Discussion Paper No. 08-050

Technological Uncertainty and Cost-effectiveness of CO_2 Emission Trading Schemes

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Non-Technical Summary

This paper studies implications of uncertainty about the arrival date of a competitive CO_2 backstop technology for the design of cost-effective carbon dioxide (CO_2) emission trading schemes. The long-run stabilization of atmospheric CO_2 concentrations at significantly lower levels requires the deployment of a wide portfolio of CO_2 emission abatement options such as input substitution, switching to less CO_2-intensive energy sources, and technical change. Especially the last abatement option has received much attention in the environmental economic literature, as it has been found that technology externalities associated with technical change can lead to improvements in the cost-effectiveness of environmental policies such as trading schemes to abate CO_2 emissions. Typically implicit in this finding is the assumption that one can foresee and anticipate all new technologies. Given the typically large technological uncertainties, however, this is not always a realistic assumption and the arrival date of a new technology can still be uncertain. In this paper, we translate technological uncertainty regarding the arrival date of a new technology into non-anticipation of the arrival date and study the implications of such non-anticipation for the design of cost-effective environmental policy.

In particular, we develop a dynamic computable general equilibrium model that captures the empirical links between CO_2 emissions associated with energy use, the rate and direction of technical change and the economy. We draw on endogenous growth models and specify technologies as stocks of knowledge capital that are sector-specific investment goods and have associated positive technology externalities (i.e. knowledge spillovers). In addition, we introduce CO_2 capture and storage (CCS) in the electricity sector as the backstop technology under study. CCS is a known CO_2 abatement technology that involves the separation and concentration of CO_2 produced in industrial and energy-related sources, the transportation to a suitable storage location (e.g. an aquifer, depleted oil field, or the ocean), and the storage preventing its release to the atmosphere for a prolonged period of time. CCS has not arrived yet and in our model the arrival date is either anticipated or not. We define the arrival date as the date at which CCS becomes commercially available and competitive. Once competitive, large scale deployment of CCS could then allow for a continued reliance on fossil fuels in the supply of primary energy while at the same time reducing CO_2 emissions over the course of this century. As it stands now, however, such competitiveness requires stringent CO_2 emission reduction policies and large uncertainties remain regarding the (cost) potential of CCS. Policy simulations and a Monte Carlo uncertainty analysis reveal the implications of uncertainty about the arrival date of CCS for the design of cost-effective CO_2 emission trading schemes.

We find that the discounted welfare loss associated with the cost-effective CO_2 emission trading schemes is lower in the simulation in which competitiveness of the CCS technology is unanticipated. CO_2 shadow prices are higher in the period before the CCS technology becomes competitive in this simulation relative to the simulation where competitiveness is anticipated, reflecting a shift of emission reduction efforts to earlier years. By not simply postponing emission reduction until the CCS technology becomes competitive in the electricity sector, one relies more on economy-wide technical change and its welfare-enhancing technology externalities, thus allowing for a slightly higher steady state in this simulation. Regarding the steady state, we find in both simulations that it is characterized by technical change which is directed toward sectors with relatively low CO_2 intensities enjoying higher levels of technology externalities than the CO_2-intensive sectors. CO_2 emission trading schemes are thus more cost-effective if they are differentiated in such a way that the CO_2-intensive sectors face the relatively high CO_2 shadow prices. Essentially, the policy is one of encouraging growth in sectors with relatively high levels of technology externalities and discouraging growth in those with relatively low levels. Our Monte Carlo uncertainty analysis confirms the robustness of our findings to an uncertain cost and performance parameterization of the CCS technology although the precise quantitative findings vary considerable with the uncertain parameterization.

Our findings underline once more the importance of technical change as an abatement option; not only through radically new abatement technology, but also in the form of incremental technical change. We should be careful not to become complacent by postponing some of our emission reduction efforts awaiting the silver bullet technology on the horizon in the energy sector. Acting in such a way is not advisable given the large uncertainties that typically surround new technologies. Besides spreading the risks that some technologies might fail, diversifying the investment portfolio can lead to lower welfare costs of environmental policy because of the technology externalities associated with technical change.

Das Wichtigste in Kürze

Dieses Papier untersucht die Implikationen von Unsicherheit bezüglich der Verfügbarkeit einer kompetitiven Technologie zur Kohlenstoffabscheidung und –speicherung auf die Ausgestaltung kosteneffektiver CO_2 Emissionshandelssysteme. Zu diesem Zweck wird ein dynamisches rechenbares allgemeines Gleichgewichtsmodell entwickelt, welches den empirischen Zusammenhang zwischen CO_2 Emissionen, Rate und Richtung des technischen Wandels und wirtschaftlichen Aktivitäten berücksichtigt. Kohlenstoffabscheidung und –speicherung wird als sogenannte Backstop-Technologie modelliert, deren Wirtschaftlichkeit antizipiert wird oder eben nicht. Die Simulationsergebnisse zeigen, dass die diskontierten Wohlfahrtsverluste der Klimapolitik niedriger sind, wenn die Technologie zur Kohlenstoffabscheidung und –speicherung nicht antizipiert wird. In diesem Fall sind die Preise für CO_2 Emissionszertifikate vor der unerwarteten Einführung der Backstop-Technologie relativ hoch. Es wird nicht einfach auf die Wirtschaftlichkeit der Kohlenstoffabscheidung und –speicherung gewartet. Vielmehr wird ohne die Berücksichtigung von Kohlenstoffabscheidung und –speicherung ein strikterer Politikpfad zur Erreichung der klimapolitischen Ziele implementiert, der die Internalisierung von technologischen Externalitäten und somit ein höheres Wohlfahrtsniveau ermöglicht. Die Umweltpolitik sollte gegeben der großen technologischen Unsicherheiten vorsichtig sein, Vermeidungsanstrengungen zu verschieben und auf eine Wunderwaffe zu Lösung des Klimaproblems im Energiesektor zu warten.

Technological uncertainty and cost-effectiveness of CO_2 emission trading schemes

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Abstract
This paper studies implications of uncertainty about the arrival date of a competitive CO_2 backstop technology for the design of cost-effective CO_2 emission trading schemes. For this purpose, we develop a dynamic general equilibrium model that captures empirical links between CO_2 emissions associated with energy use, the rate and direction of technical change and the economy. We specify CO_2 capture and storage (CCS) as the backstop technology whose competitiveness is anticipated or not. We find that the discounted welfare loss associated with the environmental target is lower if CCS is not anticipated and that CO_2 shadow prices are then relatively high in the years before CCS is competitive. By not simply postponing the implementation of an emission reduction strategy until CCS is competitive, one relies more on economy-wide technical change and its welfare-enhancing technology externalities, thus allowing for a higher steady state.

Keywords: CO_2 capture and storage, computable general equilibrium modeling, directed technical change, emission trading, technological uncertainty

JEL classification: D58, D83, H23, O33, Q43

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1. Introduction

The long-run stabilization of atmospheric carbon dioxide (CO_2) concentrations at significantly lower levels requires the deployment of a wide portfolio of CO_2 emission abatement options such as input substitution, switching to less CO_2-intensive energy sources, and technical change (IPCC, 2007). Especially the last abatement option has received much attention in the environmental economic literature, as it has been found that technology externalities associated with technical change can lead to improvements in the cost-effectiveness of environmental policies such as trading schemes to abate CO_2 emissions. Typically implicit in this finding is the assumption that one can foresee and anticipate all new technologies. Given the typically large technological uncertainties, however, this is not always a realistic assumption and the arrival date of a new technology can still be uncertain. In this paper, we translate technological uncertainty regarding the arrival date of a new technology into non-anticipation of the arrival date and study the implications of such non-anticipation for the design of cost-effective environmental policy. We refrain from studying the role technology policy can play to correct technology externalities or to overcome related uncertainties for now. Instead, we first focus on CO_2 emission trading schemes as our environmental policy under study and address related questions such as: What are the corresponding CO_2 shadow prices in both the case of a new technology's arrival date being anticipated and not anticipated? As a result, what are the effects on the rate and direction of technical change in both cases? What are the implications for the discounted welfare loss of the trading scheme? The key feature of the new technology under study is its function as a backstop for CO_2 emissions associated with energy use, in that the new technology enables society to produce a perfect substitute for CO_2-intensive electricity at a non-increasing marginal cost.

Previous investigations concerning these questions include the studies on optimal resource depletion under technological uncertainty by, among others, Dasgupta and Heal (1974), Kamien and Schwartz (1978) and Dasgupta and Stiglitz (1981). Using theoretical models, these studies analyze the effects of uncertainty regarding the arrival date of a backstop technology on the optimal depletion rate and price of an exhaustible natural resource and in the case of Kamien and Schwartz also on optimal research and development (R&D) efforts.[1] In a computable general equilibrium setting, Popp (2006), Gerlagh and van der Zwaan (2006) and Otto and Reilly (2006), among others, study optimality and cost-effectiveness of climate policy if there is a backstop technology available in the energy sector, although these studies do not account for any technological uncertainty. We proceed by combining the

[1] To gain a better understanding of the relation between these studies and our research questions, consider the absorptive capacity of CO_2 sinks such as forests and oceans as exhaustible natural resources that can be depleted by excessive CO_2 emissions.

analysis of technological uncertainty of Dasgupta and Heal (1974), Kamien and Schwartz (1978) and Dasgupta and Stiglitz (1981) with the methodology and cost-effectiveness criterion of Otto and Reilly (2006).

In particular, we build on Otto et al. (2006) and Otto and Reilly (2006) and develop a dynamic computable general equilibrium model that captures the empirical links between CO_2 emissions associated with energy use, the rate and direction of technical change and the economy. We draw on endogenous growth models of Romer (1986), Rivera-Batiz and Romer (1991) and Acemoglu (2002) and specify technologies as stocks of knowledge capital that are sector-specific investment goods and have associated positive technology externalities (i.e. knowledge spillovers). In addition, we introduce CO_2 capture and storage (CCS) in the electricity sector as the backstop technology under study. CCS is a known CO_2 abatement technology that involves the separation and concentration of CO_2 produced in industrial and energy-related sources, the transportation to a suitable storage location (e.g. an aquifer, depleted oil field, or the ocean), and the storage preventing its release to the atmosphere for a prolonged period of time. CCS has not arrived yet and in our model the arrival date is either anticipated or not. We define the arrival date as the date at which CCS becomes commercially available and competitive. Once competitive, large scale deployment of CCS could then allow for a continued reliance on fossil fuels in the supply of primary energy while at the same time reducing CO_2 emissions over the course of this century. As it stands now, however, such competitiveness requires stringent CO_2 emission reduction policies and large uncertainties remain regarding the (cost) potential of CCS (IPCC, 2005). Policy simulations and a Monte Carlo uncertainty analysis reveal the implications of uncertainty about the arrival date of CCS for the design of cost-effective CO_2 emission trading schemes.

The remainder of this paper is organized as follows. Section 2 describes the main characteristics of our dynamic general equilibrium model including the specification of technical change. Section 3 describes the knowledge capital accounting in the input-output tables underlying our model, the data and central parameter values used in the model and the calibration of the CCS technology. Section 4 discusses the simulations, their results as well as an uncertainty analysis. Section 5 concludes.

2. Model description

In our dynamic general equilibrium model several economic agents interact over time by demanding and supplying commodities on markets. These agents are a representative consumer, producers of final goods in production sectors *i* and firms in intermediate sectors *i* manufacturing sector-specific knowledge capital for the respective production sectors. The sectors are: (1) agriculture, (2) CO_2-intensive industry, (3) non-CO_2 intensive industry and services, (4) trade and transport, (5) energy, (6) CO_2-intensive electricity and (7) non-CO_2 intensive electricity, where the energy sector comprises the oil and gas industries. Primary factors include physical capital, labor and primary energy and are mobile between sectors. Agents behave rationally and, unless specified otherwise, have perfect foresight. We present a detailed structure of the model in Appendix A, and discuss the main model elements below.

2.1. Household behavior

A representative consumer maximizes intertemporal utility (henceforth referred to as discounted welfare), depending on the intertemporal budget constraint. Discounted welfare is a nested constant elasticity of substitution (CES) function of the discounted sum of consumption over the time horizon and is measured as equivalent variation (see equations A.14 and A.15 in Appendix A). Environmental quality does not enter the utility function, implying independence of the demand functions for goods with respect to environmental quality.

2.2. Production of final goods

Production of final good *i* (Y) is characterized by a production possibility frontier, which is determined by a CES function of knowledge capital (H) and a nested CES function ($KLEM$) of physical capital, labor, energy inputs and other intermediate inputs (see equation A.1 for the full specification). Intermediate usage of the primary energy inputs oil, gas, and coal entail CO_2 emissions, which might be subject to quantity constraints (i.e. the CO_2 emission trading schemes) and concomitant CO_2 shadow prices.[2] To meet these constraints, several CO_2 abatement options are available to the producer. These options include, among others, a reduction in overall energy use, a shift away from fossil fuels as input and technical change to increase efficiency of production or to develop CO_2 abatement technology. Regarding technical change, knowledge capital is rival, excludable and sector specific. Hence, owners can prevent others from using their knowledge capital by means of patent protection, but one type of knowledge capital is too different for the production of goods in other sectors. Moreover, there exists a technology externality in production ($\overline{H}$), as knowledge embodied in the sector-specific stocks of knowledge capital spills over to firms in the respective production sectors. In contrast to H, which is excludable knowledge capital, $\overline{H}$ is non excludable and firms regard it as exogenous. The technology externality is also sector specific because we assume that knowledge capital in one sector is too different to benefit from innovations in other sectors. Formally for a firm in sector *i*:

$$Y_{i,t} = \overline{H}_{i,t} \left(\alpha_i^H H_{i,t}^{\rho^H} + \left(1-\alpha_i^H\right) KLEM_{i,t}^{\rho^H} \right)^{1/\rho^H} \quad (1)$$

where ρ is related to the elasticity in production σ according to $\rho = (\sigma - 1)/\sigma$, where the α's are value shares determined by base year demands and where $0 \le \alpha_i^H \le 1$. The technology externality in

[2] We do not specify a damage function for CO_2 emissions. CO_2 emissions do therefore not lead to an environmental externality in our model and firms only reduce their CO_2 emissions because of the CO_2 emission trading schemes.

production is governed by $\overline{H}_{i,t} = H_{i,t}^{\gamma}$ where the parameter γ regulates the magnitude of the technology externality. If γ is zero, the production possibility frontier of a given firm in a sector is unaffected by the aggregate stock of knowledge capital in that sector. This specification of the production possibility frontier draws on Arrow (1962) and Romer (1986) and is also very similar to the specification used in Goulder and Schneider (1999) and Otto et al. (2007). The technology externality to an individual firm in a sector is introduced in a CES function by a scale factor, which is an increasing function of the aggregate stock of knowledge capital. Although the technology externality generates increasing returns to scale at the sector level, it is exogenous to the individual firm allowing us to avoid problems related to non-convex optimization. Together with adoption of knowledge capital, this technology externality drives productivity growth in the production sectors. Firms in production sector *i* maximize profits over time subject to their production possibility frontier. Homogeneity of degree one and perfect competition guarantee zero profits.

2.3. Investment in knowledge capital

Firms in intermediate sector *i* invest in knowledge capital that is appropriate for the production of final good *i* according to an innovation possibility frontier (see equation A.4 for the full specification)[1]. Investment in knowledge capital (R) is a deterministic process and the innovation possibility frontiers are continuous, which allows us to avoid problems due to uncertainty or integer variables. Technical change is 'directed' to a specific sector if its investment in knowledge capital increases relative to other sectors. Investments in knowledge capital merely involve final goods as input. This does not mean that final goods are directly converted into knowledge capital, but rather that the inputs necessary for production of final goods are used, in the same proportions, for innovation instead. In addition, there is a delayed technology externality in innovation since aggregate but sector-specific investments in knowledge capital ($\overline{R}$) of the previous period have a positive external effect on the efficiency of a firm's current investments in that sector. Formally for a firm in sector *i*:

$$R_{i,t} = \overline{R}_{i,t} \; Y_{i,t} \tag{2}$$

where $\overline{R}_{i,t} = R_{i,t-1}^{\xi}$ and where ξ regulates the magnitude of the technology externality in innovation. Knowledge spillovers and network effects, among others, underlie this technology externality. We also specify this technology externality operating within each sector only, since we assume that knowledge capital in the different sectors is too different to benefit from technical changes in other sectors. Knowledge capital investments accumulate into sector-specific stocks according to:

[1] Naturally, there are more institutional structures that support a decentralized equilibrium. Firms in each production sector, for example, can invest in their type of knowledge capital themselves, e.g. in house innovation. The precise institutional structure is irrelevant as long as investments in knowledge capital are made according to identical innovation possibility frontiers.

$$H_{i,t+1} = \left(1-\delta^H\right) H_{i,t} + R_{i,t} \tag{3}$$

where δ^H is the depreciation rate of knowledge capital (see equation A.5 for the full specification). Firms in intermediate sector *i* maximize profits over time subject to their innovation possibility frontier. Again, homogeneity of degree one and perfect competition guarantee zero profits.

2.4. The backstop technology

In addition to these incremental investments in knowledge capital, we introduce gas-fired electricity generation technologies with CCS (henceforth referred to as the CCS technology) as a backstop technology in the CO_2-intensive electricity sector (*CIE*). The CCS technology is considered to be a perfect substitute for gas-fired electricity generation technologies without CCS, but is not yet competitive. The CCS technology is characterized by a function of knowledge capital, physical capital (K), labor (L), intermediate natural gas inputs from the energy sector (Y_{NRG}), associated CO_2 emission rights (EM), intermediate electricity inputs (EL) and an Armington (1969) aggregate of other intermediate inputs (A). Formally for a firm in the CO_2-intensive electricity sector:

$$Y_{i,t} = \overline{H}_{i,t} \left(\alpha_i^H H_{i,t}^{\rho^H} + \left(1-\alpha_i^H\right) KLEM_{i,t}^{\rho^H}\right)^{1/\rho^H} \qquad i = CIE \tag{4}$$

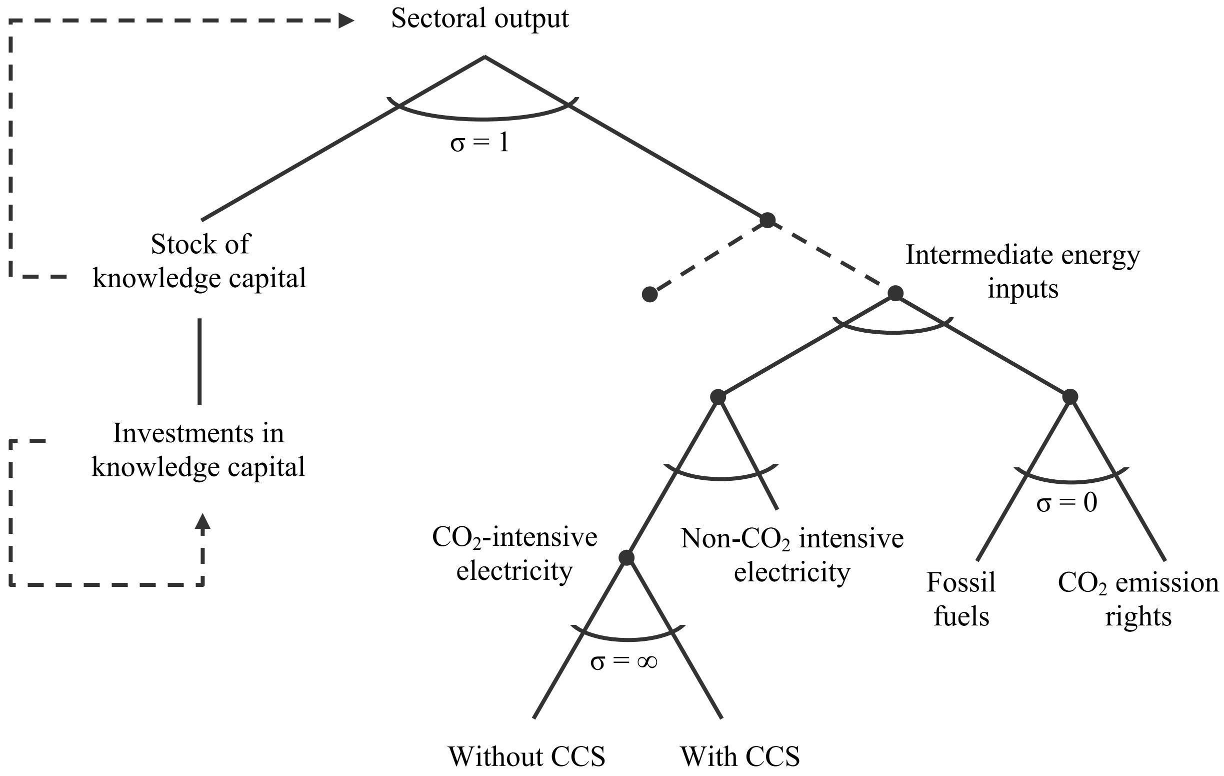
but now where:

$$KLEM_{i,t} = \left(\alpha^K K_t + \alpha^L L_t + \alpha^Y Y_{NRG,t} + \alpha^{EM} EM_{i,t} + \alpha^{EL} EL_t + \alpha^A A_{i,t}\right) \tag{5}$$

and where the value shares sum up to one. Assuming fixed proportions between inputs other than knowledge capital ensures that the CCS technology is specified as a discrete technology. We assume that engineers and scientists working in conventional power plants in the CO_2-intensive electricity sector would also be involved in applying the CCS technology and the same type of knowledge capital can therefore be used for both technologies.[3] Figure 1 illustrates the production structure and the specification of technical change in our model.

[3] Firms in the CO_2-intensive electricity sector thus invest in the type of knowledge capital also of use in the CCS technology. For an alternative specification in which the backstop technology uses a separate type of knowledge capital, of which the corresponding investment's effectiveness is uncertain, see Bosetti and Tavoni (2007) in a different model setup.

Figure 1. Production structure and specification of technical change



Notes: The specifications have been simplified for illustrative purposes. Please see equations A.1 through A.5 in Appendix A for the full specifications. The dotted arrows represent the technology externalities and σ denotes the substitution elasticities in production.

2.5. Equilibrium and growth

We solve the model so that each agent's decisions are consistent with welfare maximization in the case of the representative consumer and profit maximization in the case of firms in the intermediate and production sectors. When income is balanced and markets clear at all points in time as well, the output, price and income paths constitute an equilibrium. Markets for production factors and final goods are perfectly competitive but initially there is no market for CO_2 emission rights. The technology externalities support increasing returns in the production and innovation possibility frontiers and cause private and social returns to knowledge capital to diverge.

Economic growth reflects the growth rates of the labor supply and stocks of physical and knowledge capital. Growth of the labor supply is exogenous and constant over time (see equation A.33). Growth rates of both capital stocks stem from endogenous saving and investment behavior (see equations A.4 and A.6). The economy achieves balanced growth over time with the stocks of physical and knowledge capital growing at the same rate as the labor supply.

3. Model calibration

In this section, we describe the calibration of our model in which we pay special attention to the accounting of knowledge capital and the CCS technology. Computable general equilibrium models that build on input-output tables as part of the national accounts typically have difficulties accounting for knowledge since national input-output tables extended with satellite accounts on knowledge flows are scarce. Since investment data on knowledge capital that is consistent with the system of national accounts is presently available in the Netherlands, we calibrate our model to the Dutch economy. We describe our accounting for knowledge capital in Section 3.1. In Section 3.2 we present the data and central parameter values used in the model and in Section 3.3 we describe the calibration of the CCS technology.

3.1. Knowledge capital accounting

Knowledge capital accounting requires the identification and capitalization of knowledge flows and subsequent incorporation of these flows in the national accounting matrix (Statistics Netherlands, 2000). The UN expert group on the measurement and treatment of non-financial assets focuses on the recording of R&D and intangible capital.[4] We take a slightly broader perspective on knowledge and, besides expenditures on R&D, identify investments in information and communication infrastructure (ICT) as a knowledge flow. ICT is included because of its role in disseminating and storing knowledge. ICT is therefore an important part of the infrastructure required for knowledge to be productive (Haan and Rooijen-Horsten, 2004). A subsequent step involves capitalization of the selected knowledge flows so that we can record services derived from the knowledge stocks in separate arrays in the national accounting matrix. We capitalize knowledge flows into a single stock. An additional (column) account then registers investments in the stock of knowledge capital whereas an additional (row) account registers the derived services in the national accounting matrix. Originally, investment in ICT is reported as investment and expenditures on R&D are reported as derived services. Regarding the capitalization itself, we use the perpetual inventory method, which is a commonly used method to measure capital stocks and is in line with, for instance, the Frascati manual for surveys on R&D (OECD, 2002). A key parameter in the perpetual inventory method is the depreciation rate, for which additional information is required. We assume the Dutch economy to be on a steady state in 1999, which implies a fixed relation between investments in and services derived from the sector-specific stocks of knowledge capital. This relation then gives us the total column and row accounts for knowledge capital stemming from the two knowledge flows.

To avoid double counting of the knowledge flows, we debit selected entries of the national accounting matrix. This debiting is straightforward for expenditures on ICT: since investments in ICT are originally reported as investments in physical capital, we debit the investment (column) account

[4] This group is better known as the Canberra II Group and is formed as part of the process of updating the 1993 System of National Accounts.

with the amounts of investment in ICT. However, debiting is less straightforward for expenditures on R&D as the intermediate goods matrix of the national accounting matrix needs to be debited. In this case, we need to make an assumption as to which entries of the intermediate goods matrix to debit. One can either assume that R&D leads mostly to disembodied knowledge or that it leads to knowledge embodied in tangible goods and services.[5] If we assume that knowledge is embodied, the intermediate goods matrix can be debited in a straightforward manner proportionally to the intermediate input shares in total output of the sectors (see Terleckyj, 1974). The former assumption, however, necessitates the additional step of creating an interindustry technology matrix to debit the intermediate goods matrix proportionally to an R&D indicator such as the number of patents that a sector manufactures and uses (see e.g. Scherer, 1982). Since the superiority of using R&D indicators is not immediately clear and their availability is typically patchy for non-industrial sectors such as services, we follow Terleckyj (1974) and use intermediate input shares for our purposes. We balance the national accounting matrix by adjusting the (row) account for labor.

3.2. Data and parameter values

Besides accounting for knowledge capital, we make further data adjustments to account for CO_2 emissions associated with energy use. We divide the electricity sector into CO_2-intensive and non-CO_2 intensive electricity generation using techno-economic data for the key technologies that are sufficient to give an appropriate representation of both types of electricity generation (Böhringer et al., 2003). Table B.1 in Appendix B presents cost structures and market shares of the electricity generation technologies in the Netherlands. Further, we obtain data on fossil fuel inputs in the Netherlands from the GTAP-EG database (Paltsev and Rutherford, 2000) and match this data with CO_2 emission data for the Netherlands (Koch et al., 2002). Table B.2 presents the resulting national accounting matrix and Table B.3 reports factor and CO_2 intensities.

Turning to model parameters, we use the national accounting matrix of the base year to calibrate the parameters of the functional forms from a given set of quantities, prices and elasticities. We base our choice of elasticities and other parameter values on reviews of the relevant literature (see Tables A.5 and A.6). The substitution elasticity in discounted welfare (ρ) is assumed and lies between smaller values typically found in time series studies, e.g. Hall (1988), and larger values typically found in studies that also exploit cross-sectional data, e.g. Beaudry and Wincoop (1996). We obtain the substitution elasticities in production from the TaxInc model (Statistics Netherlands, 1990). We use the substitution elasticity between knowledge capital and remaining inputs (σ^H) from Goulder and Schneider (1999). The substitution elasticity in aggregate electricity production (σ^{EL}) is assumed. We assume a 5 percent interest rate (*r*), a 5 percent depreciation rate of physical capital (δ^K) and a 25 percent depreciation rate for knowledge capital (δ^H). Regarding the latter depreciation rate, Pakes

[5] See van Pottelsberghe de la Potterie (1997) for a more detailed discussion of both assumptions.

and Schankerman (1979) study patent renewals in the United Kingdom, Germany, France, the Netherlands and Switzerland and find a point estimate for the depreciation rate of 25 percent with a confidence interval between 18 and 35 percent. This estimate is consistent with data on life spans of applied R&D expenditures, which suggests an average service life of four to five years. In addition, we assume a coefficient value for the technology externality in innovation (ξ) of 20 percent, being the difference between the private and social returns to knowledge capital. The former is at least equal to the 25 percent depreciation rate whereas estimates of the latter lie in the range of 30-60 percent (see e.g. Mansfield et al., 1977; or Jones and Williams, 1998). We base the coefficient value for the technology externality in production (γ) on Coe and Helpman (1995), who estimate the elasticity of R&D stocks on total factor productivity at 9 percent for non-G7-OECD countries. Together with the knowledge capital accounting, these two parameter values provide the empirical basis for the technology externalities. Finally, we consider a 42-year time horizon defined over the years 1999 through 2040 and calibrate the model to a steady-state growth rate (*g*) of 1.5 percent.

3.3. Calibration of the CCS technology

Electricity generation technologies fired by natural gas and coal are being used for respectively base- and mid-load electricity demand in the Netherlands. Table 1 shows the expected costs of the electricity generation technology fired by natural gas with CCS in the Netherlands.[6] These costs are based on a natural gas combined cycle and include cost estimates for CO_2 capture, but not storage. We assume that all CO_2 captured in the Netherlands can also be stored safely for a prolonged period of time and we use a cost estimate of 5 €/t CO_2 stored, which includes pipeline transport up to 500 kilometers. Finally, we incorporate transmission and distribution costs to make a clean comparison with the cost of conventional electricity in the model.

[6] A much more detailed comparison of the various CCS technology options for The Netherlands can be found in Damen et al. (2006).

Table 1 Cost of electricity with CO_2 capture and storage (CCS) in the Netherlands (€ct/kWh)

	Without CCS	With CCS
Electricity generation and CO_2 capture		
Capital		1.5
Fuel		3.0
Operation and maintenance		0.5
CO_2 storage		0.2
Transmission and distribution		2.9
Total	7.5	8.1
Markup (%)	0	8
CO_2 capture rate (%)	0	85

Notes: The CCS technology is based on a natural gas combined cycle, which is the predominant electricity technology in the Netherlands. Fuel costs of natural gas are based on 4€/GJ and storage costs are based on 5 €/t CO_2. We draw on Damen et al. (2006) for CCS related data, IEA (1999) for transmission and distribution cost shares and Eurostat for the cost of conventional electricity.

Overall, electricity generated by the natural gas combined cycle with CCS is 8 percent more expensive than the cost of conventional electricity. This estimate corresponds with other studies (see e.g. McFarland et al., 2004). Yet, since the components of CCS are in various stages of development and none of these electricity generation technologies have yet been built on a full scale with CCS, ultimate costs of the CCS technology cannot be stated with certainty. Neither do we know its full potential with precision. We address both these uncertainties in Section 4.5 below. Nevertheless, we assume that further technical change will bring down costs or increase its potential or both over time. Finally, we assume that adoption can be immediate once the CCS technology becomes competitive to keep our policy simulation comparison focused on the implications of the (non-) anticipation assumption for the cost-effectiveness of CO_2 emission trading schemes.[7]

4. Simulations

We distinguish two simulations with respect to the anticipation of competitiveness of the CCS technology as a radically new CO_2 abatement technology. In simulation *ANT*, competitiveness of the CCS technology is anticipated. In simulation *UNANT*, however, such competitiveness is not anticipated. To ensure comparability of the welfare results between both simulations, we partition the model for simulation *UNANT* into one version for the period before the arrival of the competitive CCS technology (henceforth referred to as first period) and another version for the period after its arrival (henceforth referred to as second period). The exact arrival date is taken from simulation *ANT* and this date determines the exact periods of the partitioned model versions for simulation *UNANT*. The

[7] In reality, adoption of new technologies tends to be a more gradual process. The typical adoption path is S-shaped over time, rising only slowly in the beginning, then rising rapidly for a couple of years and finally slowing down as the technology matures and the market becomes saturated (Geroski, 2000).

UNANT model version for the first period is calibrated to the regular starting values in 1999, but without the CCS technology being an option in the model. The *UNANT* model version for the second period, however, is calibrated to the equilibrium values of the first period at the date of arrival, but now with the CCS technology being a competitive electricity generation technology in the CO_2-intensive electricity sector. As the CCS technology is not an option in the first period and the second period is only specified from the date of arrival onward, competitiveness of the CCS technology cannot be anticipated in advance.

For each simulation, we then analyze cost-effectiveness of an environmental policy that achieves a 40 percent reduction in cumulative emissions as counted from the year 2007, with the policy being implemented until the end of our model horizon. We measure the emission reduction relative to the no-policy reference case. The emission reduction approximates stabilization of CO_2 emissions at 6 percent below 1990 levels for the Netherlands, as agreed upon in the Kyoto protocol. This assumes the stabilized level would also apply in post-Kyoto commitment periods (i.e. after 2012) to the end of the model horizon. Our environmental policy takes the form of CO_2 emission trading schemes (i.e. CO_2 emission constraints) and the concomitant CO_2 shadow prices are determined endogenously in the model (see equations A.1, A.29 and A.38). We follow Otto et al. (2006) and Otto and Reilly (2006) and differentiate the CO_2 trading schemes according to the characteristics of the sectors (CO_2-intensive or non-CO_2 intensive). We label the agriculture sector, non-CO_2 intensive industries and services, and the non-CO_2 intensive electricity sector as non-CO_2 intensive sectors and CO_2-intensive industries, the trade and transport sector, the energy sector and the CO_2-intensive electricity sector as CO_2-intensive sectors. We then conduct a gridded search across the parameter space of the trading schemes to find the cost-effective differentiation between CO_2-intensive and non-CO_2 intensive sectors. Specifically, we vary the exogenous CO_2 emission constraint for the non-CO_2 intensive sectors and compute the corresponding constraints for the CO_2-intensive sectors that are necessary for total emissions in production to be reduced by 40 percent. This way, we obtain multiple sets of differentiated CO_2 emission constraints. We subsequently use the model to compute the general equilibrium result associated with each set of differentiated constraints and identify the cost-effective set. To avoid leakage of CO_2 emissions to consumption, we also abate these emissions using a separate, but otherwise identical quantity constraint (see equations A.14, A.28 and A.37). To avoid leakage of CO_2 emissions to other countries, we assume trading partners of the Netherlands to introduce similar environmental policies. The Armington specification, as opposed to a Heckscher-Ohlin specification, closes international trade in a way that limits this leakage effect (see equations A.8 and A12). Besides studying the cost-effective CO_2 emission trading schemes in Section 4.1, we explore their implications for the direction of technical change, the production structure, and discounted welfare in Sections 4.2 through 4.4 and test the sensitivity of our results in Section 4.5.

4.1. Cost-effectiveness of the CO_2 emission trading schemes in both simulations

As a first result, we find that the CCS technology becomes competitive in the year 2022 under the cost-effective CO_2 emission trading schemes in simulation *ANT* and impose this arrival date as an exogenous assumption in simulation *UNANT*. Table 2 shows the corresponding CO_2 shadow prices. We find that CO_2 shadow prices are higher in the first period (i.e. before the CCS technology is competitive) in simulation *UNANT* than they are in simulation *ANT*. In the second period (i.e. after the CCS technology has become competitive), however, not all shadow prices remain higher in simulation *UNANT* than in *ANT*. Indeed, the shadow price in the CO_2-intensive sectors is now relatively lower in simulation *UNANT*. Anticipation versus non-anticipation of the CCS technology's competitiveness explains this result. In simulation *ANT*, agents anticipate the competitiveness of the cheap CO_2 abatement option in the future and find it cost-effective to postpone some of the emission reduction until the CCS technology is competitive and abatement costs are lower. In simulation *UNANT*, agents do not anticipate this competitiveness, therefore do not initially postpone some of the emission reduction and thus initially reduce their emissions more compared to simulation *ANT*. Because of the relatively higher emission reductions in the first period, however, emission reductions can be lower in the second period in simulation *UNANT* than in simulation *ANT*. With hindsight, the CO_2 emission trading schemes have been too stringent in the first period in simulation *UNANT* and can now be relaxed somewhat in the second period. This result is in line with the theoretical findings by Dasgupta and Heal (1974) and Dasgupta and Stiglitz (1981) that uncertainty in the arrival date of the backstop technology leads to more conservation in the period before the backstop technology has arrived.[8]

Table 2 Cost-effective CO_2 shadow prices in both simulations

Simulation		Shadow prices (€/t CO_2)	
		CO_2 intensive	Non CO_2 intensive
REF	Reference case of no policy	0.0	0.0
ANT	Competitiveness of the CCS technology is anticipated	11.9	0.6
UNANT	Competitiveness of the CCS technology is unanticipated		
	First period before the CCS technology is competitive	15.5	10.6
	Second period after the CCS technology is competitive	7.7	6.5

[8] If the arrival date of the backstop technology is certain, Dasgupta and Stiglitz (1981) find it optimal to have the resource depleted by the arrival date. If this date is uncertain, however, they find it optimal to be prudent and maintain a positive stock until the backstop technology has arrived. A higher discount rate that includes a penalty for when one has depleted the resource before the backstop technology has arrived is the certainty equivalent rate and leads to the same prudence result (Dasgupta and Heal, 1974; Dasgupta and Stiglitz, 1981).

Furthermore, we find that it is cost-effective in both simulations to differentiate the CO_2 emission trading schemes between CO_2-intensive and non-CO_2 intensive sectors such that shadow prices are relatively higher in the former. In principle, cost-effectiveness of emission trading schemes requires equalization of marginal abatement costs across sectors and therefore uniform price instruments. Yet, if there are technology externalities such as knowledge spillovers or learning, it has been shown that it becomes more cost-effective to differentiate the trading schemes by sectors, according to the relative difference in technology externalities (see Otto et al., 2006 for a detailed explanation). Specifically, two effects determine the equilibrium differentiation by sectors in our model. On the one hand, technology externalities have an indirect and negative effect on abatement costs in our model and the externalities hence provide an incentive to differentiate the emission trading schemes in such a way that sectors with a relatively *high* level of technology externalities face the relatively high CO_2 shadow prices (Bramoullé and Olson, 2005; Rosendahl, 2004). Such differentiation shifts some of the abatement burden toward the sectors with the relatively high levels of technology externalities, leading to enhanced productivity of abatement efforts in these sectors and thus making best use of this abatement cost effect. On the other hand, technology externalities also have a direct and positive effect on productivity and output levels in our model and the externalities hence provide an incentive to differentiate emission trading schemes in such a way that sectors with a relatively low level of technology externalities face the relatively high CO_2 shadow prices (Otto et al., 2006). Such differentiation shifts some of the abatement burden away from the sectors with the relatively high levels of technology externalities and thus allows these sectors to make best use of this production cost effect. As the technology externalities have a direct effect on total factor productivity and only an indirect effect on abatement costs in our model, the production cost effect is strong relative to the abatement cost effect. We therefore find it cheaper to let the CO_2-intensive sectors, with relatively low levels of technology externalities, face a relatively high CO_2 shadow price and thus bear relatively more of the abatement burden.[9] Essentially, the policy is one of encouraging growth in sectors with relatively high levels of technology externalities and discouraging growth in those with relatively low levels of technology externalities.

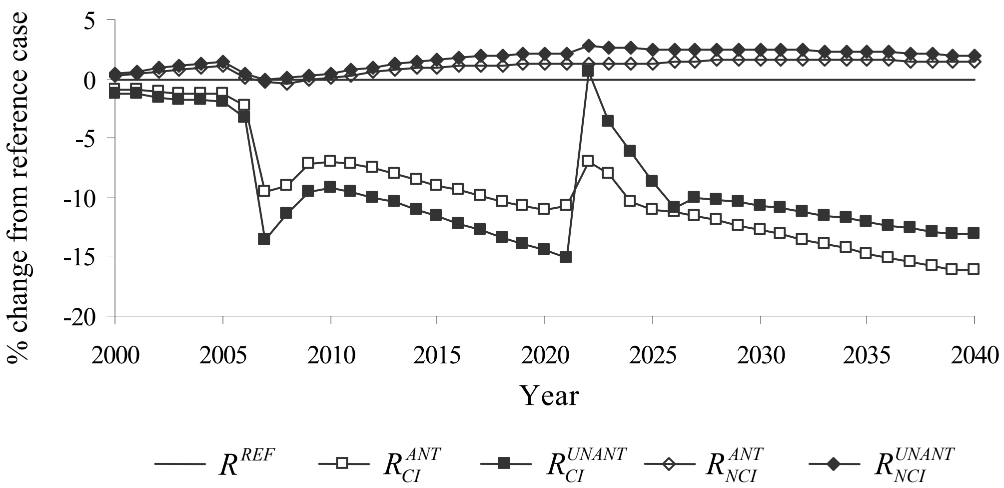
4.2. Effects on the rate and direction of technical change in both simulations

The rationale behind the different levels of technology externalities between sectors is that policy instruments aimed at CO_2 emission reduction, such as our emission trading schemes, tend to direct technical change toward non-CO_2 intensive sectors because of their relatively low CO_2 intensities, yielding relatively higher levels of technology externalities in these sectors (see for a detailed exposition of the equilibrium bias of technical change Otto et al., 2007). The electricity sectors, for example, redirect their R&D toward biomass and wind technologies resulting in relatively more

[9] Taking this finding to its logical conclusion implies that the first best set of CO_2 shadow prices are sector specific, not just a single price for all CO_2-intensive or non-CO_2 intensive sectors.

knowledge spilling over from the development of these technologies than fossil fuel electricity technologies. Figure 2 shows the effects of the cost-effective CO_2 emission trading schemes on the rate and direction of technical change in all CO_2-intensive and non-CO_2 intensive sectors in our model. We find that indeed the non-CO_2 intensive sectors overall invest more in knowledge capital compared to the CO_2-intensive sectors as well as compared to the reference case. A notable change in this investment pattern occurs during the first years after the CCS technology has become competitive, since more electricity (and hence energy) can now be generated in a non-CO_2 intensive manner and since the economy is now able to climb back to a slightly higher steady state than before the competitiveness of the CCS technology. Especially the CO_2-intensive electricity sector invests heavily in its stock of knowledge capital during this decade to be able to match supply to increased demands for its electricity that comes with both the CCS technology and the higher steady state. This change in the investment pattern corresponds well with the theoretical finding by Kamien and Schwartz (1978) that shows R&D efforts for the backstop technology to not begin immediately and to be single-peaked.

Figure 2 Effects of the cost-effective CO_2 emission trading schemes on investments in knowledge capital in both simulations



Notes: *R* is investment in knowledge capital, *CI* refers to the CO_2-intensive sectors, *NCI* refers to the non-CO_2 intensive sectors, *REF* refers to the reference case of no policy, *ANT* refers to the simulation where competitiveness of the CCS technology is anticipated and *UNANT* refers to the simulation where competitiveness of the CCS technology is not anticipated.

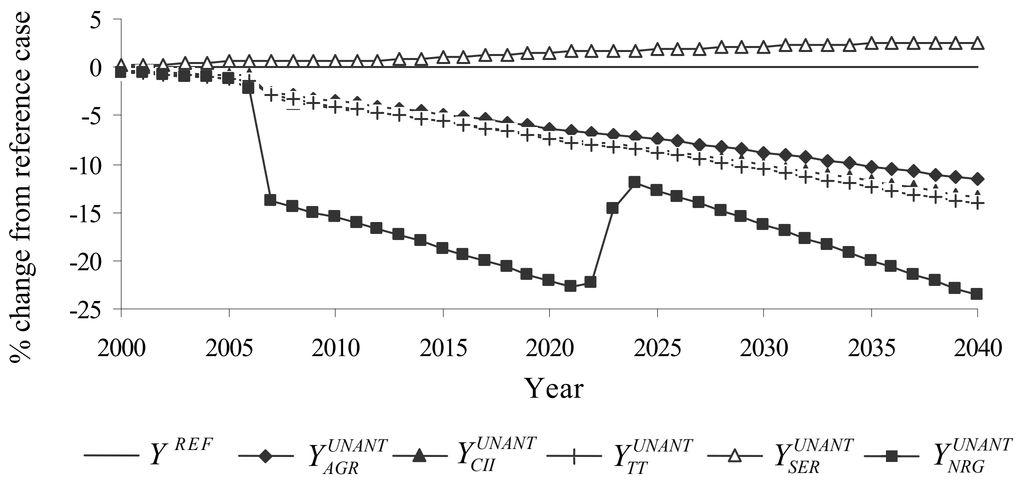
Figure 2 also shows that this investment pattern is more pronounced if competitiveness of the CCS technology is not anticipated. As discussed above, agents then do not initially postpone some of the emission reduction leading them to direct relatively more knowledge capital investments toward non-CO_2 intensive sectors in the first period before the competitiveness of the CCS technology than if they could anticipate its competitiveness. In effect, the non-CO_2 intensive sectors enjoy relatively higher levels of technology externalities, exploit therefore more of the production cost effect and lift the whole economy to a slightly higher steady state in the first period. We find this net result despite the decrease in the level of technology externalities and abatement cost effect in the CO_2-intensive sectors. After the CCS technology has become competitive in the second period, agents invest more in knowledge capital, now that the economy is in a higher steady state in simulation *UNANT* compared to simulation *ANT*. All sectors benefit from this expansion except for the non-CO_2 intensive electricity sector, which sees some of its knowledge capital investments redirected to the CO_2-intensive electricity sector for the benefit of the CCS technology.

4.3. Effects on production in both simulations

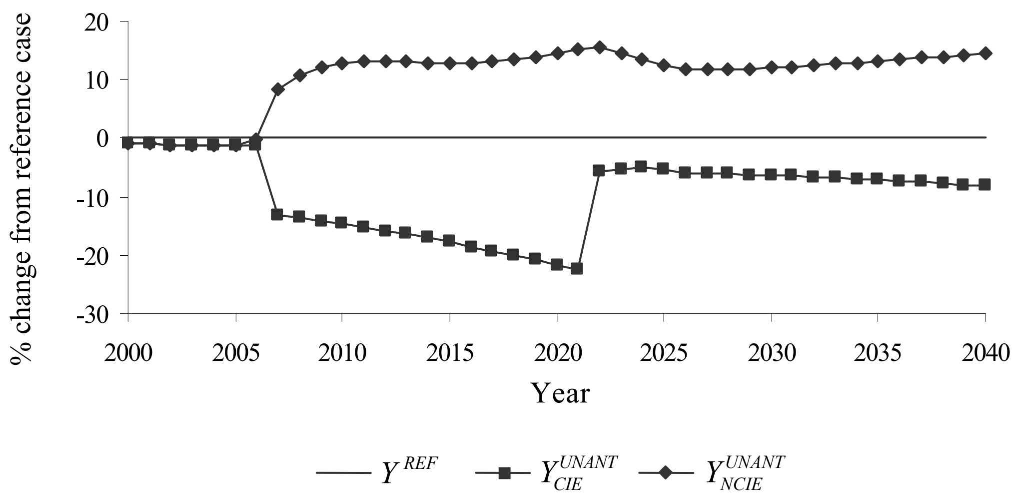
Effects of the cost-effective CO_2 emission trading schemes on the production structure are similar to the effects on investments in knowledge capital discussed above. Most notably, our emission trading schemes encourage and discourage growth according to CO_2 intensity with CO_2-intensive sectors decreasing their overall production relative to the reference case and non-CO_2 intensive sectors increasing their overall production. Figure 3 shows this pattern of biased growth for all production sectors in simulation *UNANT*. The energy sector, for example, has a relatively high CO_2 intensity, faces the higher CO_2 shadow price and therefore decreases its production significantly. The opposite applies to the non-CO_2 intensive industry and services sector. Figure 3 also shows a readjustment of production levels to the higher steady state that the competitiveness of the CCS technology allows for from 2022 onward. This readjustment is especially visible in the energy sectors. The CO_2-intensive electricity sector, for example, drastically increases electricity generation to match supply to increased demands for its electricity that come with both the CCS technology and the higher steady state. Being the supplier of fossil fuels for the CO_2-intensive electricity sector, the energy sector follows suit. To some extent, the increase in the CO_2-intensive electricity sector's output comes at the cost of the non-CO_2 intensive electricity sector's output. Consequently, the electricity market share of the latter falls back from 14.2 percent in 2021 to 12.2 percent in 2040, which is closer to the 10 percent share in the reference case.

Although not shown in Figure 3, these effects of the cost-effective CO_2 emission trading schemes on the production structure are more pronounced in simulation *UNANT* than in simulation *ANT*. As discussed above, agents do not postpone some of the emission reduction if they do not anticipate the CCS technology becoming competitive. They therefore steer the economy more forcefully in a non-CO_2 intensive direction in the first period in simulation *UNANT* and consequently to a slightly higher steady state and associated production levels in the second period.

Figure 3 Effects of the cost-effective CO_2 emission trading schemes on production in simulation UNANT



a. all production sectors except for the electricity sectors.



b. the electricity sectors

Notes: *Y* is production, *AGR* refers to the agricultural sector, *CII* refers to CO_2-intensive industries, *TT* refers to the trade and transport sector, *SER* refers to non-CO_2 intensive industries and the services sector, *NRG* refers to the energy sector, *CIE* refers to the CO_2-intensive electricity sector, *NCIE* refers to the non-CO_2 intensive electricity sector, *REF* refers to the reference case of no policy, *ANT* refers to the simulation where competitiveness of the CCS technology is anticipated and *UNANT* refers to the simulation where competitiveness of the CCS technology is not anticipated.

4.4. Effects on welfare in both simulations

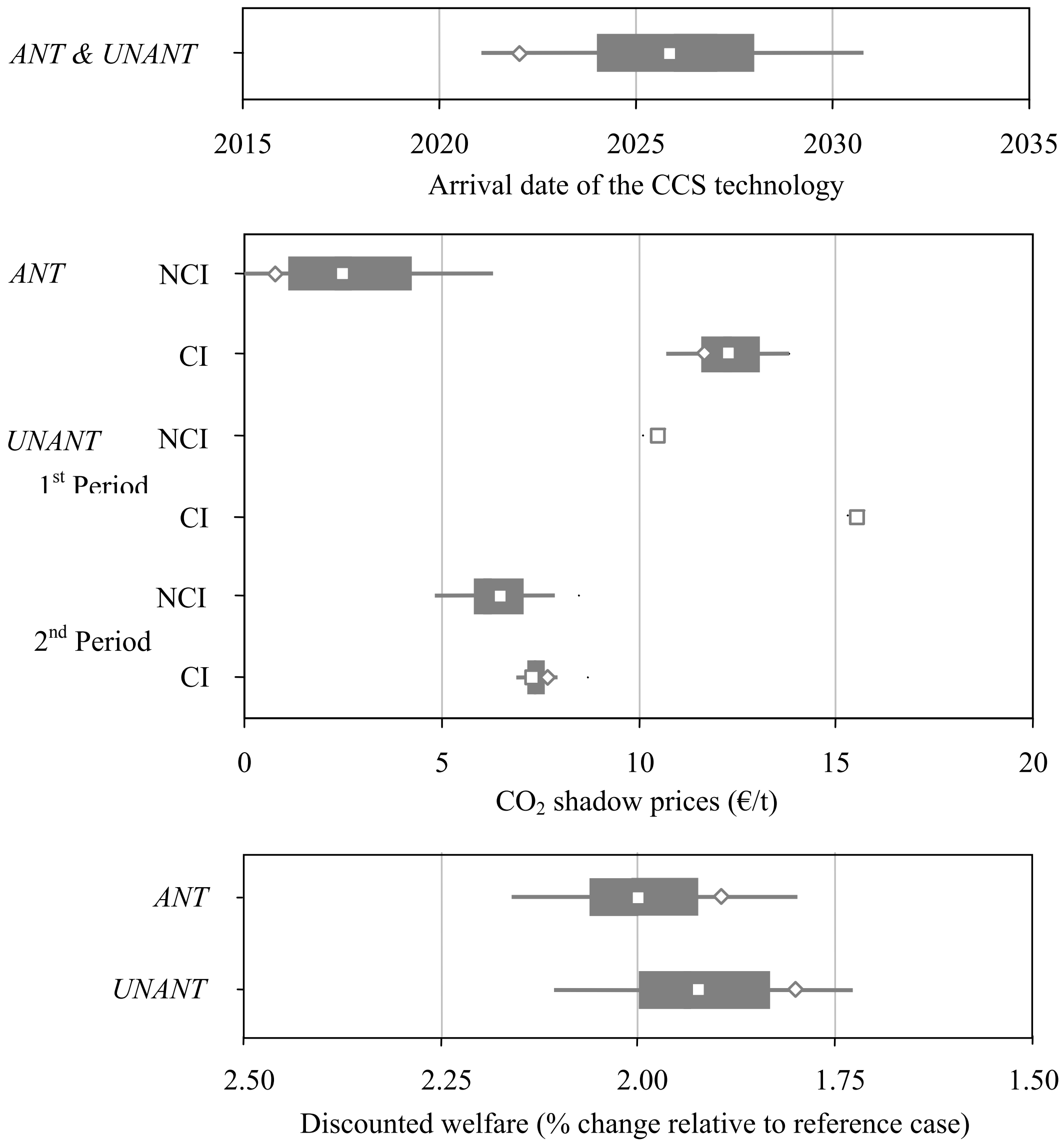
As a consequence of our steady state result, we find that the discounted welfare loss of the cost-effective CO_2 emission trading schemes relative to the reference case is reduced by 0.11 percentage points from 1.89 percent in simulation *ANT* to 1.78 percent in simulation *UNANT*. True, merely adding the CCS technology as an abatement option in the model leads to a greater reduction in the discounted welfare loss of the emission trading schemes: it decreases from 2.37 percent in a hypothetical reference case of cost-effective CO_2 emission trading schemes and no CCS technology option to the 1.89 percent in simulation *ANT*. But by not simply postponing the emission reduction until a silver bullet technology comes along, agents direct technical change even further toward non-CO_2 intensive sectors and therefore reduce the welfare losses of the emission trading schemes even further.

4.5. Uncertainty analysis

To account for parameter uncertainties regarding the competitiveness of the CCS technology, we perform a simple Monte Carlo uncertainty analysis that quantifies the overall uncertainty of our model outputs in relation to these parameter uncertainties. The Monte Carlo analysis involves random sampling from distributions of the selected parameters and successive runs of the original model. To obtain a good approximation of the output distribution, we run the model for 1000 samples. As the specific parameters subject to analysis we select the cost markup of the CCS technology over the cost of conventional electricity and the CO_2 capture rate of the CCS technology. Values of both parameters are uncertain and are expected to have a direct effect on the competitiveness of the CCS technology and hence our model and simulation results. The cost markup ranges between 7 and 15 percent and the capture rate between 85 and 95 percent. These ranges are in line with recent survey studies (Damen et al., 2006; IPCC, 2005). Since we have information only on the range of possible values for these parameters, but not on their distribution, we draw from a uniform distribution.

Figure 4 shows the results of the Monte Carlo analysis with respect to the arrival date of the CCS technology, CO_2 shadow prices and discounted welfare. The plots consist of boxes that show the interquartile ranges of these model outputs with the left and right edges drawn at the 25th percentile and 75th percentile (hinges). Whiskers extend from each hinge to the minimum and maximum observed output values. Squares indicate median values and diamonds show the original values as found in the previous sections. Although we observe some spread in the selected model outputs, we find that our main results are robust within the ranges of the markup and capture rate parameters of the CCS technology. Turning to the first of these model outputs, we find that the interquartile range for the arrival date of the CCS technology comprises 5 years from 2024 to 2028 and that the median date of arrival is 4 years later than the original year 2022. These findings confirm an expected sensitivity of the competitiveness of the CCS technology to precise values of the markup and capture rate parameters. These findings also imply that our chosen estimates of these parameter values, although in line with related studies, lead to a relatively optimistic picture regarding the technology's competitiveness. CO_2 shadow prices are not greatly affected by the different parameter values, however. The CO_2 shadow prices remain higher in the first period in simulation *UNANT* compared to both the second period and simulation *ANT.* Also, the shadow prices remain relatively higher in the CO_2-intensive sectors in both simulations in all samples. Finally, the interquartile range for discounted welfare is large and amounts to over 0.15 percentage points in both simulations, confirming that the discounted welfare loss of our emission trading schemes depends to a large extent on the CCS technology being an abatement option in the model or not and from exactly which year onward. Yet, the discounted welfare loss remains relatively smaller if competitiveness of the CCS technology is unanticipated in all samples.

Figure 4 Monte Carlo uncertainty analysis



Notes: *CI* refers to the CO_2-intensive sectors, *NCI* refers to the non-CO_2 intensive sectors, *ANT* refers to the simulation where competitiveness of the CCS technology is anticipated, *UNANT* refers to the simulation where competitiveness of the CCS technology is not anticipated, 1st period refers to the period before the CCS technology is competitive and 2nd period refers to the period after the CCS technology has become competitive. Boxes show the interquartile ranges of the selected model outputs with the left and right edges drawn at the 25th and 75th percentile. Whiskers extend from the edges to the minimum and maximum observed output values. Squares denote median values and diamonds denote the original values as found in Section 4.2. If both the median and original values overlap, only the median is shown. CO_2 shadow prices in the first period of simulation *UNANT* are unaffected by the Monte Carlo analysis as there is no CCS technology option in this period.

5. Conclusions

Technical change as a pollution abatement option has received much attention in the environmental economic literature since it has been found that technology externalities associated with technical change can improve the cost-effectiveness of environmental policies such as trading schemes to abate CO_2 emissions. Typically implicit in this finding is the assumption that one can foresee and anticipate all new technologies. Given the typically large technological uncertainties, however, this is not always a realistic assumption and new technologies can still come as a surprise. As a caveat, we did not study the role technology policy can play to bridge the gap between private and social returns to technical change or to overcome related uncertainties. Instead, we first addressed more general questions related to technological uncertainty and the design of cost-effective CO_2 emission trading schemes: What are the corresponding CO_2 shadow prices in both the case of a new technology being anticipated and not anticipated? As a result, what are the effects on the rate and direction of technical change in both cases? In which case is the discounted welfare loss of the CO_2 emission trading scheme the lowest?

To answer these questions, we developed a dynamic CGE model in which we specified CCS as a backstop technology in the CO_2-intensive electricity sector that becomes competitive at some point in the future. A comparison between a simulation where competitiveness of the CCS technology is anticipated and a simulation where competitiveness is not anticipated revealed the implications of uncertainty in the arrival date of a competitive CCS technology for the design of cost-effective CO_2 emission trading schemes.

We find that the discounted welfare loss associated with the cost-effective CO_2 emission trading schemes is lower in the simulation in which competitiveness of the CCS technology is unanticipated. CO_2 shadow prices are higher in the period before the CCS technology becomes competitive in this simulation relative to the simulation where competitiveness is anticipated, reflecting a shift of emission reduction efforts to earlier years. By not simply postponing emission reduction until the CCS technology becomes competitive in the electricity sector, one relies more on economy-wide technical change and its welfare-enhancing technology externalities, thus allowing for a slightly higher steady state in this simulation. Regarding the steady state, we find in both simulations that it is characterized by technical change which is directed toward sectors with relatively low CO_2 intensities enjoying higher levels of technology externalities than the CO_2-intensive sectors. CO_2 emission trading schemes are thus more cost-effective if they are differentiated in such a way that the CO_2-intensive sectors face the relatively high CO_2 shadow prices. Essentially, the policy is one of encouraging growth in sectors with relatively high levels of technology externalities and discouraging growth in those with relatively low levels. Our Monte Carlo uncertainty analysis confirms the robustness of our findings to an uncertain cost and performance parameterization of the CCS technology although the precise quantitative findings vary considerable with the uncertain parameterization.

Our findings underline once more the importance of technical change as an abatement option; not only through radically new abatement technology, but also in the form of incremental technical change. We should be careful not to become complacent by postponing some of our emission reduction efforts awaiting the silver bullet technology on the horizon in the energy sector. Acting in such a way is not advisable given the large uncertainties that typically surround new technologies. Besides spreading the risks that some technologies might fail, diversifying the investment portfolio can lead to lower welfare costs of environmental policy because of the technology externalities associated with technical change. Finally, our case of the CCS technology shows the political economic limitations in designing a differentiated policy instrument. With the CCS technology deployment, the CO_2-intensive sectors become much less CO_2-intensive, which blurs the traditional delineation of environmental policy along the lines of CO_2 intensity. Environmental policy has to be flexible to take into account these technological developments.

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Appendix A. Structure of the model

This appendix provides an algebraic summary of the model. We formulate the model as a mixed complementarity problem using the Mathematical Programming System for General Equilibrium Analysis (Rutherford, 1999), which is a subsystem of the General Algebraic Modeling System (Ferris and Munson, 2000). In this approach, three classes of equilibrium conditions characterize an economic equilibrium: zero profit conditions for production activities, market clearance conditions for each primary factor and good, and an income definition for the representative consumer. The fundamental unknowns of the system are activity levels, market prices, and the income level. The zero profit conditions exhibit complementary slackness with respect to associated activity levels, the market clearance conditions with respect to market prices, and the income definition equation with respect to the income of the representative consumer. The notation Π^z denotes the zero profit condition for activity *z* and the orthogonality symbol $\perp$ associates variables with complementary slackness conditions. For the sake of transparency, we use the acronyms CES (constant elasticity of substitution), CD (Cobb Douglas), and LT (Leontief) to indicate functional form. Differentiating profit and expenditure functions with respect to input and output prices provides compensated demand and supply coefficients (Hotelling's lemma), which appear subsequently in the market clearance conditions. An equilibrium allocation determines production levels, relative prices, and incomes. The model is solved for a finite number of time periods. To avoid the consumption of the complete stocks of knowledge and physical capital in the last period, terminal constraints are necessary. We constrain the growth rates of investments in the last period to the growth rate of a quantity variable—in this case intratemporal utility. The advantage of these terminal constraints is that they impose balanced growth but neither specific stocks nor specific growth rates in the last period (Lau et al., 2002). These constraints therefore suit models in which growth rates are endogenously specified. We choose the price of discounted welfare as numeraire and report all prices in present values. Tables A.1 through A.6 list the nomenclature.

A.1. Zero profit conditions

Production of goods:

$$\Pi^Y_{i,t} \equiv H^{-\gamma}_{i,t}\ CES\left(r^H_{i,t}, p^{KLEM}_{i,t}; \sigma^H\right) - p_{i,t} \geq 0 \qquad \perp Y_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad \text{(A.1)}$$

where:

$$p^{KLEM}_{i,t} = CES\left(p^A_{i,t}, CES\left(p^{KE}_{i,t}, w_t; \sigma^{KLE}_i\right); \sigma^{KLEM}_i\right)$$

$$p^{KE}_{i,t} = CES\left(r^K_t, CES\left(p^{EL}_t, p^{FF}_{i,t}; \sigma^E_i\right); \sigma^{KE}_i\right)$$

$$p_{i,t}^{FF} = p_{NRG,t} \qquad i=AGR,SER,TT,NRG \qquad t=1,..,8$$

$$p_{i,t}^{FF} = CES\left(p_{NRG,t}, p_t^{COAL}; \sigma_i^{FF}\right) \qquad i = CII, CIE$$

$$p_{i,t}^{FF} = LT\left(p_{NRG,t}, p_{NCI}^{EM}\right) \qquad i = AGR, SER \qquad t = 9,..,T$$

$$p_{i,t}^{FF} = LT\left(p_{NRG,t}, p_{CI}^{EM}\right) \qquad i = TT, NRG$$

$$p_{i,t}^{FF} = CES\left(LT\left(p_{NRG,t}, p_{CI}^{EM}\right), LT\left(p_t^{COAL}, p_{CI}^{EM}\right); \sigma_i^{FF}\right) \qquad i = CII, CIE$$

Production of electricity with the CCS technology:

$$\prod_{i,t}^{Y} \equiv H_{i,t}^{-\gamma}\ CES\left(r_{i,t}^{H}, p_{i,t}^{KLEM}; \sigma^{H}\right) - p_{i,t} \geq 0 \qquad \perp Y_{i,t} \qquad i = CIE\ ;\ t = 1,..,T \qquad \text{(A.2)}$$

where:

$$p_{i,t}^{KLEM} = LT\left(r_t^{K}, w_t, p_{j,t}, p_t^{EL}, p_{i,t}^{A}\right) \qquad j = NRG\ ; t = 1,..,8$$

$$p_{i,t}^{KLEM} = LT\left(r_t^{K}, w_t, p_{j,t}, p_{CI}^{EM}, p_t^{EL}, p_{i,t}^{A}\right) \qquad j = NRG\ ; t = 9,..,T$$

Aggregate production of electricity:

$$\Pi_t^{EL} \equiv CES\left(p_{i,t}; \sigma^{EL}\right) - p_t^{EL} \geq 0 \qquad \perp EL_t \qquad i \in EL\ ;\ t = 1,..,T \qquad \text{(A.3)}$$

Investments in knowledge capital:

$$\prod_{i,t}^{R} \equiv R_{i,t-1}^{-\zeta}\ p_{i,t} - p_{i,t+1}^{H} = 0 \qquad \perp R_{i,t} \qquad i = 1,..,I\ ; t = 1,..,T-1 \qquad \text{(A.4)}$$

$$\prod_{i,T}^{R} \equiv R_{i,T-1}^{-\zeta}\ p_{i,T} - p_i^{TH} = 0 \qquad \perp R_{i,T} \qquad i = 1,..,I$$

Stock of knowledge capital:

$$p_{i,t}^{H} = r_{i,t}^{H} + \left(1 - \delta^{H}\right) p_{i,t+1}^{H} \qquad \perp H_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T-1 \qquad \text{(A.5)}$$

$$p_{i,T}^{H} = r_{i,T}^{H} + p_i^{TH} \qquad \perp H_{i,T} \qquad i = 1,..,I$$

Investments in physical capital:

$$\Pi_t^I \equiv CD\Big(p_{i,t}, CES\big(r_t^K, p_t^{FDI}; \sigma^A\big)\Big) - p_{t+1}^K = 0 \qquad \perp I_t \qquad t = 1,..,T-1 \qquad \text{(A.6)}$$

$$\Pi_T^I \equiv CD\Big(p_{i,T}, CES\big(r_T^K, p_T^{FDI}; \sigma^A\big)\Big) - p^{TK} = 0 \qquad \perp I_T$$

where domestic investment in physical capital is first combined with foreign direct investment into an Armington (1969) aggregate, satisfying investment demand for physical capital.

Stock of physical capital:

$$p_t^K = r_t^K + \left(1-\delta^K\right) p_{t+1}^K \qquad \perp K_t \qquad t = 1,..,T-1 \qquad \text{(A.7)}$$

$$p_T^K = r_T^K + p^{TK} \qquad \perp K_T$$

Goods traded on domestic markets are combined with imported goods into an Armington aggregate, which satisfies demand for intermediate and final goods:

$$\Pi_{i,t}^A \equiv CES\Big(p_{i,t}^{IM}, CES\big(p_{j,t}; \sigma_i^M\big); \sigma^A\Big) - p_{i,t}^A \geq 0 \qquad \perp A_{i,t} \qquad \begin{cases} i = 1,..,I;\ j \notin E; \\ t = 1,..,T \end{cases} \qquad \text{(A.8)}$$

An exception is coal imports, which are directly used in certain CO_2-intensive industries and the CO_2-intensive electricity sector:

$$\Pi_t^{IM^{COAL}} \equiv p_t^{FX} - p_t^{COAL} \geq 0 \qquad \perp IM_t^{COAL} \quad t = 1,..,T \qquad \text{(A.9)}$$

Imports of goods:

$$\Pi_{i,t}^{IM^Y} \equiv p_t^{FX} - p_t^{IM} \geq 0 \qquad \perp IM_{i,t}^Y \qquad i = 1,..,I;\ t = 1,..,T \qquad \text{(A.10)}$$

Foreign direct investment:

$$\Pi_t^{FDI} \equiv p_t^{FX} - p_t^{FDI} \geq 0 \qquad \perp FDI_t \qquad t = 1,..,T \qquad \text{(A.11)}$$

Exports of goods:

$$\Pi_t^{EX^Y} \equiv CD\big(p_t^{EL}, p_{i,t}\big) - p_t^{FX} \geq 0 \qquad \perp EX_t^Y \qquad i \notin EL;\ t = 1,..,T \qquad \text{(A.12)}$$

Exports of physical capital:

$$\Pi_t^{EX^K} \equiv r_t^K - p_t^{FX} \geq 0 \qquad \perp EX_t^K \qquad t = 1,..,T \tag{A.13}$$

Intratemporal utility:

$$\Pi_t^W \equiv CES\left(p_t^{FX}, CES\left(p_{j,t}, p_t^E; \sigma_W^{YE}\right); \sigma^A\right) - p_t^W \geq 0 \quad \perp W_t \qquad j \notin E\,;\; t = 1,..,T \tag{A.14}$$

where:

$$p_t^E = CES\left(p_t^{EL}, p_{NRG,t}; \sigma_W^E\right) \qquad t = 1,..,8$$

$$p_t^E = CES\left(p_t^{EL}, LT\left(p_{NRG,t}, p_W^{EM}\right); \sigma_W^E\right) \qquad t = 9,..,T$$

Intertemporal utility (discounted welfare):

$$\Pi^U \equiv CES\left(p_t^W; \rho\right) - p^U = 0 \qquad \perp U \tag{A.15}$$

A.2. Market clearing conditions

Goods:

$$\begin{aligned} Y_{j,t} = {} & \frac{\partial \Pi_{i,t}^R}{\partial p_{j,t}} R_{j,t} + \frac{\partial \Pi_t^I}{\partial p_{j,t}} I_t + \sum_i \frac{\partial \Pi_{i,t}^A}{\partial p_{j,t}} A_{i,t} \\ & + \frac{\partial \Pi_t^W}{\partial p_{j,t}} W_t + \frac{\partial \Pi_t^{EX^Y}}{\partial p_{j,t}} EX_t^Y \end{aligned} \qquad \perp p_{j,t} \qquad j \notin E\,;\; t = 1,..,T \tag{A.16}$$

$$\begin{aligned} Y_{j,t} = {} & \frac{\partial \Pi_{i,t}^R}{\partial p_{j,t}} R_{j,t} + \frac{\partial \Pi_t^I}{\partial p_{j,t}} I_t + \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial p_{j,t}} Y_{i,t} \\ & + \frac{\partial \Pi_t^W}{\partial p_{j,t}} W_t + \frac{\partial \Pi_t^{EX^Y}}{\partial p_{j,t}} EX_t^Y \end{aligned} \qquad \perp p_{j,t} \qquad j = NRG\,;\; t = 1,..,T$$

$$Y_{j,t} = \frac{\partial \Pi_{i,t}^R}{\partial p_{j,t}} R_{j,t} + \frac{\partial \Pi_t^I}{\partial p_{j,t}} I_t + \frac{\partial \Pi_t^{EL}}{\partial p_{j,t}} EL_t \qquad \perp p_{j,t} \qquad j \in EL\,;\; t = 1,..,T$$

Electricity:

$$EL_t = \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial p_t^{EL}} Y_{i,t} + \frac{\partial \Pi_t^{EX^Y}}{\partial p_t^{EL}} EX_t^Y + \frac{\partial \Pi_t^W}{\partial p_t^{EL}} W_t \qquad \perp p_t^{EL} \qquad t = 1,..,T \tag{A.17}$$

Knowledge capital (in market):

$$\frac{r_{i,t}^{H} H_{i,t}}{r+\delta^{H}} = \frac{\partial \Pi_{i,t}^{Y}}{\partial r_{i,t}^{H}} Y_{i,t} \qquad \perp r_{i,t}^{H} \qquad i=1,..,I\ ;\ t=1,..,T \tag{A.18}$$

Knowledge capital (in stock):

$$H_{i,t=1} = H_{0i} \qquad \perp p_{i,t=1}^{H} \qquad i=1,..,I \tag{A.19}$$

$$H_{i,t} = \left(1-\delta^{H}\right) H_{i,t-1} + R_{i,t-1} \qquad \perp p_{i,t}^{H} \qquad i=1,..,I\ ;\ t=2,..,T$$

$$TH_{i} = \left(1-\delta^{H}\right) H_{i,T} + R_{i,T} \qquad \perp p_{i}^{TH} \qquad i=1,..,I$$

Physical capital (in market):

$$\frac{r_{t}^{K} K_{t}}{r+\delta^{K}} = \frac{\partial \Pi_{t}^{I}}{\partial r_{t}^{K}} I_{t} + \sum_{i} \frac{\partial \Pi_{i,t}^{Y}}{\partial r_{t}^{K}} Y_{i,t} + \frac{\partial \Pi_{t}^{EX^{K}}}{\partial r_{t}^{K}} EX_{t}^{K} \qquad \perp r_{t}^{K} \qquad t=1,..,T \tag{A.20}$$

Physical capital (in stock):

$$K_{t=1} = K_{0} \qquad \perp p_{t=1}^{K} \tag{A.21}$$

$$K_{t} = \left(1-\delta^{K}\right) K_{t-1} + I_{t-1} \qquad \perp p_{t}^{K} \qquad t=2,..,T$$

$$TK = \left(1-\delta^{K}\right) K_{T} + I_{T} \qquad \perp p^{TK}$$

Labor:

$$L_{t} = \sum_{i} \frac{\partial \Pi_{i,t}^{Y}}{\partial w_{t}} Y_{i,t} \qquad \perp w_{t} \qquad t=1,..,T \tag{A.22}$$

Coal (imports):

$$IM_{t}^{COAL} = \sum_{i} \frac{\partial \Pi_{i,t}^{Y}}{\partial p_{t}^{COAL}} Y_{i,t} \qquad \perp p_{t}^{COAL} \qquad t=1,..,T \tag{A.23}$$

Import aggregate:

$$IM_{i,t}^{Y} = \frac{\partial \Pi_{i,t}^{A}}{\partial p_{i,t}^{IM}} A_{i,t} \qquad \perp p_{i,t}^{IM} \qquad i = 1,..,I\ ;\ t = 1,..,T \tag{A.24}$$

Armington aggregate:

$$A_{i,t} = \frac{\partial \Pi_{i,t}^{Y}}{\partial p_{i,t}^{A}} Y_{i,t} \qquad \perp p_{i,t}^{A} \qquad i = 1,..,I\ ;\ t = 1,..,T \tag{A.25}$$

Foreign investments:

$$FDI_{t} = \sum_{i} \frac{\partial \Pi_{t}^{I}}{\partial p_{t}^{FDI}} I_{t} \qquad \perp p_{t}^{FDI} \qquad t = 1,..,T \tag{A.26}$$

Foreign exchange:

$$\begin{aligned} BOP_{t} = & \frac{\partial \Pi_{t}^{EX^{Y}}}{\partial p_{t}^{FX}} EX_{t}^{Y} + \frac{\partial \Pi_{t}^{EX^{K}}}{\partial p_{t}^{FX}} EX_{t}^{K} - \sum_{i} \frac{\partial \Pi_{i,t}^{IM^{Y}}}{\partial p_{t}^{FX}} IM_{i,t}^{Y} \\ & - \frac{\partial \Pi_{t}^{IM^{COAL}}}{\partial p_{t}^{FX}} IM_{t}^{COAL} - \frac{\partial \Pi_{t}^{FDI}}{\partial p_{t}^{FX}} FDI_{t} - \frac{\partial \Pi_{t}^{W}}{\partial p_{t}^{FX}} W_{t} \end{aligned} \qquad \perp p_{t}^{FX} \qquad t = 1,..,T \tag{A.27}$$

CO_2 emissions in consumption:

$$EM^{W} = \sum_{t=9}^{T} \frac{\partial \Pi_{t}^{W}}{\partial p_{W}^{EM}} W_{t} \qquad \perp p_{W}^{EM} \tag{A.28}$$

CO_2 emissions in production:

$$EM_{c}^{Y} = \sum_{i} \sum_{t=9}^{T} \frac{\partial \Pi_{i,t}^{Y}}{\partial p_{c}^{EM}} Y_{i,t} \qquad \perp p_{c}^{EM} \qquad c = CI, NCI \tag{A.29}$$

Intratemporal utility:

$$W_{t} = \frac{\partial \Pi^{U}}{\partial p_{t}^{W}} U \qquad \perp p_{t}^{W} \qquad t = 1,..,T \tag{A.30}$$

Intertemporal utility (discounted welfare):

$$U = \frac{B}{p^U} \qquad \perp p^U \qquad \text{(A.31)}$$

A.3. Income balance

$$B = \sum_i \left(H_{i,0} - p_i^{TH} TH_i \right) + K_0 - p^{TK} TK + \sum_t w_t L_t + \sum_c p_c^{EM} EM_c^Y + \sum_t p_t^{FX} BOP_t \qquad \text{(A.32)}$$

A.4. Endowments

Supply of labor:

$$L_t = \left(1+g\right)^{t-1} L_0 \qquad t = 1,..,T \qquad \text{(A.33)}$$

Balance of Payments:

$$BOP_t = \left(1+g\right)^{t-1} BOP_0 \qquad t = 1,..,T \qquad \text{(A.34)}$$

A.5. Terminal constraints

Terminal constraint for physical capital:

$$\frac{I_T}{I_{T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TK \qquad \text{(A.35)}$$

Terminal constraint for knowledge capital:

$$\frac{R_{i,T}}{R_{i,T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TH_i \qquad \text{(A.36)}$$

A.6. CO_2 emission constraints

CO_2 emission constraint in consumption:

$$EM^W = \left(1-a\right) \sum_{t=9}^{T} \left(1+g\right)^{t-1} EM_0^W \qquad \text{(A.37)}$$

CO_2 emission constraint in production:

$$EM_c^Y = (1 - a_c) \sum_{t=9}^{T} (1 + g)^{t-1} EM_{0c}^Y \qquad c = CI, NCI \qquad \text{(A.38)}$$

where:

$$\sum_c EM_c^Y = (1 - a) \sum_c \sum_{t=9}^{T} (1 + g)^{t-1} EM_{0c}^Y$$

A.7. Nomenclature

Table A.1 Sets and indices

i	$AGR, IND, TT, SER, NRG, CIE, NCIE$	Sectors and goods (aliased with *j*)
E	$NRG, CIE, NCIE$	Energy (sectors)
EL	$CIE, NCIE$	Electricity (sectors)
FF	$COAL, NRG$	Fossil fuel (sectors)
c	$CI : IND, TT, NRG, CIE$ $NCI : AGR, SER, NCIE$	Sectors according to CO_2 intensity
t	$1,..,T$	Time periods

Table A.2 Activity variables

$Y_{i,t}$	Production of goods in sector *i* at time *t*
EL_t	Aggregate production of electricity at time *t*
$H_{i,t}$	Stock of knowledge capital in sector *i* at time *t*
TH_i	Terminal stock of knowledge capital in sector *i*
$R_{i,t}$	Investments in knowledge capital in sector *i* at time *t*
K_t	Stock of physical capital at time *t*
TK	Terminal stock of physical capital
I_t	Investments in physical capital at time *t*
$A_{i,t}$	Armington aggregate of domestic and foreign intermediate goods in sector *i* at time *t*
$IM_{i,t}^Y$	Aggregate imports of goods in sector *i* at time *t*
IM_t^{COAL}	Aggregate imports of coal at time *t*
FDI_t	Foreign direct investment at time *t*
EX_t^Y	Aggregate exports of goods at time *t*

EX_t^K	Aggregate exports of physical capital at time t
W_t	Intratemporal utility at time t
U	Intertemporal utility (discounted welfare)

Table A.3 Income and endowment variables

B	Budget of the representative agent
BOP_0	Initial Balance of Payments of the domestic representative agent
BOP_t	Balance of Payments of the domestic representative agent at time t
H_{0i}	Initial stock of knowledge capital in sector i
K_0	Initial stock of physical capital
L_0	Initial endowment of labor
L_t	Endowment of labor at time t
EM_0^W	Initial allowances of CO_2 emissions in consumption
EM^W	Overall allowances of CO_2 emissions in consumption
EM_{0c}^Y	Initial allowances of CO_2 emissions in production sector c
EM_c^Y	Overall allowances of CO_2 emissions in production sector c

Table A.4 Price variables (in present values)

p	Prices
p_t^{FX}	Price of foreign exchange at time t
p^{EM}	Shadow prices of CO_2 emissions
r_t	Rental rate of capital at time t
w_t	Wage rate at time t

Table A.5 Parameters

	Description	Value
a	Overall CO_2 emissions reduction	0.40
a_c	CO_2 emissions reduction in sector c	Iterative
γ	Coefficient of technology externality in production	0.09
ξ	Coefficient of technology externality in innovation	0.20
g	Growth rate	0.015
r	Interest rate	0.05
δ^K	Depreciation rate of physical capital	0.05
δ^H	Depreciation rate of knowledge capital	0.25

Table A.6 Elasticities

	Description							Value
Elasticity of substitution in discounted welfare								
ρ	Between time periods							0.5
Elasticities of substitution in intratemporal utility								
σ_W^{YE}	Between energy and other goods							0.5
σ_W^{E}	Between electricity and fossil fuels							0.7
Elasticities of substitution in international trade								
σ^A	Between domestic and foreign commodities							4.0
Elasticities of substitution in aggregate electricity production								
σ^{EL}	Between CO_2-intensive and non-CO_2 intensive electricity							2.5
Elasticities of substitution in production		AGR	CII	SER	TT	NRG	CIE	NCIE
σ^H	Between knowledge capital & rest	1.0	1.0	1.0	1.0	1.0	1.0	1.0
σ_i^{KLEM}	Between intermediate inputs & rest	0.4	0.5	0.7	0.7	0.9	0.1	0.1
σ_i^{M}	Between intermediate inputs	0.1	0.2	0.3	0.3	0.5	0.1	0.1
σ_i^{KLE}	Between labor and remaining inputs	0.3	0.3	0.4	0.4	0.5	0.1	0.1
σ_i^{KE}	Between physical capital and energy	0.7	0.7	0.7	0.7	0.1	0.7	0.7
σ_i^{E}	Between electricity and fossil fuels	0.5	0.5	0.5	0.5	0.1	0.5	
σ_i^{FF}	Between fossil fuels	0.9	0.9	0.9	0.9	0.1	0.5	

Notes: Abbreviations of the sectors are: agriculture (AGR), CO_2-intensive industry (IND), non-CO_2 intensive industry and services (SER), trade and transport (TT), energy (NRG), CO_2-intensive electricity (CIE) and non-CO_2 intensive electricity (NCIE).

Appendix B. Data

Table B.1 Cost and market shares of electricity technologies (%)

	Cost shares					Market share
	Physical Capital	Labor	Energy	Intermediate inputs	Total	
CO_2 intensive						
Natural gas fired	24.9	5.6	62.2	7.3	100.0	56.9
Hard coal fired	38.6	5.6	23.7	9.0	76.9	25.5
Oil fired	46.9	2.2	40.3	10.6	100.0	7.6
Non CO_2 intensive						
Biomass	18.8	6.6		58.5	83.9	4.6
Nuclear	59.0	5.1		17.4	81.5	4.4
Wind	86.4	19.8			106.2	1.0

Source: Böhringer et al. (2003)

Table B.2 National accounting matrix with knowledge accounting for the Netherlands in 1999 (billion euro)

	AGR	CII	SER	TT	NRG	CIE	NCIE	EX	C	I	R	S	Total
AGR	16.8	0.1	0.1	2.3	0.0		<0.1	28.2	7.4	0.7	1.0	0.1	56.7
CII	0.9	5.9	1.8	11.1	0.2	0.1	0.1	33.2	4.0	0.3	4.9	<0.1	62.3
SER	0.6	0.8	4.1	5.6	0.3	<0.1	<0.1	79.9	7.1	0.5	1.2	<0.1	100.5
TT	4.4	5.9	18.8	103.1	1.3	0.7	0.1	30.8	160.9	89.4	22.3	0.2	437.8
NRG	1.0	1.3	2.0	2.1	4.5	0.9		9.9	5.4	0.1	0.8	0.1	28.0
CIE&NCIE	0.6	0.8	0.7	1.3	0.1	3.4	0.5	1.2	2.2	<0.1	0.4		11.1
Imports	14.3	21.0	13.8	60.3	6.2	1.3			62.9	23.6		0.3	203.6
Net taxes	0.7	0.1	1.0	4.2	4.6	0.4	<0.1						7.7
Labor	6.0	10.9	33.2	133.5	1.3	0.8	0.1						185.8
K	11.7	10.1	25.5	89.1	8.7	2.2	0.3	0.6	17.0	3.5			168.6
H	1.1	5.4	1.4	24.8	0.8	0.4	<0.1						33.9
Total	56.7	62.3	100.5	437.8	28.0	10.0	1.1	183.7	266.8	118.0	30.5	0.5	

Notes: Abbreviations are: exports (EX), consumption (C), investment in physical capital (I), Investment in knowledge capital (R), supply changes (S), services from physical capital (K), services from knowledge capital (H). Abbreviations of the sectors are: agriculture (AGR), CO_2-intensive industry (IND), non-CO_2 intensive industry and services (SER), trade and transport (TT), energy (NRG), CO_2-intensive electricity (CIE) and non-CO_2 intensive electricity (NCIE). Sources: Statistics Netherlands (2000), Haan and Rooijen-Horsten (2004), and own calculations.

Table B.3: Selected factor intensities of the Dutch economy in 1999 (% of gross sectoral output)

	Knowledge capital			Physical capital	Labor	CO_2
Sector	R&D	ICT	Total			
Production						
CO_2-intensive sectors	3.3	0.7	4.0	23.2	23.0	0.07
CO_2-intensive industry	8.3	0.4	8.7	16.2	17.5	0.08
Trade and transport	0.8	0.6	1.4	25.4	33.1	0.04
Energy	1.8	1.2	3.0	31.1	4.8	0.04
CO_2-intensive electricity	1.3	2.3	3.6	21.9	7.8	0.41
Non-CO_2 intensive sectors	3.7	1.5	5.2	20.4	28.2	<0.01
Agriculture	1.5	0.5	2.0	20.7	10.5	0.01
Non-CO_2 intensive industry and services	4.1	1.6	5.7	20.4	30.5	<0.01
Non-CO_2 intensive electricity	1.3	2.3	3.6	25.4	5.5	0.00
Consumption						0.01

Note: Capital intensities are respectively services derived from knowledge and physical capital expressed as percentages of gross sectoral output. CO_2 intensities are CO_2 emissions in Mt. expressed as percentage of gross sectoral output in billion Euros. Two types of knowledge are included in our working definition of knowledge capital: research and development (R&D) and information and communication technology (ICT). We obtain data on knowledge capital from Haan and Rooijen-Horsten (2004) and data on CO_2 emissions from the GTAP-EG database (Paltsev and Rutherford, 2000) and the Emission Monitor for The Netherlands (Koch et al., 2002).