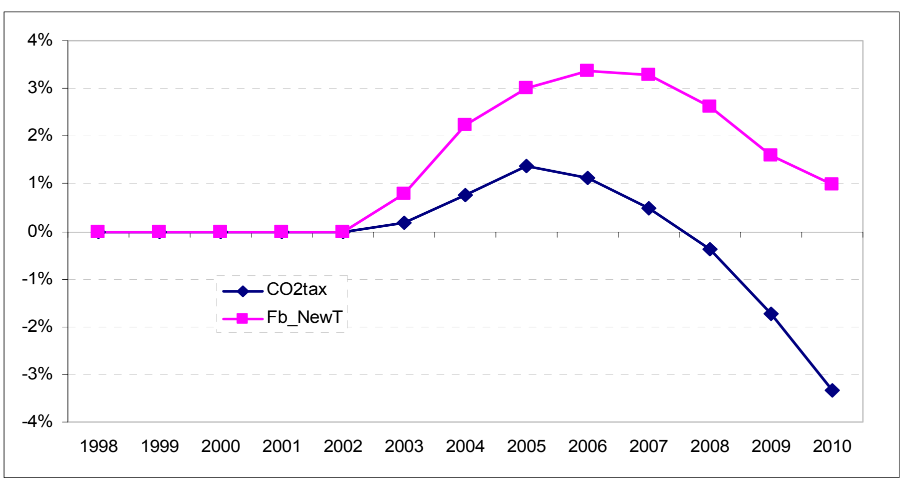
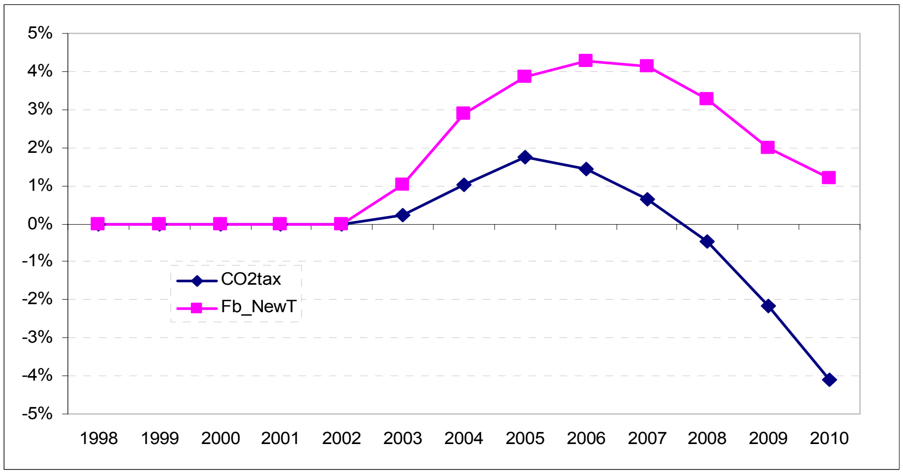


Chart 3: Projected Real Import Trends
CO2TAX with and without Health Feedback relative to Baseline



With respect to household welfare, including health feedback significantly reduces the estimated loss in household welfare which was found without consideration of health feedback. Specifically, the loss of welfare estimated without health feedback is cut almost in 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 on the real consumption of the highest income household, the government-employed household. This is due to the fact that this household group forms a small share of the total labor force. Therefore this household group benefits less from the overall labor supply increase as a result of improved health. Charts 3-5 depict these effects. Based on these comparisons, a carbon tax that would lead by 2010 to GHG emissions that are 10% lower than 2000 emissions has a much lower negative impact on the majority of the households when health feedback is considered.

Chart 3: Projected Welfare Trends for Agricultural Households
CO2TAX with and without Health Feedback relative to Baseline

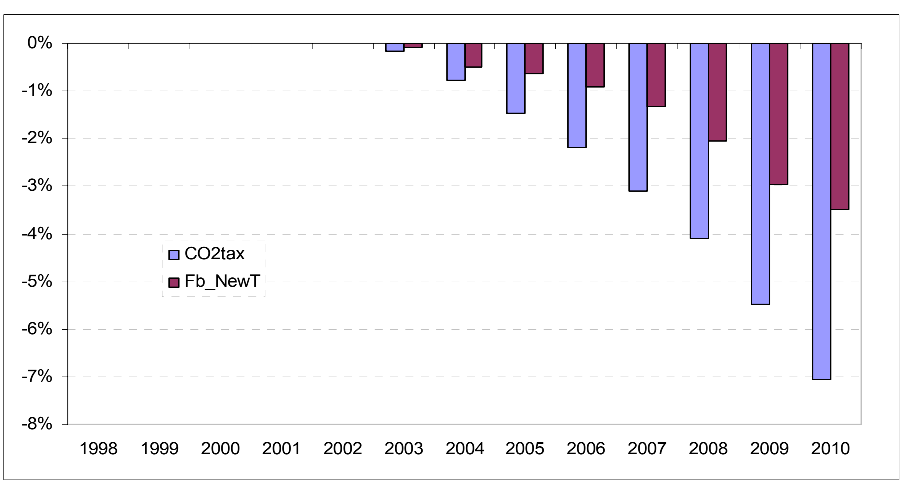


Chart 4: Projected Welfare Trends for Non-agricultural Households CO2TAX with and without Health Feedback relative to Baseline

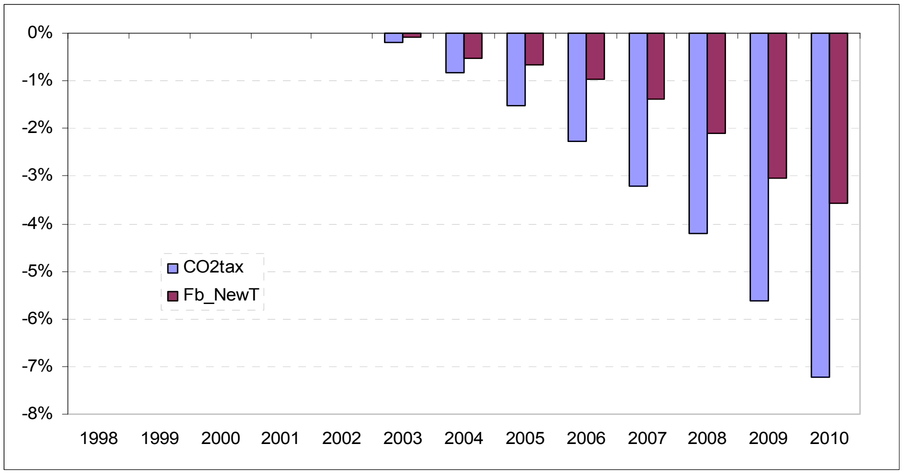
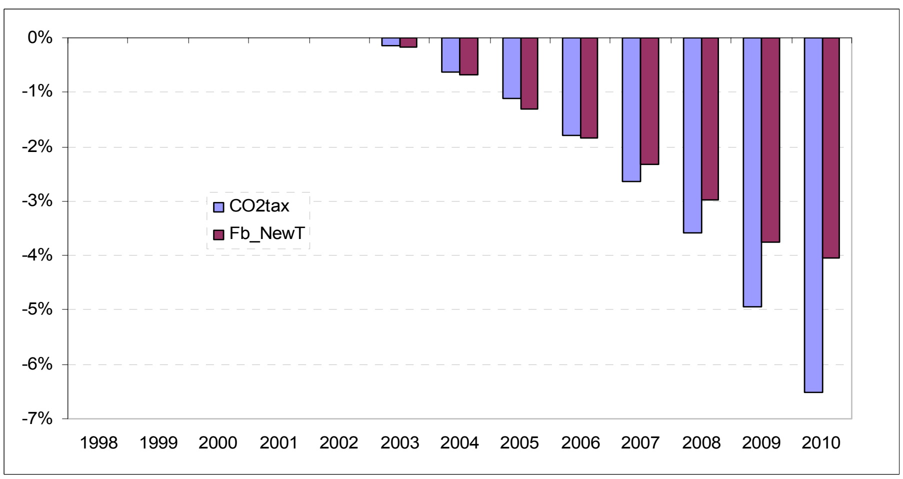


Chart 5: Projected Welfare Trends for Gov't-employed Households CO2TAX with and without Health Feedback relative to Baseline



It is important to point out that household welfare measured in real consumption is largely affected by the government chooses to use the carbon tax revenue. In the results shown in this chapter, 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. Here the author employed an alternative revenue recycling scheme to see if the households' welfares improve under the carbon tax policy (including health feedback). A revenue neutral lump sum transfer of the carbon tax revenue to the households is implemented in the following manner:

- 33% of total carbon tax revenue goes to agricultural households,

- 34% of total carbon tax revenue goes to non-agricultural households,
- and 33% of total carbon tax revenue goes to government-employed households.

The resultant projected GDP and welfare effects relative to the no policy scenario are captured in Chart 6-9 below. In terms of GDP, switching to this alternative revenue recycling scheme actually leads to higher GDP growth in the initial policy periods relative to the no policy baseline than under the old revenue recycling scheme (where all the carbon tax revenue is used by the government to save or invest). At the same time, household welfares now experience a positive change when we analyze the carbon tax with health feedback. The richest household, the government-employed household now registers a slightly negative real consumption effect only during the last period of the policy, 2010.

It is important to point out that the author does not attempt to conduct a systematic analysis of the alternative revenue recycling schemes. Rather, the intent here is to show that alternative revenue recycling schemes have at least the potential to significantly reduce or even eliminate the negative private welfare effects while still maintaining a significantly higher GDP than that [predicted under the no-policy scenario. A systematic exploration of the optimal revenue recycling scheme will have to be left for future studies.

Chart 6: Projected GDP
Carbon Tax with Health Feedback (Fb_NewT) Versus No Policy Baseline
Alternative Revenue Recycling Schemes

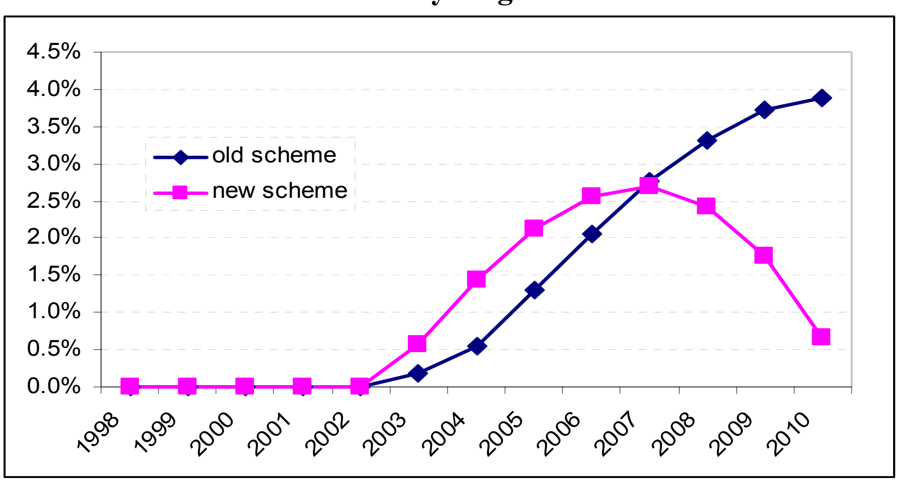


Chart 7: Projected Welfare for Agricultural Households
Carbon Tax with Health Feedback (Fb_NewT) Versus No Policy Baseline
Alternative Revenue Recycling Schemes

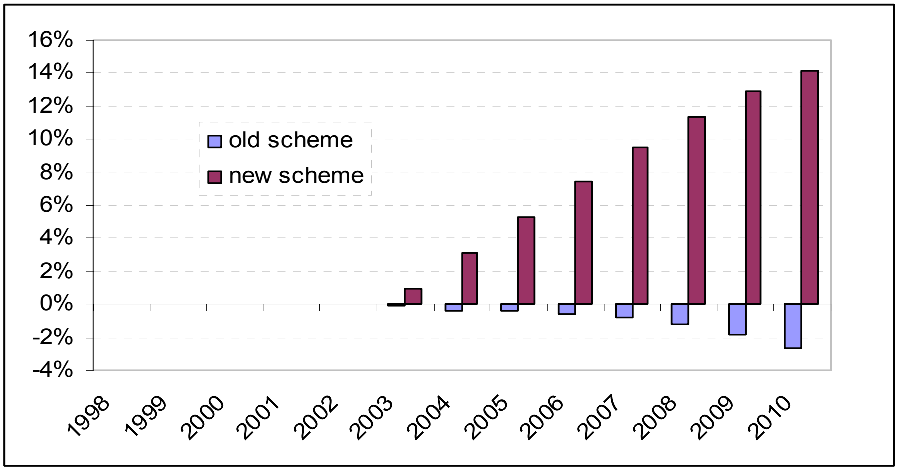


Chart 8: Projected Welfare for Non-Agricultural Households
Carbon Tax with Health Feedback (Fb_NewT) Versus No Policy Baseline
Alternative Revenue Recycling Schemes

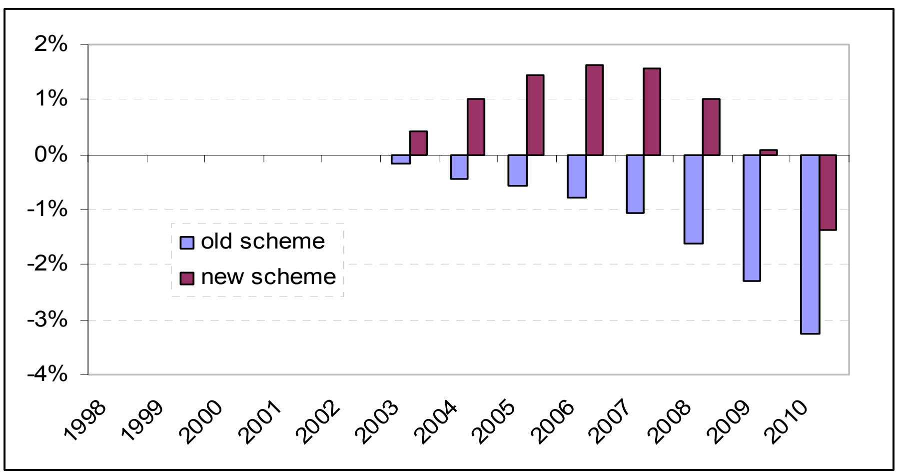
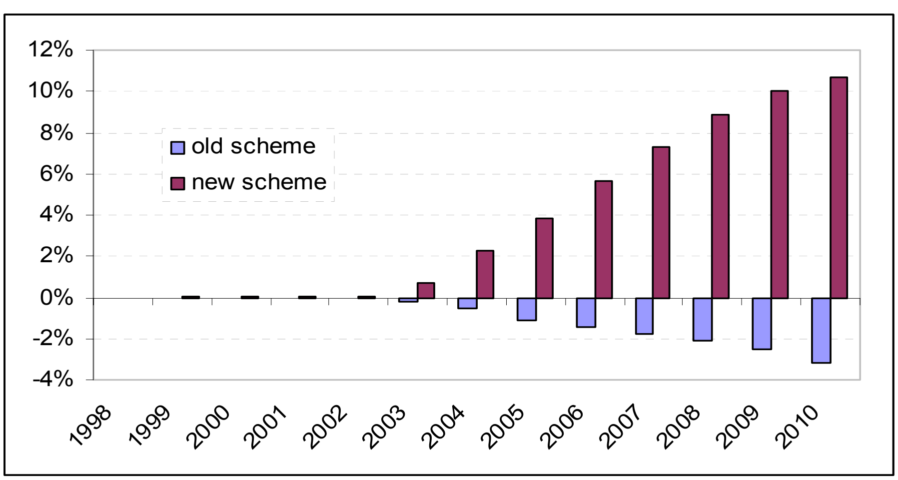


Chart 9: Projected Welfare for Government-employed Households
Carbon Tax with Health Feedback (Fb_NewT) Versus No Policy Baseline
Alternative Revenue Recycling Schemes



4. Sensitivity Analysis

In this section, sensitivity analyses of the previous comparison between estimates of the economic effect of the carbon tax without health feedback (NonBase A) and with health feedback (NonBase B) as described in Section 5.2 will be presented. In order to produce a single measure to compare these two scenarios and the baseline, we did the following:

Take the average of the *Difference* in Equations 1 and 2 over 12 years.

$$Difference_{AorB}^{GDP} = \left[\sum_{t}^{12} \left(\frac{GDP_t^{NonBase_{A,B}} - GDP_t^{Baseline}}{GDP_t^{Baseline}} \right) \right] \bullet \frac{1}{12} \tag{3}$$

Here $Difference_{AorB}{}^{GDP}$ stands for the temporally-averaged difference between each of the two alternative scenarios (*NonBase A and NonBase B*) and the baseline with respect to GDP (averaged over the 12 years of the study period). In other words, there is one temporally averaged difference for the analysis without health feedback and one for the analysis with health feedback. A positive difference in this case means the carbon tax policy produced an increase in that measure on average during the simulation period relative to the scenario of no policy, while a negative difference means the carbon tax policy produced a decrease in that measure on average during the simulation period.

Then, to determine whether the introduction of health feedback into the analysis produced a difference in the results of the analysis, we take the increment in the absolute value of the distance between the average ‘differences’ from the carbon tax with health feedback to that without (both including revenue recycling) in the following manner:

$$Increment^{GDP} = Difference_{B}^{GDP} - Difference_{A}^{GDP} \tag{4}$$

This provides a measure of the difference in predicted economic measure (here, GDP) caused solely by the consideration of health feedback (the primary focus of this paper). Where this increment is positive, the introduction of health feedback into the analysis has produced a higher average GDP relative to the no policy baseline than not including the health feedback. When this increment is negative, including health feedback in analyzing a carbon tax produced a lower average GDP relative to the no policy baseline than when we did not incorporate the health feedback.

Similar calculations are carried out to find the increment between the two scenarios for each of the other economic indicators and all the welfare indicators.

Sensitivity analyses were then conducted to determine how sensitive the measure "Increment" is to uncertainty in each parameter considered. The question to be addressed is whether there are plausible parameter values that significantly reduce this increment, indicating that the improvement in economic performance noted previously when health feedback was included might be significantly over-stated, or whether the inverse might be true (there are plausible parameter values under which the improvement is significantly better than estimated previously in this chapter).

The sensitivity analysis was performed for eleven key parameters. Table 2 describes these parameters, their default values, and the plausible alternative values tested. The first four parameters are elasticities of substitution that determine the ease with which producers substitute their inputs. In CGE analysis, these are typically key parameters that control the uncertainty in the model output as most CGE analyses do not have econometrically measured elasticities of substitution available and therefore these values are usually highly uncertain. Therefore it is important to test whether using alternative assumptions about these values would significant impact the results. In this case, the default values were based on cross-country studies by Dessus and Bussolo (1998), among others. The higher and lower values were chosen based on the range of values observed for each elasticity in the literature.

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 8 energy inputs), *AGGENG*
- Input Elasticity for Value Added (or substitutability between labor and capital), *AGGVA*
- 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 U.S. 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 μg/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 μg/m^3 rise in PM_{10}, *RAD*
- The assumption about the inclusion of Agricultural household in RAD computation, *RAD_AgHH* s

The *Frisch* parameter, as described earlier in the methodology chapter, characterizes the share of subsistence consumption represented in total consumption. The default value of –2, informed by the practice recommended by Dervis et. al. (1982), assumes that 50% of household consumption goes to subsistence consumption. The alternative values chosen are -1.5 and 3 which correspond with 37.5% and 75% of subsistence consumption over total consumption.

The ratio of purchasing power parity (*PPP*) between Thailand and the U.S. is applied in the case of Reduced Activity Days calculations in that the dose-response function (DRF) measuring RAD and PM_{10} exposure was originally assessed for the U.S. The default value of 4.5 was from the National Economic and Social Development Board of Thailand; the alternative values of 3.5 and 5.29 were from the Big Mac index and the Asian Development Bank.

The *K coefficients* determine the distribution of contribution to PM_{10} concentration by emission sources. The PM_{10} emission shares at origin by industrial, transportation, and background sources were from the Pollution Control Division in Thailand. The shares were estimated to be approximately 36%, 10%, and 54% respectively. With the application of an empirical air dispersion model, we assume the PM_{10} concentration is contributed at these same shares by these sources. To test the sensitivity of the results (economic indicators and welfare indicators) to alternative assumptions about these shares, we test the sensitivity of the results to a set of four alternative distributions determined to represent lower and upper ends of a plausible range. Given that the author does not know the probability distribution of the various possible distributions of *Kcoeff*, the author chose alternative distributions to test what happens when a higher, middle, and lower contribution is made by each of the three sources. In the absence of probabilistic information, the alternative distributions are assumed equally likely to occur.

- 30%, 50%, 10%
- 10%, 45%, 45%
- 50%, 25%, 25%, and
- 33.3%, 33.3%, 33.3%

Kscale represents the capital-to-output ratio, or how much capital is used to produce one unit of GDP. Through the specification of *kscale*, we targeted the GDP growth path of 3 to 4% from 1998 to 2010. This required a *kscale* value of 0.355. There exist more optimistic projections about GDP growth (reaching up to 5% by 2010) as well. To test the effect of a more optimistic assumption about GDP growth in Thailand on the results, we test the *kscale* value of

0.405. Although it seems less likely that the Thai economy will experience a low growth of 2-3% in this period, we test the corresponding *kscale* value to check the robustness of the results to this assumption.

b stands for the slope of the dose-response function(DRF) for premature mortality and PM_{10} exposure. The DRF function was estimated for Thailand. The author of the DRF provides upper (1.3) and lower bound (0.062) slopes for the function for premature mortality per μg/m^3 rise in PM_{10}. These were the alternative values used in this sensitivity analysis.

The DRF for RAD was initially estimated for the U.S. The author scales the RAD results by the ratio of PPP between Thailand and the U.S. There is uncertainty associated with the slope value of the exposure-response function itself for RAD per μg/m^3 rise in PM_{10}. To test the effect of this uncertainty on the results, we test the effects of using the upper and lower bound values provided in the original study
(0.072, 0.0435).

RAD_AgHH s stands for the assumption about whether agricultural households
are included in the calculation of RAD. The default scenarios with health feedback assume that only urban households see their labor productivity change as a result of PM_{10} pollution change. Here we test what happens to the results should a quarter of the non-urban households, or agricultural households, also see their labor productivity change. This is in terms of reduced activity days alone, with the assumption that the premature mortality of agricultural households remains unaffected.

Table 10: 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% subsistence, and 50% disposable)	-1.5 (corresponds with 37.5% subsistence, and 62.5% disposable)	-3 (corresponds with 75% subsistence, and 25% disposable)
PPP	5.29	3.5	4.5
K Coe	Background: 36% Industrial: 10% Transportation: 54%	Kcoeff EQ Background: 33% Industrial: 33% Transportation 33%	K coeff A Background: 36% Industrial: 54% Transportation: 10%
		Kcoeff B Background: 10%	K coeff C Background: 50%

		Industrial: 45% Transportation 45%	Industrial: 25% Transportation: 25%
Kscale	0.355 (for 3-4% average GDP growth)	0.305 (for 2-3% average GDP growth)	0.45 (for 5-6% average GDP growth)
B	0.1	0.062	0.13
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% of this population experience a change in major and minor RAD per μg/m^3 rise in PM10 concentration	

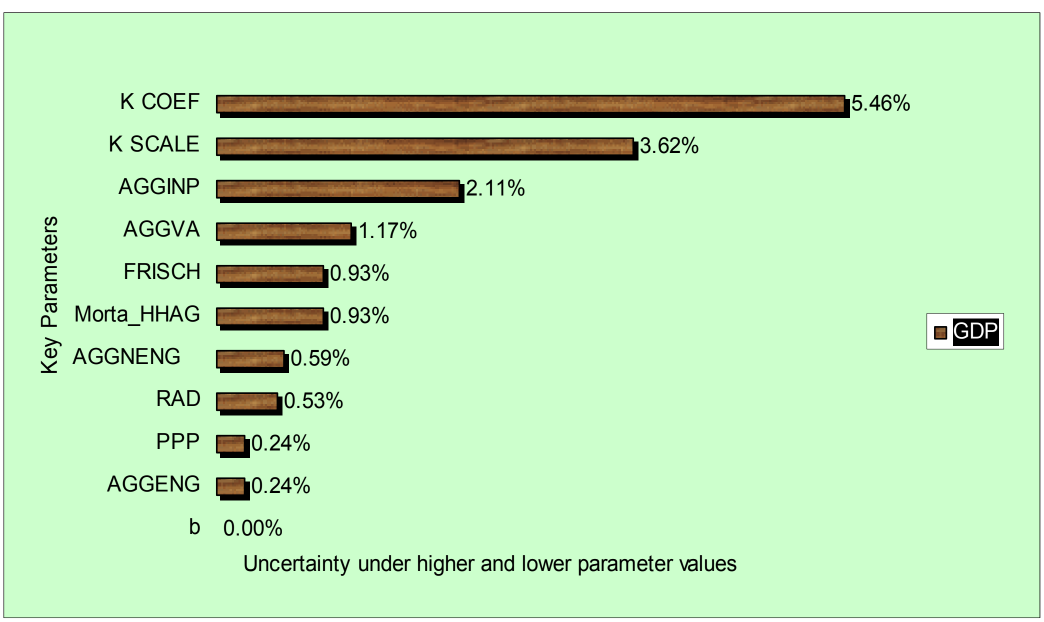
Table 11 shows the default *Increment*^{GDP} calculated for scenarios *NonBase A and NonBase B* using the procedure laid out on page 16. The default value of 1.73% implies that including health feedback leads to this much higher average GDP than estimated without health feedback when a carbon tax with revenue recycling is instituted. Under alternative assumptions for the key parameters laid out above, the results all lead to the same 'sign' for the increment in all cases; i.e. they all lead to greater projected average GDP when health feedback is included (See Table 3 below). Note the value of *Increment*^{GDP} varies from a low of 0. 17% (a significantly smaller difference in GDP attributable to introduction of healoth feedback in the analysis) to a high of 5.67% (a significantly larger difference in GDP attributable to introduction of health feedback in the analysis).

The higher and lower than default parameter values essentially providea range of plausible average GDP increments around the default average GDP increment of 1.73%. This range is essentially the 'distance' between the two average GDP increments under the high and low bound assumptions; it is the absolute value of the high/or low bound average GDP increment minus the low/or high bound GDP average increment. The wider the range associated with a parameter, the more important it is to minimize the uncertainty of that particular parameter, as the result is more sensitive to that parameter. Chart 24 presents these ranges for the various parameters. It is apparent that the average GDP increment is highly sensitive to the assumption made about the distribution of PM_{10} source contribution to PM_{10} concentration, or *K coefficients*. It is also highly sensitive to the assumption made about average economic growth rate during the 2003-2010 period, *Kscale*. In addition, the average GDP increment is very sensitive to assumptions made about the substitutability among aggregate input categories (aggregate energy input, aggregate non-energy input, and aggregate value-added), or *AGGINP*.

Table 11: Sensitivity analyses for *Increment*^{GDP} (default value in the middle column, results using low and high values in the left and right columns, respectively)

	GDP	
AGGNENG (0.25)		**AGGNENG (0.65)**
1.93%	1.73%	2.52%
AGGENG (0.35)		**AGGENG (0.9)**
1.80%	1.73%	1.56%
AGGVA (0.4)		**AGGVA (0.9)**
1.97%	1.73%	0.81%
AGGINP (0.25)		**AGGINP (0.75)**
2.27%	1.73%	0.17%
FRISCH (-1.6)		**FRISCH (-4)**
1.70%	1.73%	0.77%
PPP (3.5)		**PPP (5.29)**
0.88%	1.73%	0.64%
K COEF (50 25 25)		**K COEF (50 10)**
0.21%	1.73%	5.67%
KSCALE (0.305)		**KSCALE (0.45)**
0.26%	1.73%	3.88%
b (0.062)		**b (0.13)**
1.73%	1.73%	1.73%
RAD (0.0435)		**RAD (0.0720)**
1.32%	1.73%	0.79%
RAD_agHH		**RAD (default)**
0.80%	1.73%	1.73%

Chart 10: Sensitivity Analysis: Increment in Average GDP between CO2TAX without Health Feedback CO2TAX with Health Feedback Scenarios



Improvement in household welfare from CO2tax scenario to Fb_NewT scenario is quite robust when evaluated under alternative parameter values (See Tables 4 to 6). 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.

However, under the lower bound parameter assumption for *Kcoeff* (where the shares of contribution by source to PM_{10} concentration is assumed to be 50%, 25%, and 25% for background, industrial, transportation respectively) higher bound parameter for *AGGINP* (by using *AGGINP* = 0.75), and lower bound parameter assumption for *Kscale*, the policy implications are different than those under the other parameter assumptions. At the present time, the probability distributions for these parameters cannot be well established. It is recommended that further studies focus on better establishing the probability density functions describing uncertainty in *Kcoeff* and *AGGINP* parameters studied here.

With respect to policy implications, under this assumed distribution of PM_{10} source contribution, a carbon tax that takes into account health feedback now leads to a GDP and private welfare that are both lower under the with-health-feedback carbon tax scenario than under the <u>no policy</u> scenario (recall that under the default parameter values, private welfares are also lower under the carbon tax with-health-feedback scenario than the no policy scenario, but the average GDP is much higher). The negative impact on GDP is only slightly greater than under the default assumption about *Kcoeff*; whereas the negative impact on private welfare is about twice that under the default *Kcoeff*. That is because this distribution assumes that the non-controllable source of local pollution or background pollution takes up a much greater share than pollution from industrial and transportation sources. Should this distribution represent the reality better than the default case, there seems no longer an economic or welfare case to be made for adopting a carbon tax policy or carbon emission reduction, even when the health feedback of doing so is factored in. Regarding the likelihood of having in reality this alternative distribution of source contribution to PM_{10}, the author is moderately confident that chances are small for this to be true (which assumes that 50% of PM_{10} concentration is contributed by background, 25% by industrial, and 25% by transportation sources as opposed to 36%, 10%, and 54% respectively).

With respect to policy implications, under this lower bound assumption about the rate of economic growth (lower economic growth), a carbon tax that takes into account health feedback now produces almost no change to GDP relative to the no policy baseline. Even lower private welfare relative to the no policy scenario is now projected compared to under the default assumption about economic growth. Should this distribution represent the reality better than the default case, there is no longer an economic or welfare case to be made for adopting a carbon tax policy or carbon emission reduction, even when the health feedback of doing so is factored in. Regarding the likelihood of having in reality another economic crisis in Thailand (therefore the low *Kscale* value), the author is confident that chances are very small for Thailand to experience only 2-3% GDP growth by 2010.

With respect to policy implications, under the high bound assumption of *AGGINP* (=0.75), GDP under a carbon tax with-health-feedback is almost at the same level as that under the no policy scenario up to 2007 and becomes relatively lower by around 1% by 2010. Private welfare under the with-health-feedback carbon tax drops slightly more than that under the no policy scenario. Hence, when the substitutability among aggregate inputs is 50% higher than that under the default assumption, the benefits (as captured in this study) no longer seem to outweigh the cost for adopting the carbon tax policy. Policy makers will be less likely to adopt the carbon tax policy. Regarding the likelihood of having in reality a greater substitutability among the aggregate inputs (or having *AGGINP* = 0.75) rather than the default assumption of *AGGINP=0.5*, the author is confident that chances are small for this to be true in Thailand.