Energy Economics 48 (2015) 306–315

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Gains from emission trading under multiple stabilization targets and technological constraints

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ARTICLE INFO

Article history:
Received 11 October 2013
Received in revised form 25 November 2014
Accepted 3 December 2014
Available online 3 January 2015

JEL classification:
D58
Q48
Q54

Keywords:
Emission trading
Climate mitigation policy
CGE model
Technological assumptions

ABSTRACT

This study quantified the effectiveness of emission trading by considering multiple technological constraints, burden sharing schemes, and climate stabilization targets. We used a global computable general equilibrium model, and evaluated the effectiveness of emission trading using welfare losses associated with climate mitigation for scenarios with and without emission trading, as measured by the Hicksian Equivalent Variation (HEV). We found that emission trading contributed to a reduction in the economic losses associated with climate mitigation for all technological assumptions, burden sharing schemes, and stabilization targets. The net global welfare losses in scenarios without emission trading ranged between 0.7% and 1.9%, whereas emission trading reduced the losses by 0.1% to 0.5%. The range depended on the assumptions in the burden sharing schemes, technological constraints, and stabilization targets. The percentage change in welfare gain from emission trading varied regionally, and was relatively high in low-income or middle-income countries (0.2% to 1.0% and −0.1% to 1.2%, respectively) compared to high-income countries (−0.1% to 0.3%). Some regions displayed negative values with regard to the effectiveness of emission trading, which might be due to the change in goods and service trades associated with emission trading. If the usage of carbon capture and storage was constrained, welfare loss became large and the effectiveness of emission trading ultimately increased. The use of a burden sharing scheme was a significant factor in changing the effectiveness of emission trading, and the per capita emission convergence in 2050 was more effective for emission trading than a per income convergence.

1. Introduction

The 4th IPCC assessment report revealed, with very high confidence, that the global average net effect of human activities since 1750 has been a major factor in global warming (IPCC, 2007). In addition, the future impact of climate change on natural ecosystems and human society was projected, with a large range of uncertainty, to be highly significant. Given this situation, some countries are undertaking mitigation measures, and have declared their own greenhouse gas (GHG) reduction targets.

Integrated assessment models (IAMs) have been used to assess strong climate mitigation policy scenarios, such as stabilizing the atmospheric CO_2 concentration at a 450 ppm equivalent. Clarke et al. (2009) compiled the analysis results of 10 models and showed how the difficulties associated with climate mitigation differed depending on the CO_2 concentration stabilization level (e.g., 450 ppm or 550 ppm) and the time-path of international participation (e.g., whether the participation of developing countries is delayed). The study summarized the results of the Energy Modeling Forum 22. Although the definition of the stabilization target was different from recent works (only Kyoto gases were treated), the study provided meaningful insights into the technological aspects of CO_2 stabilization. Most of the models provide solutions for the 550 ppm CO_2 equivalent concentration target, but not the 450 ppm target. Furthermore, the feasibility depends on whether or not an overshoot is allowed, and the availability of biomass combined with carbon capture and storage (CCS) technology. Six of the ten models provided feasible solutions for the 450 ppm target, and their carbon prices varied greatly. More recent studies can reach 450 ppm or equivalent emission pathways, mainly by considering the use of biomass combined with CCS (Tavoni and Socolow, 2013).

Many studies have clarified the importance of emission trading. Böhringer and Welsch (2004) analyzed the effect of emission allocation and emission trading on welfare using an inter-temporal computable general equilibrium (CGE) model. Recently, Böhringer et al. (2009) and Ciscar et al. (2013) assessed the EU's 2020 climate policy. They both analyzed the effect of emission trading under various assumptions, such as changing burden sharing schemes and the level of gross

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http://dx.doi.org/10.1016/j.eneco.2014.12.011
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domestic product (GDP). Carbone et al. (2009) discussed whether an emission trading system induces participation in international abatement agreements. Webster et al. (2010) estimated the value of international emission trading under the condition of uncertain future economic growth.

All of these studies have contributed to the assessment of the effectiveness of emission trading, but two questions remain: (1) How is the value of emission trading affected by the strength of climate mitigation targets and different burden sharing schemes? and (2) Do technological constraints affect the value of emission trading, and if so, by how much?

The goal of this study was to answer these questions using the AIM/CGE model, which is a global CGE model with a rich descriptive capacity for power generation, bioenergy, and land use. The scenarios were prepared considering four dimensions: socioeconomic assumptions, technological assumptions, level of emission targets (no target, 450 ppm, or 550 ppm CO_2eq concentration stabilization), and availability of emission trading. We used two burden sharing schemes for emission allowance allocation with the convergences of per capita and GDP emissions in 2050. The former is so-called Contraction and Conversion (C&C). Emission trading was only used in the sense of a right to transfer emissions; we did not specify the method of the exchange. Moreover, emission trading was defined as inter-regional trading, and excluded trading among industries within a country.

2. Methodology

2.1. Asia-Pacific integrated model/computable general equilibrium (AIM/CGE) model

The AIM/CGE model has been widely used for the assessment of climate mitigation (e.g., Masui et al. (2011)). The CGE model used in this study is a recursive dynamic general equilibrium model that covers all regions of the world. It is recursive in the sense that current period investment and consumption decisions are made on the basis of current period prices. This model has both a global (Fujimori et al., 2014a,b,c; Hasegawa et al., 2014) and national version (Thepkhun et al., 2013). We used the global version, which includes 17 regions and 42 industrial classifications (see Supplementary Information (SI) SI Table 1 and SI Table 2 for a list of the regions and industries). It is a characteristic of the industrial classification that energy sectors, including power sectors, are disaggregated in detail, because energy systems and technological descriptions are crucial for the purposes of this study. Moreover, to assess bioenergy and land use competition appropriately, agricultural sectors are also highly disaggregated (Fujimori et al., 2014a). This CGE model is based on the “Standard CGE model” (Lofgren et al., 2002). Details of the model structure and mathematical formulas are given by Fujimori et al. (2012).

The production sectors are assumed to maximize profits under multi-nested constant elasticity substitution (CES) functions and each input price. Energy transformation sectors input energy and value-added as a fixed coefficient, whereas energy end-use sectors have elasticities between energy and value-added. They are treated in this manner to deal appropriately with energy conversion efficiency in the energy transformation sectors. Power generation from several energy sources are combined by a logit function (Clarke and Edmonds, 1993), although a CES function is often used in other CGE models. We chose this method for the consideration of energy balance because the CES function does not guarantee a material balance (Schumacher and Sands, 2006). Household expenditures on each commodity are described by a linear expenditure system (LES) function. The saving ratio is endogenously determined to balance saving and investment, and capital formation for each item is determined by a fixed coefficient. The Armington assumption is used for trade, and the current account is assumed to be balanced.

In addition to energy-related CO_2 emissions, CO_2 from other sources, CH_4, and N_2O (including changes resulting from land use and non-energy related emissions), are included as GHG emissions in this model. Global warming potentials (GWPs) are used in the consideration of CO_2, CH_4, and N_2O emissions.

Once an emission constraint is placed on a region, the carbon tax becomes a complementary variable to that constraint. This tax raises the price of fossil fuel goods when emissions are constrained, and promotes energy savings and the substitution of fossil fuels by energy sources with lower emissions. The emission tax, called the GHG emission price, is also an incentive to reduce non-energy-related emissions (the method is explained in Section 2.2). The revenue from this tax is assumed to go to households.

2.2. Technological representation and emission trading in the model

2.2.1. CCS technology

CCS is a key technology in climate mitigation, and involves the use of chemical processes to capture CO_2, which is then stored underground or in the deep sea. It is mainly available for large point sources of CO_2 emissions, and in this study, we applied it to fossil fuel-fired power plants, biomass power plants, oil refineries, and coal transformation plants as well as to non-metal and mineral, chemical, and paper and pulp industries. These sectors input CCS services as intermediate inputs, and the CCS service is assumed to be provided by a CCS service sector that has an independent production function.

The costs of the technology, which are different among sectors (Table 1), were taken from IEA (2008). Because IEA (2008) provides a range of estimates, we used the median values. When the GHG emission price surpasses the technology costs, CCS technology is assumed to be installed with a maximum increase of 5% per year. Because CCS technology is still being developed, we assumed it would only become available after 2020.

2.2.2. Non-energy-related GHG emissions reduction

We used Eq. (1) to determine non-energy-related GHG emissions reductions, such as reductions in agricultural CH_4 and N_2O emissions.

$$RD_{r,j,g} = (PGHG_r + 1)^{-\sigma^{ner}_{r,j,g}} \qquad (1)$$

where $RD_{r,j,g}$ is the non-energy-related GHG emissions reduction ratio relative to the no stabilization target scenario for region r, sector j, and gas g ($/t$CO_2$); $PGHG_r$ is the GHG emission price; $\sigma^{ner}_{r,j,g}$ is the elasticity parameter of the non-energy reduction ratio relative to the no stabilization target scenario for region r, sector j, and gas g. The parameter $\sigma^{ner}_{r,j,g}$ was calibrated based on Lucas et al. (2007). An example of the emissions reduction rate for a constrained case, in this example rice production, relative to the reference scenario is shown in SI Fig. 1.

2.2.3. Renewable energy

We followed the assumptions of the Energy Technology Perspective (IEA, 2012), which gives prospective future costs. In the model, the input coefficients of intermediate goods and production factors in the renewable energy sectors are changed. As mentioned in Section 2.1,

Table 1
CCS technology costs.

	Sector	Price (US$/t$CO_2$)
Manufacturing	Petroleum refinery coal transformation	100
	Non-metal and mineral	200
	Paper and pulp	150
	Chemical	150
Power	Coal fired	50
	Oil fired	70
	Gas fired	70
	Biomass fired	120