Economic modeling of directed technical change: The case of CO_2 emission reduction

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Preface

It was during my studies in Maastricht that I developed an interest in environmental issues and their interplay with economics, but it was during my internship in Nairobi and the subsequent travels that I realized the importance of technology in this interplay and that I needed to know more about it. So I was grateful when Ekko van Ierland and Tinus Pulles offered me the possibility to pursue a Ph.D. on this topic. The present dissertation contains the main results of my Ph.D. research. On some days, I like to think that I know more about this topic now. Yet, on most days I realize how much more there is still to know.

I could not have written this dissertation without the support of many others. First and foremost, I would like to thank my four supervisors who together made for an excellent team. Ekko van Ierland, who not only provided me with a position within his group, but who also provided me with the means and space to develop myself professionally. I am also grateful for the trust that he confided in me when I was making the transition from my travels to my research as well as when I was working elsewhere. Tinus Pulles of the Netherlands Organisation for Applied Scientific Research TNO, who with his great knowledge about technologies and the energy sector helped me to understand my research in a way that I wouldn't have otherwise. He also challenged me to focus on the practical applicability of my research. And Timo Kuosmanen of Agrifood Research Finland and, prior to that, Wageningen University, who introduced me to several nonparametric estimation techniques and who had the patience with me to wait until I got all the computations right. As the youngest supervisor, he also taught me many tricks of the trade of being a young economist. And last but not least, John Reilly of the Massachusetts Institute of Technology (MIT), who with his great knowledge and humor about the economics of climate change influenced the thesis a great deal. He also inspired me to take a closer look at the policy implications of my research. It has been a true pleasure to work with you.

Having stayed at several research institutes over the course of my Ph.D. research, I have been blessed not just with one group of nice colleagues but four. At Wageningen University, special thanks go to Rob Dellink for putting me on track regarding economic modeling and for the pleasant cooperation. I also would like to give special thanks to Xueqin Zhu for being a wonderful officemate and to Wil den Hartog and Sjoukje Atema for their secretarial support. Frank Vöhringer, Sara Scatasta, Hans Peter Weikard, Daan Ooms, Marijke Kuiper and all my other colleagues at the Environmental Economics and Natural Resources Group are very much appreciated for their many constructive comments and help. At the Netherlands Organisation for Applied Scientific Research TNO special thanks go to Toon van Harmelen, who has always taken the time and effort to review my work and provide me with many useful comments. All other colleagues are very much appreciated for making me feel right at home. At the Centre for

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At this point, I also would like to gratefully acknowledge the various sorts of financial support I have received over the course of the research. First of all, I thank the Netherlands Organisation for Applied Scientific Research TNO for financing my research position at the Environmental Economics and Natural Resources Group of Wageningen University for four years and MIT's Joint Program on the Science and Policy of Global Change for supporting me thereafter. I am also very grateful to the Department of Social Sciences of Wageningen University as well as MIT's Joint Program for being so generous to bridge the gap between the cost of living in the Netherlands and Boston. The European Commission is gratefully acknowledged for the Marie Curie fellowships and the Finnish Emil Aaltonen Foundation for their financial support of conferences in San Jose, Bilbao, Stockholm and Helsinki.

Outside my life in the office, I would like to thank Daniel Rozenburg (Dadara) and my sister Susanne for designing the colorful cover, my wonderful housemates Albert, Juan Carlos, Anthony and Martha, Kim, and Gil for putting up with me, my friends for sparring with me and giving the necessary distraction, the Lind family for being my family away from home, and Karin for having been with me all the way even though we always seem to be somewhere else on this planet. Finally, I am forever indebted to my parents Martin and Margreet and my sister Susanne, for their love and patience in raising me to believe in myself and to persevere.

Abstract

The potential of technical change for cost-effective pollution abatement typically differs from technology to technology. It therefore is the aim of this thesis to study how policy instruments can direct technical change to those technologies with the greatest potential for cost-effective pollution abatement. In the light of the climate change problem, this thesis uses climate policy and concomitant reduction of carbon dioxide (CO_2) emissions associated with energy use as a case study.

A first part of the study deals with the determinants of directed technical change. I derive these determinants using an economic model analysis of directed technical change. A main finding is that the consumption side of the economy is important for the direction of technical change. In particular, the extent to which consumers can substitute between goods determines the direction. Technology externalities reinforce the existing direction of technical change. Further, I explore a frontier approach for empirical analysis of delayed feedback in technical change that is based on the literature of productive efficiency analysis. I illustrate this approach using aggregate production data of 25 OECD countries for the years 1980 through 1997. I find evidence that the benefits of technical change accrue gradually over time, with the delayed response continuing up to eight years.

A second part of the study deals with the possibilities of directed technical change and technology externalities for the design of climate policy. Applying the model analysis at the aggregate level of the current Dutch economy, I find that CO_2 emission reduction becomes more cost effective if climate policy takes the form of a combination of traditional environmental policy and technology policy. Regardless of the particular policy instruments chosen, however, I find that technology externalities can justify differentiation of climate policy between non-CO_2 intensive- and CO_2-intensive sectors, such that the latter face a higher CO_2 price. This result is considerably different from the conventional environmental economic conclusion that equal marginal abatement costs across the economy lead to a cost-effective emission reduction. Finally, focusing the model analysis more on the energy sector of the Dutch economy, I study cost effectiveness of combining the environmental policy with technology policy aimed at reducing the cost and speeding the adoption of a specific CO_2 abatement technology. I take CO_2 capture and storage in the Dutch electricity sector as a case study. I find that such a policy combination leads to faster adoption of CO_2 capture and storage and improves cost effectiveness of the emission reduction.

Summary

Introduction

This thesis presents an economic analysis of the role of technical change for cost-effective pollution abatement. Technical change is the process of developing and introducing new techniques. Since costs and abatement potentials are technology dependent, the potential of technical change for cost-effective pollution abatement typically differs from technology to technology. It therefore is the aim of this thesis to study how policy instruments can direct technical change to those technologies with the greatest potential for cost-effective pollution abatement. In the light of the climate change problem, this thesis uses climate policy and concomitant reduction of carbon dioxide (CO_2) emissions associated with energy use as a case study.

A first part of the study deals with the determinants of directed technical change, where specific attention is paid to the potential role that technology externalities play in the process of technical change. Technology externalities are costs or benefits associated with one agent's technical change that are imposed on other agents in the economy but for which no financial compensation takes place. I conduct this part of the study in Chapters 2, 3, and 4. A second part of the study deals with the possibilities of directed technical change and possible technology externalities for the design of climate policy. I conduct this part of the study in Chapters 5 and 6. Finally, Chapter 7 provides concluding remarks, a policy perspective as well as suggestions for future research.

Directed technical change

What determines the direction of technical change is typically not made clear in economic model studies of climate policy. Yet, to ensure that climate policy directs technical change toward CO_2 emission reduction in a cost effective manner, it is necessary to first disentangle the various effects that are at play when directing technical change and understand the determinants of the direction. To come to such an understanding, I derive these determinants using an economic model analysis of directed technical change in Chapter 3. Specifically, I develop the 'Dynamics of Technology Interactions for Sustainability' (DOTIS) model, which is an intertemporal dynamic CGE model that explicitly captures links between energy, the rate and direction of technical change, and the economy. At the same time, I test the model to see if it is able to project the direction of technical change following the oil shock in the late 1970's in the Netherlands.

A main finding is that the consumption side of the economy is important for the direction of technical change. In particular, the extent to which consumers can substitute one good for

another determines the direction. The oil shock directs technical change toward the now relatively scarce goods (intensive in their use of the energy resource) if substitution possibilities between goods are limited. The scarcity has the leverage to increase incentives to develop new technologies that can be used in the production of the scarce goods. Substitution possibilities between energy and the rest of the economy, for example, are limited and the oil shock directs technical change toward the energy sector. If substitution possibilities between goods increase, however, scarcity has less leverage and there are now more incentives to develop technologies that can be used in the production of the relatively abundant goods (not intensive in their use of the energy resource) for which there ultimately is a bigger market. Consequently, technical change is directed toward the relatively abundant goods. There are ample substitution possibilities within the energy sector, for example, and the oil shock now directs technical change away from oil toward non-oil energy industries. Further, possible technology externalities reinforce the existing direction of technical change.

Regarding the technology externalities, I find that they do play a role in technical change and that they are positive. As technology externalities are by definition not included in firms' decision making processes, they cause the market mechanism to yield less technical change than what is socially optimal. A survey of the relevant literature shows that estimates of the private returns to technical change lie in the range of 5-30 percent whereas the social returns have been estimated around 50 percent.

Chapter 4 focuses on estimating these social returns as well as their time profile, recognizing that benefits of technical change are likely to accrue gradually over time. Specifically, I study delayed feedback in technical change, which exists if previous technical change has an effect on today's technical change. To a certain extent, individual firms do not anticipate this feedback and as such it is an aggregate estimate of the technology externalities. I explore a frontier approach for empirical analysis of the feedback that is based on the literature of productive efficiency analysis. I illustrate this approach at the macro level using aggregate production data of 25 OECD countries for the years 1980 through 1997.

Similar to the previous literature, I find that social returns to technical change are sizable. In addition, however, I find evidence that the benefits extend over time, with the delayed response continuing up to eight years. The feedback effect is strong: I find, for example, that a one percent increase in productivity ascribed to technical change six years ago still results in almost a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*.

Policy

Technology externalities associated with directed technical change provide a rationale to study cost effectiveness of climate policy if it takes the form of traditional environmental policy, or technology policy, or both. Environmental policy is primarily aimed at reducing CO_2 emissions, but might also induce technical change. Likewise, technology policy is primarily aimed at correcting the technology externalities, but can also be used to reduce CO_2 emissions. In addition, to the extent technology externalities differ from sector to sector, differentiating climate policy between sectors might be a means to direct technical change and increase cost efficiency.

Chapter 5 studies these implications for the cost effectiveness of climate policy at the aggregate level of the Dutch economy. I present the DOTIS model and discuss its calibration to the Dutch economy. I subsequently construct simulations to reveal the cost-effective set of environmental- and technology policies to achieve a 10 percent emission reduction relative to the reference case, including the desirability of differentiating policies between CO_2-intensive and non-CO_2 intensive sectors. Environmental policy takes the form of CO_2-trading schemes and technology policy takes the form of subsidies for research and development (R&D).

As a result, I find that the emission reduction becomes more cost effective if the CO_2 trading schemes are combined with R&D subsidies. This combination allows both instruments to be used for their first-best purpose and achieves the emission reduction, while improving welfare by about 27 percent over a 27-year time span and avoiding any output contractions in CO_2-intensive sectors.

Regardless of the particular policy instruments chosen, I find that technology externalities call for differentiation of instruments between non-CO_2 intensive- and CO_2-intensive sectors, such that the latter bear relatively more of the abatement burden. Regarding the CO_2-trading schemes, this implies that there are two schemes yielding two CO_2 shadow prices, where CO_2-intensive sectors face the higher CO_2 price generated by the tighter trading scheme. This result is considerably different from the conventional environmental economic conclusion that equal marginal abatement costs across the economy lead to a cost-effective emission reduction. The intuition of this result is that climate policy instruments tend to direct technical change toward non-CO_2 intensive sectors leading to higher technology externalities and hence higher opportunity costs of abatement in these sectors. The welfare gain for differentiated CO_2-trading schemes is relatively small compared with uniform schemes. The gain is large for the differentiation of R&D subsidies. When R&D subsidies are used as the sole climate policy, for example, their differentiation leads to a 13 percent welfare improvement over a 27-year time span relative to uniform R&D subsidies.

Chapter 6 also studies the implications of technology externalities for the cost effectiveness of climate policy, but focuses more on the energy sector of the Dutch economy. Specifically, I take the differentiated CO_2-trading schemes from Chapter 5 as a starting point, and study the cost effectiveness of combining these schemes with technology policy with respect to adoption of a specific CO_2 abatement technology and ultimately with respect to reduction of CO_2

emissions. I take CO_2 capture and storage in the Dutch electricity sector as a case study of a specific CO_2-abatement technology. CO_2 capture and storage is a process consisting of the separation of CO_2 from industrial- or energy sources and the transport to a storage location where the CO_2 is isolated from the atmosphere. Possible storage locations include geological formations such as saline aquifers or oil- and gas fields. I discuss the techno-economic data relating to this abatement technology as well as its incorporation into the DOTIS model. I subsequently construct additional simulations to reveal the cost-effective set of policies to achieve a 40 percent emission reduction relative to the reference case. This emission reduction approximates the stabilization of CO_2 emissions at 1990 levels for the Netherlands, as agreed upon in the Kyoto protocol while assuming similar post-Kyoto targets. Technology policy now takes the form of adoption- or R&D subsidies.

As a result, I find that combining the CO_2 trading schemes with technology policy leads to faster adoption of CO_2 capture and storage and improves cost effectiveness of the emission reduction. Welfare improves as technology policy corrects for technology externalities that underlie non adoption of the CO_2 capture and storage. This result is robust to the use of adoption- or R&D subsidies as technology policy. Most cost effective in this model analysis is to combine the CO_2-trading schemes with optimally differentiated R&D subsidies because of the internalization of technology externalities throughout the economy. Welfare then improves by about 14 percent over a 32-year time span.

Policy perspective

The model analyses in this thesis show an important role for technology policy as part of climate policy. Yet, the difficulty is how to design such climate policy in reality. It has proven difficult, for example, to correct for technology externalities even without regard to emission reduction. Our best past efforts, patent protection and government funded R&D, leave us with significant underinvestment. The unrealized welfare gain from the technology externalities is evidence of that. To implement the cost-effective climate policies identified above requires that we introduce other technology policies than just government funding and intellectual property rights protection. In a similar vein, the model analyses in this thesis show that a CO_2 price that is differentiated to direct technical change and economic growth toward non-CO_2 intensive sectors is more cost effective than a uniform price. Again, the difficulty is how to design such climate policy in reality. Lobbying and other rent seeking activities, for example, are expected barriers on the way as policy differentiation opens more doors for lobbying firms to seek preferential treatment and avoid abatement costs. Thus, the present thesis shows ways forward for technology oriented climate policy, including the promotion of CO_2 capture and storage, but also indicates a need for more detailed analyses regarding the design of such climate policy.

Samenvatting

Economisch modelleren van gerichte technologische verandering: Een case studie voor vermindering van CO_2 emissies

Inleiding

Dit proefschrift presenteert een economische analyse van de rol die technologische verandering speelt voor het terugdringen van milieuvervuiling op een kosteneffectieve manier. Technologische verandering is het proces van het ontwikkelen en introduceren van nieuwe technologieën. Aangezien de kosten en baten van vermindering van de uitstoot van vervuilende stoffen afhankelijk zijn van de gekozen technologie, verschilt het potentieel van technologische verandering voor een kosteneffectieve reductie van vervuiling van technologie tot technologie. Het doel van dit proefschrift is te bestuderen hoe beleidsinstrumenten technologische verandering kunnen richten op die technologieën die het grootste potentieel hebben voor een kosteneffectieve reductie van vervuiling. In het kader van het klimaat probleem gebruik ik klimaatbeleid en vermindering van van koolstof dioxiode (CO_2) emissies verbonden aan het gebruik van energie als case studie.

Een eerste deel van de studie behandelt de determinanten van de richting van technologische verandering, waarbij speciale aandacht wordt geschonken aan de mogelijke rol die technologie-externaliteiten spelen in het proces van technologische verandering. Technologie-externaliteiten zijn kosten of baten voor andere partijen in de economie die samenhangen met technologische verandering, maar die niet in de technologie beslissing worden meegenomen en waarvoor geen financiele compensatie plaats vindt. Een voorbeeld is het weglekken van bruikbare kennis naar andere bedrijven in de industrie tijdens de ontwikkelingsfase van een nieuwe technologie. Ik behandel dit deel van de studie in hoofdstukken 2, 3 en 4. Een tweede deel van de studie behandelt de mogelijkheden van gerichte technologische verandering en mogelijke technologie-externaliteiten voor het ontwerpen van klimaatbeleid. Ik behandel dit deel van de studie in hoofdstukken 5 en 6. Tot slot geeft hoofdstuk 7 de belangrijkste conclusies weer, plaatst het beleid in perspectief, en geeft suggesties voor verder onderzoek.

Gerichte technologische verandering

Wat de richting van technologische verandering bepaalt wordt doorgaans niet duidelijk gemaakt in economische modelstudies van klimaatbeleid. Om er echter zeker van te zijn dat klimaatbeleid de technologische verandering in een kosten-effectieve manier op CO_2 emissie reductie richt, is het nodig om eerst de verschillende effecten uit te zoeken die optreden bij het richten van technologische verandering. Ook is het nodig de determinanten van de richting te begrijpen. Om tot zo'n begrip te komen, leid ik in hoofdstuk 3 deze determinanten af uit een economische model analyse van gerichte technologische verandering. Met name ontwikkel ik het 'Dynamics of Technology Interactions for Sustainability' (DOTIS) model, hetgeen een intertemporeel-dynamisch algemeen evenwichtsmodel is dat de relaties tussen energie, de snelheid en richting van technologische verandering, en de economie expliciet weergeeft. Tegelijkertijd test ik het model om te zien of het de richting van technologische verandering na de olieschok eind jaren zeventig in Nederland kan projecteren.

Mijn bevinding is dat de consumptie-kant van de economie belangrijk is voor de richting van technologische verandering. Met name de mate waarin consumenten bepaalde goederen door andere kunnen vervangen bepaalt de richting. De olieschok richt technologische verandering op goederen die nu relatief schaars zijn (intensief in het gebruik van olie als energie hulpbron) als de vervangingsmogelijkheden tussen goederen beperkt zijn. De schaarste geeft dan voldoende prikkels om technologieën te ontwikkelen die gebruikt kunnen worden in de productie van de nu relatief schaarse goederen. Vervangingsmogelijkheden tussen energie en de rest van de economie, bijvoorbeeld, zijn beperkt en de olieschok richt technologische verandering met name op de energiesector. De schaarste geeft echter minder van zulke prikkels als de vervangingsmogelijkheden tussen goederen toenemen. Er zijn dan meer prikkels om technologieën te ontwikkelen die gebruikt kunnen worden in de productie van de nu relatief overvloedige goederen (niet intensief in het gebruik van olie als energie-hulpbron), waarvoor uiteindelijk een grotere afzetmarkt bestaat. Als gevolg is de technologische verandering nu op deze goederen gericht. Er zijn bijvoorbeeld uitgebreide vervangingsmogelijkheden binnen de energiesector en de olieschok richt technologische verandering met name op die energiebedrijven die weinig of geen olie als energie-hulpbron gebruiken. Mogelijke technologie externaliteiten versterken tenslotte de bestaande richting van technologische verandering.

Met betrekking tot de technologie-externaliteiten zijn mijn bevindingen dat ze wel degelijk een rol spelen in technologische verandering en dat ze positief zijn. Aangezien technologie-externaliteiten per definitie niet in technologiebeslissingen worden meegenomen, leiden deze externaliteiten ertoe dat de marktwerking minder technologische verandering voortbrengt dan optimaal is voor de samenleving als geheel. Een overzicht van de relevante literatuur laat zien dat schattingen van het private rendement van technologische verandering tussen de 5 en 30 procent liggen en dat het sociaal rendement rond de 50 procent wordt geschat.

Constaterend dat de baten van technologische verandering geleidelijk over de tijd binnen komen, concentreert hoofdstuk 4 zich op het schatten van het sociaal rendement alsmede het tijdprofiel. In het bijzonder bestudeer ik vertraagde feedback in technologische verandering.

Deze feedback treedt op als vorige technologische veranderingen een effect hebben op huidige technologische verandering. Tot een bepaalde hoogte verwachten individuele bedrijven deze feedback niet en inzoverre is het een geaggregeerde schatting van de technologie-externaliteiten. Ik verken een methode voor empirische analyse van de feedback die gebaseerd is op de literatuur over productiviteit en efficiëntie-analyse. Ik demonstreer deze methode op een macroniveau, waarbij ik gebruik maak van productie data voor 25 OESO landen tussen 1980 en 1997.

Net als in de vorige literatuur is het mijn bevinding dat het sociaal rendement van technologische verandering groot is. Bovendien vind ik bewijs dat de baten zich over tijd uitstrekken met een vertraging tot en met acht jaar. Het feedback effect is sterk: Ik vind bijvoorbeeld dat een één procent toename in productiviteit die zes jaar geleden is toegeschreven aan technologische verandering nog tot een half procent toename leidt in de huidige bijdrage van technologische verandering aan productiviteitsgroei, *ceteris paribus*.

Beleid

Technologie-externaliteiten vormen een reden om de kosteneffectiviteit van klimaatbeleid te bestuderen als het de vorm aanneemt van traditioneel milieubeleid, technologiebeleid, of beide. Milieubeleid is hoofdzakelijk gericht op het terugdringen van CO_2 emissies, maar kan ook technologische verandering stimuleren. Technologiebeleid is daarentegen hoofdzakelijk gericht op het verschaffen van economische prikkels zodat de technologie-externaliteiten mee worden genomen in technologie beslissingen (d.w.z. internaliseren), maar kan ook gebruikt worden om CO_2 emissies te reduceren. Verder biedt differentiatie van klimaatbeleid tussen sectoren een mogelijkheid om de kosten effectiviteit verder te vergroten, inzoverre technologie-externaliteiten verschillen van sector tot sector.

Hoofdstuk 5 bestudeert deze gevolgen voor de kosteneffectiviteit van klimaatbeleid op het geaggregeerde niveau van een economie. Ik presenteer het DOTIS model en beschrijf de kalibratie van dit model voor de Nederlandse economie. Vervolgens ontwikkel ik simulaties om de kosteneffectieve set van milieu- en technologiebeleid te bepalen dat CO_2 emissies met 10 procent reduceert ten opzichte van het referentieniveau. Hierbij kijk ik ook naar de wenselijkheid om het beleid te differentiëren tussen CO_2-intensieve en niet-CO_2 intensieve sectoren. Milieu- en technologiebeleid nemen de vorm aan van respectievelijk CO_2 handelsystemen en subsidies voor research en development (R&D).

Mijn bevinding is dat de kosteneffectiviteit van de emissiereductie toeneemt als CO_2 handelsystemen gecombineerd worden met de R&D subsidies zodat beide instrumenten optimaal worden benut. Deze combinatie behaalt de emissiereductiedoelstelling terwijl het welvaart doet toenemen met ongeveer 27 procent over een periode van 27 jaar en productie verliezen in CO_2-intensieve sectoren voorkomt.

Afgezien van de keuze voor een bepaald beleidsinstrument is het mijn bevinding dat technologie-externaliteiten differentiatie rechtvaardigen van de beleidsinstrumenten tussen CO_2-intensieve en niet-CO_2 intensieve sectoren, zodaning dat de eerstgenoemde sectoren een relatief groter aandeel van de emissiereductie voor hun rekening nemen. Met betrekking tot de CO_2 handelsystemen houdt dit in dat er twee systemen zijn met als gevolg twee CO_2 (schaduw)prijzen, waarbij de hogere prijs voor de CO_2-intensieve sectoren geldt. Dit resultaat verschilt aanzienlijk van de standaard milieu-economische conclusie dat gelijke marginale kosten van emissiereductie tot een kosteneffectieve oplossing leidt. De intuitie achter dit resultaat is dat klimaatbeleid technologische verandering op de niet-CO_2 intensieve sectoren richt, met als gevolg dat er in deze sectoren nu relatief meer technologie-externaliteiten optreden en de alternatieve kosten van emissiereductie daarom hoger zijn in deze sectoren. De welvaartstoename voor gedifferentieerde CO_2 handelsystemen is relatief klein vergeleken met gelijke systemen. De welvaartstoename is groot voor de differentiatie van R&D subsidies. Wanneer de R&D subsidies bijvoorbeeld als het enige klimaatbeleid worden gebruikt, leidt de differentiatie tot een welvaartstoename van 13 procent over een periode van 27 jaar ten opzichte van gelijke R&D subsidies.

Hoofdstuk 6 bestudeert ook de gevolgen van technologie-externaliteiten voor de kosteneffectiviteit van klimaatbeleid, maar richt zich meer op de energiesector van de Nederlandse economie. Met name neem ik de gedifferentieerde CO_2 handelsystemen van hoofdstuk 5 als uitgangspunt en bestudeer vervolgens de gevolgen van het combineren van deze systemen met technologiebeleid voor de adoptie van een specifieke CO_2 reductietechnologie en uiteindelijk voor de kosteneffectiviteit van emissiereductie. Ik gebruik het afvangen van CO_2 in de Nederlandse electriciteitsector en het ondergronds opslaan daarvan als een case studie van een CO_2 reductietechnologie. Zoute aquifers en uitgeputte olie- en gasvelden zijn voorbeelden van mogelijke opslaglocaties. Ik beschrijf de techno-economische data van deze reductietechnologie alsmede de opname ervan in het DOTIS model. Ik ontwikkel vervolgens simulaties om de kosteneffectieve set van beleidsinstrumenten te bepalen teneinde de CO_2 emissies met 40 procent te reduceren ten opzichte van het referentieniveau. Deze emissie-reductie benadert de stabilisatie van CO_2 emissies in Nederland op het niveau van 1990, zoals afgesproken in het Kyoto verdrag. Technologiebeleid neemt nu de vorm aan van R&D subsidies en subsidies voor technologie-adoptie.

Mijn bevinding is dat het combineren van de CO_2 handelsystemen met technologiebeleid tot een snellere adoptie van de CO_2 afvang en opslag leidt en de kosteneffectiviteit van de emissiereductie verbetert. Welvaart neemt toe, aangezien het technologiebeleid de technologie-externaliteiten internaliseert. Ik vind deze resultaten ongeacht de keuze voor adoptie- of R&D subsidies als technologiebeleid. In deze model analyse is het meest kosteneffectief om de CO_2 handelsystemen te combineren met de optimaal gedifferentieerde R&D subsidies, vanwege de internalisatie van technologie-externaliteiten in de gehele economie. Welvaart neemt dan toe met ongeveer 14 procent over een periode van 32 jaar.

Beleidsperspectief

De modelanalyses in dit proefschrift laten zien dat technologiebeleid een belangrijke rol kan spelen als onderdeel van een breder klimaatbeleid. De moeilijkheid is echter om zo'n klimaatbeleid te realiseren. Het is bijvoorbeeld al moeilijk gebleken om technologie-externaliteiten te internaliseren zonder oog te hebben voor emissiereductie. Onze beste pogingen tot nu toe, octrooibescherming en van overheidswege gefinancierde R&D, leiden nog steeds tot te weinig technologische verandering vergeleken met wat optimaal zou zijn voor de samenleving als geheel. De niet gerealiseerde welvaartstoenames die verband houden met de technologie-externaliteiten zijn daarvan het bewijs. Om het hierboven vermelde kosteneffectieve klimaatbeleid uit te voeren is het vereist dat we ook ander technologiebeleid dan enkel overheidsfinanciering en bescherming van intellectuele eigendomsrechten introduceren. Op een zelfde manier laten de model analyses in dit proefschrift zien dat gedifferentieerde CO_2 prijzen ten gunste van de niet-CO_2 intensieve sectoren de kosteneffectiviteit van een bepaalde emissiereductie verbetert ten opzichte van gelijke CO_2 prijzen. Opnieuw is het de moeilijkheid om zo'n klimaatbeleid daadwerkelijk te realiseren. Beleidsdifferentiatie is vatbaar voor lobbyen en andere activiteiten om voorkeursbehandelingen te krijgen zonder dat er economische waarde wordt toegevoegd ('rent seeking'). Dit proefschrift laat dus zien hoe een technologisch-georiënteerd klimaatbeleid er uit kan zien, maar geeft tegelijkertijd ook aan dat meer gedetailleerde studies omtrent het ontwerpen van zulk klimaatbeleid nodig zijn.

Chapter 1 Introduction

1.1 Introduction

This thesis presents an economic analysis of the role of technical change in combating environmental problems in a cost-effective manner. Technical change is the process of developing and introducing new techniques. To play a role in environmental management, technical change must be directed towards changing specific attributes of the technologies applied in polluting processes in the economy. A power plant equipped with a new pollution abatement technology, for example, will emit less pollution per kWh electricity generated than a power plant equipped with an old or without abatement technology. Technical change aimed at improving either the technical ('lower emissions') or the economic performance ('lower costs') of abatement applied at such processes will potentially decrease the environmental pressures.

Treatment of technical change within an economic model is based on the observation that economic incentives can induce firms to undertake research and development (R&D) and direct these activities to produce less costly pollution abatement techniques. As such, technical change can be evaluated as a profit-motivated investment activity and policy instruments now offer the opportunity to direct technical change by changing relative costs. A pollution tax, for example, might induce the owners of the power plant to equip it with the new pollution abatement technology, by increasing costs of not implementing abatement. Obviously, the potential of technical change for cost-effective pollution abatement typically differs from technology to technology, since both costs and abatement potentials are technology dependent. It therefore is the aim of this thesis to study how policy instruments can direct technical change to those technologies with the greatest potential for cost-effective abatement.

In the light of the climate change problem, this thesis uses reduction of carbon dioxide (CO_2) emissions associated with energy use as a case study. CO_2 is the greenhouse gas that the Intergovernmental Panel on Climate Change (IPCC) has concluded is most responsible for increased climate forcing over the past 150 years (IPCC, 2001). Without significant policy, CO_2 emissions are expected to grow during the 21st century. Most of these emissions are associated with combustion of fossil fuels used throughout the economy (IPCC, 2001). Since fossil fuels are expected to remain a substantial part of the primary energy sources, CO_2 emissions from combustion of these fuels might be an important environmental drawback of increasing energy demand in a growing economy.

One option to abate CO_2 emissions is aiming at the decrease of the CO_2 emission factor, representing the ratio between the fossil fuel combusted and the resulting emissions. Apart from changing fuel quality, needing hardly any technical change, an important technology available in this respect is CO_2 capture and subsequent storage in permanent reservoirs (see IPCC, 2005).

CO_2 capture can occur both pre-combustion when high carbon content fuels are transformed in low carbon content fuels or even hydrogen, or post combustion by capturing flue gasses in smoke stacks. Other abatement options, aimed at lowering the energy use of production processes, include increased efficiency of production processes, process-integrated measures such as input substitution, changes in the fuel mix, as well as reduction of economic activity.

This chapter is organized as follows. Section 1.2 provides the background necessary for understanding how policy instruments can direct technical change to those technologies with the greatest potential for cost-effective abatement. As such, this section includes brief discussions on the climate change problem, the treatment of technical change in economics in general and in economic models of climate policy in particular, and the possibilities to direct technical change toward emission reduction. Section 1.3 defines the research problem and Section 1.4 develops the concomitant research questions. Section 1.5 briefly describes the methodology used to answer these questions and Section 1.6 outlines the structure of the thesis.

1.2 Background

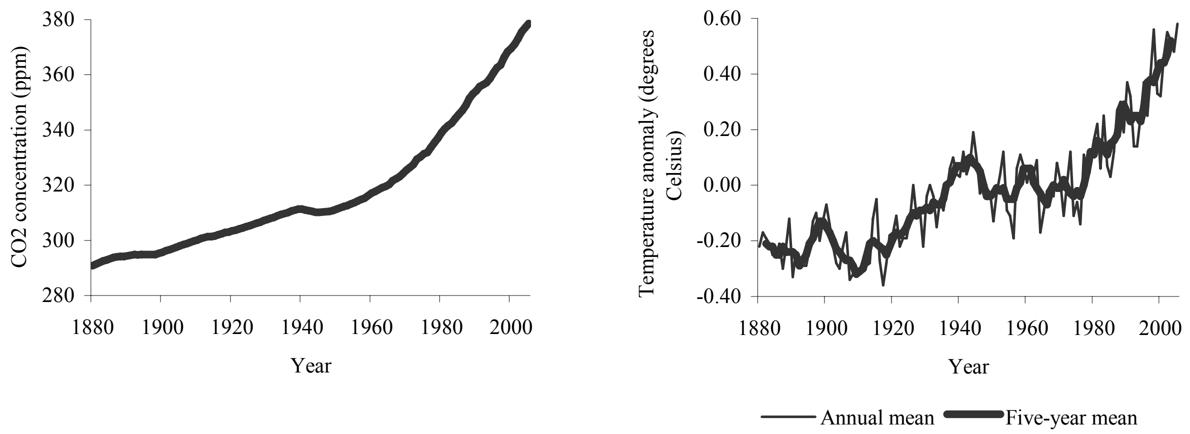
Climate change problem

Since the early 1990s, climate change has moved high up on the political agendas, both internationally and domestically in many countries. 189 nations have ratified the United Nations Framework Convention on Climate Change (UNFCCC, 1992), an international environmental agreement aiming at

> "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system to be achieved within a time-frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened and to enable economic development to proceed in a sustainable manner (Article 2)".

Since the early days of industrialization, the heat-trapping capacity of the atmosphere seems to be increasing, leading to a gradual increase in average global temperature ('climate forcing'). Temperature increase now appears to be at a level that cannot be attributed to natural variations (IPCC, 2001). Since CO_2 has a strong radiative absorption in the infrared range of the spectrum and is transparent in the visible range, this gas plays an important role in the heat balance of the atmosphere. Fossil fuel combustion, basically the chemical transformation of carbon and hydrocarbons to CO_2 and water, increased dramatically over the past 150 years leading to a gradual increase of CO_2 concentrations in the atmosphere. This in turn is believed to be a main contributor to higher temperatures (see Figure 1.1). Destruction of carbon stocks present in biomass has also been a substantial source of atmospheric CO_2 although most projections indicate that by far the largest contribution to rising CO_2 concentrations will be combustion of fossil fuels (IPCC, 2001).

Figure 1.1 Indicators of the climate change problem



(a) Atmospheric CO_2 concentrations (ppm) (b) Temperature change (degrees Celsius)

Note: Temperature anomaly is the deviation in temperature from the average temperature in the 1951-1980 period.

Source: Goddard Institute for Space Studies (http://data.giss.nasa.gov)

The UNFCCC has set a goal of stabilization of greenhouse gas concentrations in the atmosphere with the intent of stopping the increase of climate forcing. This can only be done by reducing CO_2 emissions substantially below current levels and eventually to near zero. Such large emission reductions are needed because the lifetime of CO_2 in the atmosphere spans many decades (IPCC, 2001).

Because energy consumption is central to almost all economic processes and fossil fuels are still an abundant and relatively cheap source of primary energy, CO_2 emission reductions are difficult to achieve. Indeed, energy demand is still increasing globally (IPCC, 2001). Consequently, increasing amounts of fossil fuel carbon are oxidized to CO_2 and emitted into the atmosphere. Without additional measures, global CO_2 emissions are projected to increase substantially during the 21st century (IPCC, 2001).

In this thesis, I adopt an economic perspective to study the climate change problem and to identify possible pathways towards solutions via technical change. In this economic perspective, the atmosphere is a common property resource. In the absence of a price for CO_2 emissions, individual agents have no incentive to limit use of the atmosphere for disposal of CO_2. The standard economic policy prescription in such a situation is to price CO_2 emissions so to take into account the damage they cause for other agents in the economy. Emitting agents, facing these CO_2 prices, would then undertake emission abatement. The damage costs, as far as these are not reflected in the price of emissions, are said to constitute a 'negative external effect' and are henceforth referred to as the 'climate externality'.[1] If there indeed is a climate externality, CO_2 concentrations in the atmosphere increase more than is optimal for all agents in the economy together.

Environmental-policy instruments that are available to the policy maker include direct regulation, commonly referred to as *command-and-control* instruments, and *market-based instruments*. Both instrument types provide agents with incentives to reduce their CO_2 emissions. Command-and-control instruments include standards, such as performance- or technology standards, providing varying degrees of flexibility in meeting the standard. A performance standard, for example, would merely set an emissions limit leaving the decision of how to achieve the limit up to the polluter whereas a technology standard would dictate the exact technology to be used.

Market-based instruments essentially are price instruments, such as taxes and trading schemes, providing maximum flexibility in the internalization of the climate externality by leaving the precise allocation of the abatement burden as well as the choice of technology up to market forces and thus encouraging cost-effective or efficient abatement. A carbon tax, for example, adds the climate externality to the agents' marginal costs of abating CO_2 emissions and relies on profit maximization for achieving the abatement target. A CO_2-trading scheme sets the abatement target and relies on trade between agents for the precise allocation of the abatement burden, as currently occurs in the EU Greenhouse Gas Emission Trading Scheme.

Both command-and-control and market-based instruments aim to correct or 'internalize' the climate externality (Baumol and Oates, 1988). Much work in economics has therefore investigated their cost-effectiveness and efficiency.[2] These instruments differ along other lines as well, such as regulatory- and administrative burdens, information- and monitoring requirements, and adaptability. A general conclusion is that under most circumstances market-based instruments are more efficient or cost effective (see for a comprehensive comparison Harrington *et al*., 2004).

[1] Formally, an 'external effect' or 'externality' is the effect of actions by an agent in the economy on another agent's well-being or production possibilities for which no compensation takes place (Mas-Colell *et al*., 1995). An externality can be either positive when an external benefit is generated or negative when an external cost is generated.

[2] Taxes and trading schemes can be shown to be equally efficient instruments if there is certainty regarding the marginal costs of damages and abatement. If there is uncertainty regarding the marginal costs, however, the curvature of the marginal cost functions determine the economic attractiveness of taxes and trading schemes as instrument (see Weitzman, 1974, for the original discussion). In the trading schemes, trade only occurs if demand for the emission permits is higher than their supply. The number of permits is set by government action and trading schemes therefore have a command-and-control element.

Technical change

In the economics literature, technical change is defined as the development and introduction of new techniques of converting inputs into outputs such that with the same inputs, more outputs can be produced than previously was feasible, or that the same amount of output can now be produced with fewer inputs. Inputs or outputs can be aggregated, in which distinct inputs and outputs are each weighted by their relative value as measured by their market price. As an example of technical change, the development of new electricity generation technologies might allow power plants to generate electricity with less labor, physical capital or energy inputs than before. A technique becoming feasible is what distinguishes technical change from substitution. If these electricity generation technologies would have been used before, for example, their current use would merely constitute substitution of one technology by another or substitution between inputs. In the context of a production function, technical change is defined as 'neutral' if the required inputs for a given level of outputs decrease proportionally, say 10 percent less labor, physical capital and energy. Technical change is defined as 'biased' if the input requirements decrease more for some inputs than other. For example, the same amount of labor and physical capital is used but 10 percent less energy input. As such, biased technical change means that the relative productivity of inputs changes.

Economic theories of technical change can be traced back to Schumpeter (1942), who distinguished the invention, innovation and diffusion phases of technical change. Invention is the development of a new or improved product or process, and innovation is the commercialization of an invention. Together, invention and innovation are usually referred to as R&D. Diffusion then occurs when the innovation is successful and gains market share. In (neoclassical) economics, it is common to view invention, innovation and diffusion as special types of investment activities that firms undertake to maximize their profits.

Specific properties of these investment activities secure that they are not regular investment activities. One property is that knowledge generated by these investment activities is nonrival in that use of the knowledge by one agent does not preclude its use by another agent. Once the knowledge is generated for one technology, the knowledge can be used over and over again for other technologies at no additional cost (Romer, 1990). Another –related– property is that these investment activities are prone to technology externalities in that these activities entail costs or benefits to other agents in the economy for which no financial compensation takes place. The nonrival knowledge, for example, 'spills over' to other agents (Griliches, 1979). Network externalities are another example existing if adoption of a product or process by some users causes the value of adopting compatible products or processes to increase (Katz and Shapiro, 1986). Empirical evidence suggests that overall technology externalities are positive (Griliches, 1992). As a consequence, the investor does not receive some or all of the returns to technical change and is therefore likely to underinvest relative to what is optimal for society as a whole (Spence, 1984).

In economic models of climate policy, technical change has for long been treated as an exogenous variable driving economic growth (Löschel, 2002). Economic activities then have no effect on technical change. Besides assuming a certain percentage improvement in overall productivity, these models typically introduce exogenous technical change by a parameter reflecting autonomous energy efficiency improvements or by including exogenously provided specific energy technologies that have already been invented but that are not yet commercial (often referred to as 'backstop' technology) (Azar and Dowlatabadi, 1999). Examples of backstop technologies include renewable energy technologies such as photovoltaics and wind, and CO_2 abatement technology such as CO_2 capture and storage (see, for example, Manne *et al.,* 1995; and Paltsev *et al.*, 2005).

A newer generation of economic models of climate policy, however, has tried to draw on the insights from the economic literature as discussed above. Such models of climate policy introduce learning or knowledge spillovers in one form or another, or specify investment variables for R&D, or both (see Azar and Dowlatabadi, 1999; and Löschel, 2002, for surveys). The result is that economic activities now have an effect on technical change. Yet, the new generation of these models comes with new difficulties because the process of technical change is complex and its empirical foundation is still weak (Löschel, 2002).

Directing technical change

Modeling technical change as a profit-motivated investment activity implies that the model can be used to analyze possibilities to induce or direct technical change by economic activities or policy instruments. Specifically, 'induced' or 'directed' technical change refers to the notion that changes in relative (factor) prices affect the rate or bias of technical change, or both. In this thesis, I use both concepts interchangeably. As first articulated by Hicks (1932, p.124): "A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind –directed to economizing the use of a factor which has become relatively expensive". Indeed, several studies have shown that the introduction of environmental policy implicitly or explicitly makes environmental inputs more expensive and induces technical change aimed at economizing the use of these inputs (Jaffe *et al.,* 2002a). The CO_2-trading schemes, for example, put a price on CO_2 emissions and hence provide incentives for the development and adoption of CO_2 abatement technologies. Induced technical change in turn has the potential to reduce abatement costs (see Löschel, 2002, for an overview of the effects of induced technical change on environmental policy design).

The presence of technology externalities has led some to argue that technology policy, aimed at internalizing the technology externalities, should complement or substitute for environmental policy to make climate policy as an economy-wide response to the climate externality more cost effective (see *e.g.* Goulder and Schneider, 1999; Fischer and Newell, 2004; and Popp, 2004a). In practice, however, it is difficult to sort out possible interaction effects of policy instruments. For example, a R&D subsidy may internalize technology externalities and induce development of cleaner technology throughout the economy but, by increasing welfare, may also lead to more CO_2 emissions, which in turn would require more stringent environmental policy. If the policy interactions are taken into account in an economic model, it can be studied under which conditions both policies are cost-effective and hence what roles both policies should play as part of a climate policy.

Finally, the extent to which there are technology externalities might differ from sector to sector, possibly affecting the overall costs of environmental policy. If this is the case, differentiating policies between sectors might be an option to increase cost efficiency and might be a means of directing technical change. Using cost-minimization models, Rosendahl (2004) and Bramoullé and Olson (2005) show that this might be the case and that the cost-effective or efficient carbon tax for technologies enjoying relatively high technology externalities is *higher* than a uniform carbon tax. As the technology externalities reduce marginal abatement costs in their models, these costs now differ between technologies. Agents do not take the cost reductions into account and overall costs can therefore be saved by letting those technologies enjoying relatively high technology externalities bear relatively more of the abatement burden.

1.3 Problem definition

Recognizing the importance of reducing CO_2 emissions associated with energy use for the climate change problem and the role that technical change can play in this, the present thesis has the objective to contribute to economic modeling of directed technical change such that CO_2 emissions associated with energy use are reduced and climate policy becomes more cost effective. I pay specific attention to the potential role that technology externalities play in the process of technical change. For this reason, the thesis deals with technology policy in conjunction with CO_2-trading schemes as climate policies. Finally, I focus attention on application of the modeling approach for the Netherlands and in particular its energy sector.

1.4 Research questions

To achieve the objective, I will deal with the following research questions in this thesis.

Q1 What are the determinants of the direction of technical change?

To ensure that climate policy directs technical change toward CO_2 emission reduction in a cost effective manner, it is necessary to first disentangle the various effects that are at play when directing technical change and understand the determinants of the direction. To come to such an understanding, I derive these determinants using an economic model analysis of directed technical change.

Q2 Do technology externalities play a role in technical change?

Technology externalities are a key issue in that their possible presence and magnitude determine the extent to which agents are likely to underinvest in technical change. Given the concomitant implications for the design of technology- and environmental policy as well as for the possible impacts that these policies have throughout the economy, it is necessary to have an understanding of the extent to which there are technology externalities. Besides their magnitude, I pay specific attention to the duration of technology externalities in dealing with this question.

Q3 Which policy instruments can direct technical change such that CO_2-emission reduction becomes more cost effective?

If technology externalities do indeed play a role, there might be a rationale from a welfare perspective for technology policy to complement or even replace traditional environmental policy as preferred policy to reduce CO_2 emissions. The third research question therefore concerns the possibilities of directed technical change and possible technology externalities for the design of climate policy. Specifically, I first study cost effectiveness of climate policy if it takes the form of CO_2-trading schemes or R&D subsidies, or both. I subsequently study whether differentiation of climate policy across sectors will make the CO_2 emission reduction more cost effective. The answer to this research question will provide insight regarding cost-effectiveness of the allocation of emission reduction across sectors as well as the role that R&D subsidies ideally could play. In dealing with this research question, I apply the economic model analysis to the Dutch economy.

Q4 Which policy instruments induce adoption of a specific CO_2-abatement technology such that CO_2-emission reduction is cost effective?

The fourth research question deals with potential adoption of a backstop technology at a disaggregated level. CO_2 capture and storage as a specific CO_2-abatement technology in the Dutch electricity sector is taken as a case study. I take differentiated CO_2-trading schemes as a starting point and study cost implications of combining these schemes with several technology policies with respect to adoption of the CO_2 abatement technology and ultimately with respect to abatement of CO_2 emissions. Such cost implications might lead to a more cost-effective CO_2 emission reduction. I consider R&D and adoption subsidies as technology policies.

These research questions are of practical relevance. The European Union has introduced an emission trading scheme as a strategy for member states to fulfill their emission reductions agreed upon in the Kyoto Protocol of the UNFCCC. The Bush Administration, however, has taken the United States out of the Kyoto Protocol and instead adopted a technology policy that includes support for R&D as an alternative strategy. Answers to these research questions provide insights which will assist policy makers in designing strategies and measures to direct technical change away from CO_2 emissions associated with energy use. Not merely general insights regarding how to use technical change for sustainable development, but also more specific insights as to which policy instruments to use and which technologies or industries to focus abatement on.

1.5 Methodology

To answer these research questions, I use computational experiments using economic models as research method, which involves the following three steps: (i) use theory to build a model economy; (ii) calibrate the model economy such that it reflects important characteristics of the real economy as closely as possible; and (iii) design the model for experiments that answer the research questions set out above (Kydland and Prescott, 1996).

First, theory is used in the construction of a model economy. I take general equilibrium theory and in particular, its workhorse, the computable general equilibrium (CGE) model as a starting point. This theory is well-tested and CGE models have been shown to give reliable answers to a wide class of questions (Mas-Colell *et al.*, 1995). In general equilibrium theory, the economy is viewed as an interrelated system of markets in which equilibrium values of all prices and quantities are determined simultaneously. If one wants to analyze economic effects of instruments that affect many markets simultaneously, such as the policy instruments under study, linkages across markets cannot be ignored and general equilibrium theory becomes essential. Specifically, I develop the 'Dynamics of Technology Interactions for Sustainability' (DOTIS) model, which is an intertemporal dynamic CGE model that builds on Acemoglu's (2002) model of directed technical change. DOTIS explicitly captures links between energy, the rate and direction of technical change and the economy. I calibrate the model to the Dutch economy, and in particular its energy sector, and subsequently test the model to see if it is able to project the direction of technical change following the oil shock in the late 1970's. I 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).

Second, DOTIS is calibrated so that it reflects characteristics of the current Dutch economy as closely as possible along key dimensions, which relate to energy and technical change in this thesis. Therefore, I pay specific attention to the calibration of technologies and in particular those in the energy sector. Further, I study delayed feedback in technical change in detail given a relative lack of information. There is delayed feedback if previous technical change has an effect on today's technical change (Arthur, 1990). To a certain extent, individual agents do not take this feedback into account and as such it sheds light on the magnitude and duration of technology externalities. Specifically, I explore a particular route for empirical analysis of feedback in technical change based on the literature of productive efficiency analysis.

Finally, I perform experiments with the DOTIS model that take the form of policy simulations, in which I compare equilibrium paths of the economy with the various policy shocks to the equilibrium path of the economy without the shocks. I subsequently map effects of the shocks on welfare. This way, cost-effective policies can be identified, of which I present the economic impacts.

1.6 Outline of the thesis

Chapter 2 provides a brief overview of the relevant literature to see how technical change is treated in both economic theory and economic models for climate policy and provides entry points for further reading.

Chapter 3 presents a stylized version of the DOTIS model building on Acemoglu's (2002) model of directed technical change. In DOTIS, technology is modeled as knowledge capital, which is an investment good and which leads to technology externalities. The determinants of the direction of technical change are derived and at the same time it is shown how the model can be used in thinking about directed technical change by testing the model to see if it is able to project the direction of technical change following the oil shock in the late 1970's in the Netherlands.

Chapter 4 outlines a two-stage estimation procedure for the delayed feedback effect in technical change. The first stage of the estimation procedure involves nonparametric data envelopment analysis whereas the second stage involves a panel data model with finite distributed lag structure. The two-stage estimation procedure is then illustrated and applied at the macro level using aggregate production data of 25 OECD countries for the years 1980 through 1997.

Chapter 5 presents the DOTIS model and discusses its calibration to the Dutch economy, in which availability of investment data for knowledge capital that is consistent with the national accounting framework allows for special attention to the accounting of knowledge capital. Simulations are constructed to reveal the cost-effective set of climate policies, including the desirability of differentiating the policies between CO_2-intensive and non-CO_2 intensive sectors. Subsequently, it is studied how the policies direct technical change and what the economic impacts are in the rest of the Dutch economy.

Chapter 6 presents the DOTIS model with CO_2 capture and storage as a specific CO_2-abatement technology in the Dutch electricity sector. Techno-economic data related to the CO_2 capture and storage technology is discussed as well as its incorporation into the DOTIS model. Additional simulations are subsequently constructed to reveal the cost-effective set of climate policies with respect to adoption of the CO_2 capture and storage technology and ultimately with respect to abatement of CO_2 emissions.

Finally, Chapter 7 summarizes the answers to the research questions and provides concluding remarks, policy recommendations as well as suggestions for future research.

Chapter 2 Economics of technical change and the environment

2.1 Introduction

The economic literature on technical change is vast and diverse. Topics that have received ample attention include: the measurement and analysis of productivity growth (see *e.g.* Jorgenson, 1995; and Griliches, 1998); incentives for research and development (see *e.g.* Nelson and Winter, 1982; Tirole, 1988; and Griliches, 1998); the measurement and analysis of externalities resulting from research and development (see *e.g.* Griliches, 1992); adoption of new technologies (see *e.g.* Geroski, 2000); and the role of technical change in economic growth (see *e.g.* Romer, 1994; and Grossman and Helpman, 1994).

This chapter provides a brief overview of this literature, in particular as far as it relates to the environment or to environmental policy (see Jaffe *et al.,* 2002a; 2002b, for more elaborate surveys). It enables us to place the current thesis in the literature. Section 2.2 provides a conceptual framework that economists often use when thinking about technical change. Section 2.3 discusses the literature dealing with the hypothesis that environmental policy can induce or direct technical change in an environmentally friendly direction. Section 2.4 analyzes the role of technical change in macroeconomic growth theories and models. Section 2.5 reviews how technical change is accounted for in economic models of climate policy. Finally, Section 2.6 indicates how this thesis contributes to the analysis of technical change and the environment.

2.2 Conceptual framework

The concept of technical change can easily be understood with help of the production possibility frontier

$$Y = f\left(K, L, E, M, t\right) \tag{2.1}$$

in which Y is aggregate output, K, L, E, M are inputs (respectively physical capital, labor, energy and intermediate inputs, although more inputs can be included) and t notates time. Technical change is then defined as the development and introduction of new techniques of converting inputs into outputs over time, such that more outputs can be produced with the same inputs or that fewer inputs are needed to produce the same amount of output. Inputs or outputs can be aggregated, in which distinct inputs and outputs are each weighted by their relative value as measured by their market price.

To gain further understanding, we take logarithms of both sides of equation (2.1) and totally differentiate to get

$$\hat{Y}=\beta_K\hat{K}+\beta_L\hat{L}+\beta_E\hat{E}+\beta_M\hat{M}+\beta_t\hat{t} \tag{2.2}$$

in which the hats denote percentage growth rates of the variables and the β's represent output elasticities. The last term on the right represents the rate of growth after growth of the various production factors has been accounted for and as such β_t corresponds to 'neutral' technical change. Relative productivity of the production factors can also change if their respective β's change over time, giving rise to 'biased' technical change.

The process of technical change

Equations (2.1) and (2.2) reveal nothing about the sources of technical change. For that, we need to turn to economic theories of technical change, which can be traced back to Schumpeter (1942), who thought of technical change as a process comprising the phases of invention, innovation and diffusion. Invention is the development of a new or improved product or process, and innovation is the commercialization of an invention. Invention and innovation are viewed as intentional investment activities that firms undertake to maximize their profits and are usually referred to jointly as research & development (R&D). Diffusion then occurs when the innovation is successful and gains market share as a result of firms' rational investment decisions regarding adoption of the innovation.

Specific properties of these investment activities, however, secure that they are not regular investment activities. One property is that knowledge generated by these investment activities tends to be nonrival in that use of the knowledge by one firm does not preclude its use by another (Romer, 1990). A new design of an airplane wing or an organizational structure of a firm, for example, both constitute knowledge that might be generated for one firm but that is difficult to protect and can therefore be used over and over again by other firms at no or little additional cost if it is not protected by patents.

Another –related– property is that these investment activities are prone to technology externalities in that these activities entail costs or benefits to other agents in the economy for which no financial compensation takes place. The nonrival knowledge, for example, 'spills over' to other agents for free (Griliches, 1979). Network externalities are another example that exist if adoption of a product or process by some users causes the value of adopting compatible products or processes to increase (Katz and Shapiro, 1986). The telephone is a classic example: A single telephone is useless to its user but the value of every telephone increases with the total number of telephones in the network. An example of a negative technology externality is the rent-stealing effect, which exists if the expected profits by one firm undertaking R&D are reduced because of another firm undertaking R&D (Mankiw and Whinston, 1986). The invention of the

VHS standard for video cassette recorders, for example, significantly reduced expected profits of R&D related to the Betamax standard. Empirical evidence, however, suggests that overall technology externalities are positive (Griliches, 1992). As a consequence, the investor does not appropriate some or all of the returns to technical change and is therefore likely to underinvest relative to what is optimal for society as a whole (Spence, 1984). Indeed, studies show that the social returns to R&D are bigger than the private returns (see *e.g.* Mansfield *et al.*, 1977; Pakes, 1985; Jones and Williams, 1998; and Baumol, 2002).

2.3 Induced technical change

Considering technical change as a profit-motivated investment activity implies that it can be induced or directed by economic activities or policy instruments. Specifically, 'induced' or 'directed' technical change refers to the notion that changes in relative (factor) prices affect the rate or bias of technical change, or both. In this thesis, we use both concepts interchangeably. As first stated by Hicks (1932): "A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind –directed to economizing the use of a factor which has become relatively expensive" (p.124).[1] Relative output prices matter as well. In fact, demand-side factors become relatively more important when a technology moves through the phases of technical change (Jaffe *et al.*, 2002b). Inventions are done with the objective to find cheaper and better technologies, innovations are undertaken when sales are anticipated and technologies are adopted when they are expected to be used.

Interaction between technology externalities on the one hand and environmental externalities on the other provides a justification to induce or direct technical change toward reducing environmental pollution. The bigger the environmental problem is and the longer it is expected to last, the more important it becomes to induce such technical change. Technology policy, aimed primarily at internalizing technology externalities, has been proposed as a suitable instrument for this purpose. Carraro and Siniscalco (1994) propose a combination of environmental- and technology policy and show that R&D subsidies can be used to attain the same environmental target as environmental policy can, but without the reduction in output that accompanies the latter policy. Goulder and Schneider (1999) do not make such a strong claim, but do show that an optimal climate policy combines an environmental policy to internalize the environmental externality with an R&D subsidy to internalize the technology externalities. Using data on the diffusion of thermal insulation in new home construction in the USA, Jaffe and Stavins (1995) find that technology adoption subsidies have significantly greater effects on the diffusion of thermal insulation than energy taxes.

[1] Yet another closely related concept is 'endogenous' technical change, which is similar in content but is primarily used as a modeling concept. Specifically, endogenous technical change refers to the notion that technical change is explained within a scientific model (see Section 2.4 below).

Environmental policy, aimed primarily at internalizing environmental externalities, also has the potential to induce technical change aimed at reducing environmental pollution. Indeed, the incentives provided by environmental policy instruments for technical change that reduces environmental pollution have for long been proposed as one of the most important criteria in the instrument choice (Kneese and Schultze, 1975). There is a consensus in the literature that market-based instruments are typically more effective in inducing such technical change than command-and-control instruments (Jaffe *et al.*, 2002a; Requate, 2005). Command-and-control instruments essentially are forms of direct regulation, such as performance- or technology standards, and as such can in principle be designed to induce technical change. Performance standards, for example, can require performance levels that currently are not yet feasible and technology standards can require the use of technologies that have been invented but are not yet in use. A problem with these instruments is that it is difficult for the regulator to know exactly how tight to design the standard and these instruments therefore tend to be either unambitious or too tight (Jaffe *et al.*, 2002b). Market-based instruments essentially are price instruments, such as taxes and trading schemes, and in contrast to command-and-control instruments, have strong potential to induce technical change. A tax on carbon dioxide (CO_2) emissions, for example, directly adds to the cost of production and hence continues to provide incentives for the development and adoption of new technologies that reduce CO_2 emissions until it becomes cheaper to pay the tax instead. We classify the effects of environmental policies on technical change according to its invention, innovation, and diffusion phases.

Invention and innovation

There have been many theoretical studies that compare various environmental policies with respect to their effect on innovation (see Jaffe *et al.,* 2002b; and Requate, 2005, for more comprehensive surveys). Dating back to the 1970's, Magat (1978) develops a model of induced innovation and shows that emission taxes and standards have distinctly different implications for innovation of abatement technology. In a later study, Magat (1979) includes more policy instruments in the comparison and shows that all instruments direct innovation toward abatement technology although technology standards provide the weakest incentives. Two decades later, Ulph (1998) also studies emission taxes and standards and finds that their net effects on R&D are ambiguous because of two competing effects. There is both a direct effect of increased costs, which provides incentives to develop new abatement technologies, and an indirect effect of reduced output, which reduces these incentives because there now is a smaller output market. Fischer *et al.* (2003) compare taxes and two types of permits (grandfathered and auctioned) and find that all instruments can induce innovation, although the differences between instruments are too complex to conclude that one instruments induces more innovation than another. Similar conclusions are made under noncompetitive circumstances. Montero (2002) compares permits and emission- and performance standards under oligopolistic competition and finds that firms do no longer take only a positive effect of induced innovation on profits into account because of lower marginal abatement costs, but also a negative effect because of changes in output levels of competitors due to knowledge spillovers.

There exist ample empirical studies as well, despite the difficulty to obtain good data on environmental policies and innovation. Shadow prices of pollution are perhaps the ideal indicator of environmental policies but are difficult to observe (Jaffe *et al.*, 2002a). Empirical studies therefore use various proxies, such as pollution abatement expenditures and energy prices. Using case studies instead, Porter and van der Linde (1995) show that the introduction of environmental regulation can lead to the development of new technologies leaving firms actually better off. This is a disputed outcome, however, and most subsequent studies use statistical- or econometric tools to analyze the effects of environmental policies on innovation (Jaffe *et al.*, 2002a).

The empirical evidence that these studies yield, generally shows that the proxies for environmental policy have a positive effect on innovation aimed at reducing pollution. Lanjouw and Mody (1996) find that pollution abatement expenditures are associated with increased rates of patenting in related technical fields. Using panel data at the industry level, Jaffe and Palmer (1997) do not find a significant and positive effect of pollution abatement expenditures on patenting, although the positive effect is significant if R&D expenditures are used as proxy for innovation instead. Using data on product characteristics of several energy-using goods, Newell *et al.* (1999) find that although changes in energy prices or energy-efficiency standards have no significant effect on the overall rate of innovation, they do have a significant and positive effect on energy-saving innovation. More specifically, they find that innovations in air conditioners were energy using when real energy prices were falling in the 1960's but that such innovations became energy saving after the oil shocks of the 1970's. Popp (2002) uses patent data of several energy technologies and shows that patent applications for these energy technologies respond rapidly to energy price increases. He finds, for example, significant increases in patenting for renewable energy technologies during the energy crises of the 1970's. In a subsequent study, Popp (2003) uses the introduction of the Clean Air Act of 1990 in the USA to compare innovation in flue gas desulphurization units (scrubbers) under a technology standard and a sulfur dioxide trading scheme. He finds that although total innovation decreased after the introduction of the Clean Air Act, innovations that increased the removal efficiency of the scrubbers increased.

Diffusion

Theoretical studies comparing various environmental policies with respect to their effect on diffusion typically use a discrete-choice model: Firms consider the adoption of a particular innovation that reduces marginal abatement costs, but that also entails an up-front cost. Using such a model, Milliman and Prince (1989) find that all environmental policies under study induce firms to adopt pollution control technology. Command-and-control policies usually provide less of these incentives. In a subsequent study, Milliman and Prince (1992) show that their results are robust to heterogeneous abatement costs among firms. More recently, Jung *et al.* (1996) extend the analyses by Milliman and Prince from the firm to the industry level and find very similar results. Requate and Unold (2003) confirm that all environmental policy instruments under study induce firms to adopt pollution control technology, but challenge the previous studies by showing that equilibrium considerations must be taken into account when studying induced diffusion. Their critique especially applies to tradable permit schemes: As diffusion lowers the equilibrium price of a permit, it reduces the incentives (for other firms) to adopt additional pollution abatement technology. Finally, van Soest (2005) takes adoption of energy-saving technologies at unknown future dates as given and analyzes the effects of environmental policy instruments on the timing of adoption. He finds that increased stringency of the instruments does not necessarily induce early adoption as the option value of waiting for the arrival of an even better technology increases.

Empirical evidence on induced diffusion generally confirms that environmental policies provide incentives for adoption of new technologies aimed at reducing environmental pollution. Rose and Joskow (1990) use data on the electric utility industry in the USA and find a positive effect of fuel prices on the adoption of fuel-saving technologies. Jaffe and Stavins (1995) find a positive and significant effect of energy taxes on adoption of thermal insulation in new home construction in the USA, although they find adoption subsidies more effective as discussed above. Using panel data on citizens' tax returns and state tax policies to encourage residential conservation investments, Hassett and Metcalf (1995) find a positive and significant effect of changes in the tax rate on the probability of making the conservation investment. Finally, Kerr and Newell (2003) use panel data on oil refineries during the US phase down of lead in gasoline and find a large, positive and significant response of lead-reducing technology adoption to increased stringency of environmental policies. Moreover, they find evidence that a tradable permit scheme provides incentives for efficient rates of adoption.

Implications for environmental policy design

Induced technical change tends to reduce marginal costs of abatement and as such has several implications for environmental policy design. Goulder and Mathai (2000) find that the cost reduction can be large if cost effectiveness is the policy criterion. Under an efficiency criterion instead, lower marginal abatement costs make it optimal to abate more and total costs of abatement might therefore actually increase with induced technical change (Goulder and Mathai, 2000). In a similar vein, the optimal timing of environmental policy and abatement can change. Goulder and Mathai (2000) find that under R&D induced technical change it is optimal to shift some abatement of CO_2 emissions from the present to the future. The induced technical change reduces marginal abatement costs in the future and thereby lowers the shadow price of pollution today.

Finally, induced technical change provides a justification to differentiate environmental policy across pollution sources to the extent the induced technical change is external to the pollution source. Using a cost-minimization model, Rosendahl (2004) shows that the cost-effective carbon tax for CO_2 emission sources for which induced technical change is external, is higher than a uniform carbon tax. As technology externalities reduce marginal abatement costs in this model, these costs now differ between technologies. Agents do not take the cost reductions into account and overall costs can therefore be saved by letting those technologies that are enjoying relatively high technology externalities bear relatively more of the abatement burden. Using a similar model, Bramoullé and Olson (2005) study the efficiency of carbon taxes and come to similar conclusions.

2.4 Technical change in economic growth models

In (neoclassical) growth models, technical change is traditionally considered the factor determining long-run economic growth in terms of per capita output. Solow (1957) and Swan (1956), for example, argue that labor-augmenting technical change is necessary to offset the dampening effects of diminishing returns to capital investment and hence to explain long-run growth of per capita output. In their models, Solow and Swan define technical change as growth of the current state of technical knowledge (A) over time, that is a public good that any firm can access at zero costs:

$$Y_i = A(t) L_i^{1-\alpha} K_i^{\alpha} \qquad (i = 1,..,I) \tag{2.3}$$

in which Y_i is output of a firm i, L_i and K_i are the firm's labor- and physical capital inputs and in which $0 \leq \alpha \leq 1$. Though being the factor driving economic growth in the long run, technical change is specified exogenously in these models. The main reason for the exogenous specification is that until recently, economists did not know how to specify product space and technology endogenously in general equilibrium theory (Aghion and Howitt, 1998).

The underlying problem was how to reconcile increasing returns to scale, stemming from an endogenous specification of technical change, with the necessary condition of non-increasing returns imposed by general equilibrium theory (Aghion and Howitt, 1998). At the heart of this theory is the (Walrasian) competitive equilibrium, which requires that all factors are paid their marginal product. Euler's theorem, however, implies that with increasing returns not all factors can be paid just their marginal product.

A first approach to specify technical change endogenously reconciled increasing returns with the competitive equilibrium by letting technical knowledge take the form of an externality. While knowledge remained specified as a public and free good, knowledge now came about as a side effect of various economic processes. As a result, the amount of knowledge is now endogenously determined at the economy level while at the firm level this public good is not taken into account in the profit maximization decisions. All production factors are paid their marginal product and the non-increasing returns condition holds. Pioneering this approach, Arrow (1962) specified –labor augmenting– technical change as growth in a technical knowledge stock resulting from experience gained with producing capital goods, which he referred to as learning-by-doing. A firm's technical knowledge stock consequently is a function of aggregate production of capital goods:

$$Y_i = A_i(K)L_i^{1-\alpha}K_i^{\alpha} \qquad (i = 1,..,I) \tag{2.4}$$

in which $0 \leq \alpha \leq 1$. Frankel (1962) uses the same approach but specifies the technical knowledge stock as a function of the capital-labor ratio in the economy instead of learning-by-doing. Romer (1986) uses a similar specification of the technical knowledge stock but treats knowledge as a disembodied capital good that can be used in production next to other production factors or that can be stored if unused.

In subsequent approaches, technical change is specified not merely as an unintended side effect but especially as an intended effect of economic processes.[2] For both specifications to be feasible simultaneously, the pure public good assumption of knowledge has to make way for the joint assumptions of nonrivalry and partial excludability. The use of knowledge by one firm still does not preclude use by another firm, but for there to exist an incentive to generate knowledge firms need to be able to appropriate at least some of the returns to knowledge. Romer (1990) and Rivera-Batiz and Romer (1991), for example, introduce R&D activities in an intermediate (capital) goods sector. Specifically, firms producing the intermediate goods first engage in R&D to create new technical knowledge, *e.g.* designs of the intermediate goods. Based on the Dixit-Stiglitz (1977) model of product variety, markets for intermediate goods are monopolistically competitive and firms are therefore rewarded with monopoly rents if the knowledge results in a successful innovation of a new intermediate good. Innovations do not render older intermediate goods obsolete, but instead add to its variety:

[2] This paragraph focuses on knowledge-based approaches. A related approach with strong links to labor economics relies on human capital to drive long-run economic growth. An important difference between both approaches is that human capital is treated as a rival and excludable good whereas knowledge is treated as a nonrival and partially excludable good. See, for example, Lucas (1988); Galor and Moav (2000); and Jones (2002).

$$Y_i = L_i^{\alpha} \sum_{j=1}^{\infty} \left(X_{ij} \right)^{1-\alpha} \qquad (i = 1,..,I) \tag{2.5}$$

in which X_{ij} is firm i's use of intermediate good j and in which $0 \le \alpha \le 1$. The knowledge implicit in all innovations of intermediate goods is available for anyone engaged in R&D and output is specified here as an additively separable function of all the different intermediate goods, allowing for continued growth. In a variation on the intermediate goods approach, Aghion and Howitt (1998) let innovations of new intermediate goods improve the production technology's quality and render old intermediate goods obsolete rather than add to their variety. The innovations result from profit-maximizing R&D activities but arrive in a stochastically determined sequence in their model.

The most recent approach to date focuses on an endogenous specification of the direction of technical change, in addition to an endogenous specification of the rate of technical change. Showing that it is not essential whether technical change results from expanding varieties of goods or quality improvements, Acemoglu (2002) chooses one particular specification and presents an equilibrium framework for studying directed technical change. Using this framework, he identifies three effects that together determine the direction of technical change. First, a 'price' effect increases the expected returns of improving productivity of relatively scarce factors and hence of allocating more resources to R&D activities favoring scarce factors. Second, a 'market size' effect increases expected returns of improving productivity of relatively abundant factors and hence of allocating more resources to R&D activities that favor abundant factors. Third, current R&D activities that depend positively on the state of previous R&D activities increase the expected returns of these R&D activities. He shows that the price effect outweighs the market size effect if the production factors are gross complements, resulting in technical change being biased toward the relatively scarce factor. The opposite holds if the factors are gross substitutes.

2.5 Technical change in economic models of climate policy

Following the developments in the macroeconomic growth literature, the appropriate treatment of technical change has since been an important issue in economic modeling of climate policy. Numerous model studies have shown the costs and benefits of climate policy to be sensitive to assumptions about technology (Azar and Dowlatabadi, 1999; Löschel, 2002). Given the scope of this thesis as outlined in Chapter 1, we restrict the discussion below to economy-wide models of climate policy and in particular those that illustrate key methods to specify endogenous technical change. We refer the interested reader to Löschel (2002) and Sue Wing (2006) for more elaborate surveys.

Exogenous technical change

In economic models of climate policy, technical change has traditionally been treated as an exogenous variable driving economic growth (Löschel, 2002). Economic activities then have no effect on technical change. Besides assuming a certain percentage annual improvement in overall productivity, these models typically introduce exogenous technical change by a parameter reflecting autonomous energy efficiency improvements (AEEI) or by including exogenously provided specific energy technologies that have already been invented but that are not yet commercial (often referred to as 'backstop' technology) (Azar and Dowlatabadi, 1999).

The AEEI parameter is an average measure of all autonomous improvements in the energy efficiency of production (see *e.g.* Nordhaus, 1993; Manne *et al.,* 1995; Alcamo *et al.,* 1998; Paltsev *et al.*, 2005). The AEEI parameter is typically included to augment energy as a factor in aggregate production functions but can also be included to augment all factors in disaggregate production functions of more energy efficient sectors or technologies. As an average measure, this parameter may represent both structural change, *e.g.* change in share of energy goods in total output over time, and technical change, *e.g.* change in energy input requirements per unit output over time (Löschel, 2002). A main difficulty with the AEEI parameter therefore is to distinguish between both types of changes.

As stated above, backstop technologies are specific energy technologies that have already been invented but that are not yet commercially viable. These technologies are exogenously provided in the model specification and are more costly than conventional technologies, but when in use they typically are assumed to be able to produce unlimited output at constant- or decreasing marginal costs. Backstop technologies are adopted when their costs decrease (as a result of the R&D or technology policy), or when production costs of conventional technologies increase (as a result of increasing energy prices or environmental policy). Examples of backstop technologies relevant to climate change policy include renewable energy technologies such as photovoltaics and wind, and CO_2 abatement technology such as CO_2 capture and storage (see, for example, Manne *et al.*, 1995; Popp, 2004b; Kverndokk *et al.*, 2004; and Paltsev *et al.*, 2005).

Endogenous technical change

Recognizing that economic activities do have an effect on technical change, there have since been several attempts to specify technical change as an endogenous variable in economic models of climate policy. The first of such attempts draws on insights gained from the induced innovation literature as reviewed above. Using a model of the US economy in which all parameters in the behavioral functions have been econometrically estimated, Jorgenson and Wilcoxen (1990) specify productivity growth of the various production factors as a function of their price. They dub this 'the factor price bias of technical change'. Based on historical observations that energy price increases have led to energy efficiency improvements, Dowlatabadi (1998) simply replaces the AEEI parameter with a price-induced energy efficiency improvement variable in the third version of the Integrated Climate Assessment Model (ICAM).

A newer generation of economic models of climate policy, however, draws not only on insights gained from the induced innovation literature but also on insights gained from the endogenous growth literature. Several models of climate policy follow Arrow (1962), by introducing learning or knowledge spillovers in one form or another, but many models follow Romer (1990) nowadays by also specifying investment variables for R&D that create stocks of knowledge. In a pioneering and comprehensive study, Goulder and Mathai (2000) use a cost-minimization model to consider both R&D and learning-by-doing in abatement as possible but separate ways to build a stock of knowledge. Knowledge accumulation is costly if it requires R&D but is free if it is the result of learning-by-doing. The knowledge stock in turn reduces abatement costs.

Building on his Dynamic Integrated Climate-Economy (DICE) model, Nordhaus (2002) incorporates both R&D and knowledge spillovers in an updated version of this world-wide model called R&DICE. Expenditures on R&D build a stock of knowledge and improve the carbon-energy efficiency of world-wide production. Nordhaus accounts for knowledge spillovers by assuming the social rate of return to R&D to exceed the private rate of return by a factor four. In turn, Popp (2004c) follows Nordhaus (2002) in incorporating R&D and knowledge spillovers in a spin-off of the DICE model called ENTICE. A key difference between the R&DICE and ENTICE models, however, is that technical change is economy-wide in the former whereas technical change takes place in an energy sector in the latter. Expenditures on R&D build a stock of knowledge in an energy-R&D sector and improve total factor productivity of energy production.

Buonanno *et al.* (2003) build on the Regional Integrated model of Climate and the Economy (RICE) by incorporating R&D and knowledge spillovers in a new version of this model called ETC-RICE.[3] Expenditures on R&D build regional stocks of knowledge that enter the production functions as a factor of production. As such, R&D has the effect of improving total factor productivity. In addition, the knowledge stocks have a negative effect on emission-output ratios. To capture knowledge spillovers between the regions, Buonanno *et al.* aggregate the regional knowledge stocks into a world-wide stock, which then operates in an identical fashion as the regional stocks. In a more recent version of the ETC-RICE model, learning-by-doing has been incorporated as a free alternative to R&D as driver of technical change (Castelnuovo *et al.*, 2005). Learning-by-doing is a function of installed capacity of physical capital and has both a positive effect on total factor productivity and a negative effect on emission-output ratios.

In a similar vein, Gerlagh and Lise (2005) specify many drivers of technical change in a second version of the Decarbonization Model with Endogenous Technologies for Emission

[3] See Nordhaus (1993; 1994) for a presentation of the DICE model and Nordhaus and Yang (1996) for a presentation of the RICE model.

Reduction (DEMETER) model. Specifically, they introduce aggregate energy R&D building a stock of knowledge to be used in the production of two types of energy, one of which has net zero CO_2 emissions. Not all returns to these R&D activities can be appropriated, however, and the knowledge is therefore treated not only as a production factor but also as a knowledge spillover in the production of the two energy types. Moreover, experience gained in energy production builds a second stock of knowledge, which is also considered a factor in the production of the energy types.

The ICAM, DICE, R&DICE, ENTICE, RICE, ETC-RICE, and DEMETER models are predominantly used for integrated assessments of climate policy and hence combine economic models with climate sub-models. Because integrated assessments are complex undertakings, these models feature highly aggregated specifications of the economy. Economic models of climate policy that do not include climate sub-models can therefore specify the economy in greater detail. As such, these models are well suited for more detailed assessment of the causes, interactions and effects of technical change throughout the economy. Goulder and Schneider (1999) specify the economy in greater detail and distinguish multiple economic sectors. R&D, the resulting stocks of knowledge as well as concomitant knowledge spillovers are now all sector specific and improve the sectors' total factor productivity. Finally, Sue Wing (2003) limits himself to aggregate R&D and an aggregate knowledge stock, although knowledge improves total factor productivity in the various sectors throughout the economy.

2.6 Conclusions on way forward

This chapter has provided a brief overview of the economic literature on technical change as it relates to the environment and environmental policy. Essentially all of this literature deals with the effects of environmental policy on the process of technical change, the environmental impacts of technical change or both. Given the scale and long-term nature of the climate change problem, it is important that we better understand the process of technical change and how it relates to the environment and environmental policy. This thesis therefore focuses on endogenous technical change and its implications for the design of policies to reduce CO_2 emissions.

Current economic models of climate policy still rely on many ad hoc assumptions and future work should focus on improving the empirical basis and realism of these models. One important way forward is to extend current econometric analyses to provide a stronger empirical basis for the models. In Chapter 4 of this thesis, an attempt is therefore made to contribute to this empirical basis by estimating the extent to which previous technical change has an effect on today's technical change; *i.e.* the delayed feedback in technical change. Another important way forward is to study the direction of technical change in greater detail. Regulatory measures such as environmental policy affect different technologies differently and, depending on their economic characteristics, can therefore lead to different environmental and economic impacts. Although current model analyses of climate policy recognize this point, it is not explicitly captured in these models. Chapter 3 of this thesis therefore derives the determinants of the direction of technical change whereas Chapters 5 and 6 focus on its implications for policy design.

Chapter 3 Energy and directed technical change: A CGE analysis*

3.1 Introduction

During the last two decades, theoretical growth models emerged in which technical change was no longer specified exogenously but endogenously. Well-known examples of such models are the product-variety model of Romer (1990) and the quality-ladder model of Aghion and Howitt (1992). For long, attention has mainly been focused on sustaining growth and therefore on the rate of technical change. In most situations, however, technical change does not improve the productivity of all production factors or technologies proportionally but rather changes their relative productivity; *e.g.* technical change is directed toward some technologies and away from others. Recently, directed technical change is receiving further attention since Acemoglu (2002) presented a modeling framework in which both the rate and direction of technical change are specified endogenously. Directed technical change is of public concern, as regulatory measures affect different technologies differently. Depending on the economic characteristics of technologies, regulatory measures can therefore lead to different societal impacts and welfare costs. In addition, if technologies have different external effects, or if markets for technologies are imperfectly competitive, or both, a case for directed policy intervention arises. Thus, endogenous technical change is not as straightforward as it may appear.

Beside these theoretical contributions, several recent modeling studies show the importance of an endogenous specification of the rate of technical change for climate-change analysis. Studies by, among others, Nordhaus (2002), Goulder and Schneider (1999), Goulder and Mathai (2000), Buonanno *et al.* (2003), Popp (2004c), Gerlagh and Lise (2005), and Sue Wing (2003) all analyze effects of endogenous technical change on the design, timing, or attractiveness of climate-change policies. Though these studies recognize the importance of the direction of technical change for climate change analysis, they do not capture this issue explicitly in their models. Goulder and Schneider, for example, capture the direction of technical change when showing the importance of opportunity costs of technical change although it remains unclear what exactly the determinants of this direction are in their framework. Jorgenson and Wilcoxen (1990) capture the direction of technical change explicitly in the form of factor bias. Yet, their

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bias depends only on selected input prices and the aggregate rate of technical change remains autonomous in their specification.

Given the importance of the direction of technical change and the apparent gap in applied modeling studies, we proceed by studying the direction of technical change as it relates to energy. For this purpose, we develop a stylized version of the 'Dynamics of Technology Interaction for Sustainability' (DOTIS) model. DOTIS is an intertemporal dynamic computable general equilibrium (CGE) model that builds on endogenous growth models, in particular Acemoglu's (2002) model of directed technical change. DOTIS explicitly captures links between energy, the rate and direction of technical change, and the economy. We derive the determinants of the direction of technical change and show the importance of technology externalities and substitution possibilities in consumption in this light. At the same time, we test if the model is able to project the direction of technical change following the oil shock in the late 1970's in the Netherlands.

This chapter is organized as follows. In Section 3.2, we describe the main features of the DOTIS model and derive the determinants of the direction of technical change. Section 3.3 outlines the simulations used to test the model and discusses the results. Section 3.4 concludes. Finally, we present a detailed structure of the stylized version of the DOTIS model in Appendix 3A and the underlying data in Appendix 3B.

3.2 Model description

Several economic agents interact over time by demanding and supplying commodities on markets. These agents are producers of goods in production sector i, firms in intermediate sector i manufacturing knowledge capital goods for the respective production sectors, and a representative consumer. Each agent behaves rationally and has perfect foresight. Markets for the goods and production factors labor and physical capital are perfectly competitive whereas markets for knowledge capital goods are characterized by monopolistic competition based on the Chamberlinian large-group assumption – firms have a monopoly over their own variety of knowledge capital goods although there are many close substitutes available. Monopolistic competition and technology externalities support nonconvexities in the production possibility frontiers of the goods, which are due to a nonrival knowledge input. Nonrival inputs also cause nonconvexities in the innovation possibility frontier that are supported by technology externalities only.

Each agent solves its own optimization problem and when all markets clear simultaneously, the allocation- and price vectors constitute an equilibrium. Economic growth is determined by the growth rates of the stocks of physical- and knowledge capital, and of the labor supply. Growth of labor supply is exogenous and constant over time. Growth rates of capital stocks are endogenous and reflect investment decisions of the representative consumer. The economy achieves steady-state growth over time with the stocks of physical- and knowledge capital growing at the same rate as the labor supply.

Utility and consumption

The representative consumer maximizes her intertemporal utility subject to the lifetime budget constraint. Intertemporal utility is a nested constant-elasticity-of-substitution (CES) function of the discounted sum of consumption goods (see equations 3A.8 and 3A.9 in appendix 3A). Environmental quality does not enter the utility function, implying independence of the demand functions for goods with respect to environmental quality.

Production

Production of goods ($Y_{i,t}$) is characterized by a production possibility frontier, which is determined by a CES function of an aggregate of available varieties of knowledge capital goods ($Z^A_{i,t}$) and a nested CES function of physical capital ($K_{i,t}$), labor ($L_{i,t}$), energy resources ($E_{i,t}$), intermediate inputs ($M_{i,t}$) (see equation 3A.1 in Appendix 3A for the precise nesting structures per simulation). The top nest of the CES function has a unitary elasticity of substitution (*i.e.* Cobb-Douglas), but we relax this assumption in the sensitivity analysis below. Knowledge capital good *i* is 'appropriate' for particular combinations of inputs only, *i.e.* the production function of good *i* (Basu and Weil, 1998). Hence, one type of knowledge capital goods cannot be used in the production of the other good. Further, there exists a technology externality in production as knowledge embodied in intermediate sector *i*'s stock of knowledge capital spills over, increasing total factor productivity of production:

$$Y_{i,t} = \overline{H}^{\gamma}_{i,t}\ CES\left(Z^A_{i,t}, CES\left(K_t, L_t, E_t, \sum_j M_{i,j,t}; \sigma^{KLEM} \right); \sigma^Z \right) \quad (i = 1,..,I),\ (t = 1,..,T) \qquad (3.1)$$

in which $\overline{H}_{i,t}$ is the knowledge spillover with coefficient γ and in which σ denotes the substitution elasticities. This specification of the production possibility frontier is similar to Goulder and Schneider (1999). Knowledge spillovers to an individual producer in a sector are introduced by a scale factor in a Cobb-Douglas type production function that is an increasing function of intermediate sector *i*'s aggregate research and development (R&D) activities. Although the knowledge spillovers generate increasing returns to scale at the sector level, knowledge spillovers are external to the individual producer allowing us to avoid problems related to non-convex optimization. Together with adoption of knowledge capital goods, these spillovers drive productivity growth in the production sectors. Firms in production sector *i* maximize their profits over time subject to their production-possibility frontier. Homogeneity-of-degree-one, in addition to perfect competition, guarantees zero profits. Market clearing implies that the relative price of goods has to satisfy the product-mix efficiency constraint. Formally for any two goods $(i = X, Y)$:

$$\frac{p_{Y,t}}{p_{X,t}} = \left(\frac{\theta_W^X}{\theta_W^Y} \frac{Y_{Y,t}}{Y_{X,t}} \right)^{\frac{-1}{\sigma_W}} \qquad (t = 1,..,T) \tag{3.2}$$

in which $p_{i,t}$ is the price of good *i*, θ_W^i is the share of good *i* in intratemporal utility and σ_W is the substitution elasticity between final goods in intratemporal utility. An increase in the relative supply of a good lowers its relative price, satisfying the law of demand. The change in relative price is smaller the more substitutable the goods are.

Technical change

Firms in intermediate sectors manufacture the various varieties of knowledge capital goods (Z_i) appropriate for production of good *i*. Knowledge capital goods are excludable but nonrival: Its owner can prevent others from using it by deciding not to sell or rent but use by one firm does not preclude use by another. Software is an example. To be able to manufacture knowledge capital goods, however, firms in the intermediate sectors require knowledge capital. One can think of knowledge capital as blueprints. Knowledge capital is also nonrival but, in contrast to knowledge capital goods, is only partially excludable. Owners can prevent others from using their knowledge capital by means of patent protection, but cannot completely prevent knowledge from spilling over to other researchers or producers. This partial excludability causes private- and social returns to knowledge capital to diverge.

There exist multiple institutional structures that support a decentralized equilibrium (Romer, 1990). We think of firms manufacturing knowledge capital goods separate from firms manufacturing goods. Alternatively, one can think of firms in each production sector manufacturing their type of knowledge capital goods themselves. The institutional structure is irrelevant as long as innovation possibility frontiers are identical. Likewise, it is irrelevant whether the manufacturing of new varieties occurs within departments of one firm or in separate firms as long as these new varieties are manufactured according to identical innovation possibility frontiers and as long as the manufacturing decision is separable from the patent-pricing decision. In either case, the firm that owns the patent extracts the same monopoly profit. We assume that the firm that invests in, and patents the new varieties of knowledge capital also manufactures these new varieties and that he is the sole manufacturer so that there is a one-to-one correspondence between firms and varieties of knowledge capital goods in the intermediate sectors. We therefore characterize manufacturing of knowledge capital goods in each intermediate sector by a single production possibilities frontier that comprises a fixed- and a variable cost component. The fixed costs are the investments in knowledge capital (*i.e.* R&D of the blueprint) that a firm must incur once in order to be able to manufacture the new variety of knowledge capital goods. The variable cost component relates to their actual manufacturing. Finally, manufacturing of knowledge capital goods is a deterministic process and aggregate innovation possibility frontiers are continuous, which allows us to avoid problems due to integer variables and uncertainty.[1]

Investments in knowledge capital ($R_{i,t}$) merely involve final goods, and only at the time of entry. Rivera-Batiz and Romer (1991) refer to this specification as the lab-equipment specification for its emphasis on physical inputs. As they also point out, 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 investment in knowledge capital instead. Further, previous investments in knowledge capital have a positive external effect on current investments.[2] Knowledge spillovers and network effects, among others, underlie this delayed technology externality in innovation, which exists within each intermediate sector only because types of knowledge capital are too different to benefit from each other's technical changes. Rivera-Batiz and Romer refer to this as the knowledge-based specification of R&D. Formally:

$$R_{i,t} = \overline{R}_{i,t-1}^{\xi} \; \theta_i^R Z_{i,t} \quad (i = 1,..,I),\ (t = 1,..,T) \tag{3.3}$$

in which $\overline{R}_{i,t-1}$ is the delayed technology externality in innovation with coefficient ξ and θ_i^R denotes investment in knowledge capital by firms in intermediate sector *i* expressed as share of their total production of knowledge capital goods $Z_{i,t}$. This specification implies that energy and knowledge capital are used indirectly, rather than directly, as inputs for investments in knowledge capital. Equation (3.3) reveals several implications for the rate of investments in knowledge capital. First, higher investments in knowledge capital increase its rate. Second, a higher rate of investment in knowledge capital increases the productivity of resources devoted to such investment. Yet, a third implication is that this increase in productivity levels off if the technology externality coefficient is smaller than one. If this is indeed the case, it eventually becomes more productive to devote the resources elsewhere in the economy. Once a new variety of knowledge capital has been developed, it is added to its respective stock ($H_{i,t}$) and although it depreciates is available for more than one period (see equation 3A.12).[3]

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[1] Even though indivisibility of knowledge capital and uncertainty related to the investment processes are facts of life, averaging out makes these facts matter less at aggregate levels (Romer, 1990).

[2] For illustrative purposes, we limit ourselves to a one-period delay only.

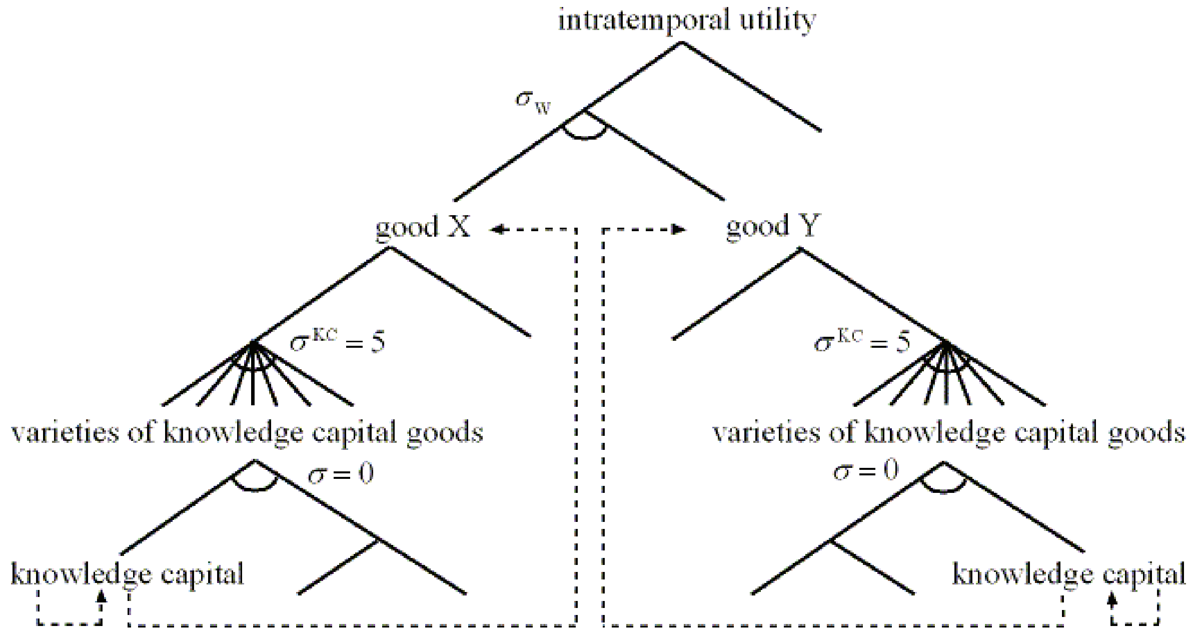
[3] Alternatively, one can take the view that knowledge doesn't depreciate at all. This assumption is likely to be valid if the sector or industry under study is narrowly defined and its stock of knowledge capital changes only slowly (Griliches, 1988). This assumption is less likely to be valid, however, if one defines sectors more broadly or for periods in which one might suspect more rapid obsolescence of knowledge capital such as the years following the oil shocks.

We specify the production of a new variety of knowledge capital goods similarly to the sectoral production function in equation (3.1). Variable costs of manufacturing the new variety are a Cobb-Douglas function of labor and physical capital in any period. Formally:

$$Z_{i,t} = K_t^{\theta_{Z_{i,t}}^K} L_t^{1-\theta_{Z_{i,t}}^K} \qquad (i=1,..,I),\ (t=1,..,T) \tag{3.4}$$

in which $0 < \theta_{Z_{i,t}}^K < 1$. Figure 3.1 summarizes the specification of technical change in our model.

Figure 3.1 Specification of technical change in the model



Assuming symmetric cost structures for firms in the intermediate sectors ensures that all varieties of knowledge capital goods are initially supplied at identical levels and allows us to express aggregate output of each intermediate sector in period *t* as:

$$Z_{i,t}^A = \left(H_{i,t} Z_{i,t}^{\varphi}\right)^{\frac{1}{\varphi}} \qquad \varphi = \tfrac{\sigma^{KC}-1}{\sigma^{KC}} \qquad (i=1,..,I),\ (t=1,..,T) \tag{3.5}$$

in which the elasticity of demand for an individual variety, φ, equals the compensated elasticity of substitution between varieties. This is the usual Chamberlinian large-group assumption in monopolistic competition that determines the height of the constant mark-up over marginal costs. The mark-up, in turn, drives a wedge between the marginal- and average costs of manufacturing knowledge capital goods and therefore causes the innovation possibilities frontier to be characterized by increasing returns to scale. The technology externality adds to these increasing returns.

Firms in each intermediate sector maximize profits over time subject to these innovation possibility frontiers. The increasing returns generate profits in the immediate short-run, which attract new firms. Given that manufacturing knowledge capital goods is a deterministic process and firms can enter freely and have perfect foresight, a new firm will enter at time *t* if, and only if, the present-value of profits, V_i, is non-negative. This implies that the present-value of future revenues must be equal to or greater than the investments in the new variety of knowledge capital (suppressing time subscripts to simplify notation from now on):

$$V_i \equiv \left[Z_i \frac{1}{\sigma^{KC}-1} \geq \theta_i^R Z_i \right] \qquad (i = 1,..,I) \tag{3.6}$$

in which θ_i^R are the knowledge capital investment shares that are constant and equal across sectors. The elasticity of substitution between varieties of knowledge capital goods is also equal for all types, which allows us to write the relative profitability of manufacturing knowledge capital good *i* appropriate for production of Y_i for any two sectors $(i = X, Y)$ as

$$\frac{V_Y}{V_X} = \frac{Z_Y}{Z_X} \tag{3.7}$$

in which technical change is directed toward sector *Y* if this ratio increases. To gain further understanding, we substitute the dual form of equation (3.5) (see equation 3A.2) into the market clearance condition for $Z_{i,t}$ (see equation 3A.11) and rearrange terms to get an expression for the relative demand of $Z_{i,t}$, which we substitute in equation (3.7):

$$\frac{V_Y}{V_X} = \frac{\theta_Y^Z}{\theta_X^Z} \frac{p_X^Z}{p_Y^Z} \frac{p_Y}{p_X} \frac{Y_Y}{Y_X} \tag{3.8}$$

We identify four effects. The first term on the right-hand side is the substitution effect in production: To the extent Z_i^A is substituted for other factors in production, the profitability of manufacturing knowledge capital goods appropriate for production of Y_i increases. As we assume unitary elasticities of substitution between knowledge capital goods and the other factors, however, this term stays constant. Second, technology externalities in innovation have a negative effect on the relative profitability of manufacturing knowledge capital goods, as shown by the fact that V_i is decreasing in p_i^Z. The sign of this term is ambiguous as it depends on the sign and magnitude of technology externalities in both intermediate sectors. Finally, we identify price- and market size effects (Acemoglu, 2002). V_i is increasing in the good prices, p_i, confirming that there is an incentive to manufacture knowledge capital goods appropriate for the production of more expensive goods. V_i is also increasing in Y_i, confirming that at the same time there is an incentive to manufacture knowledge capital goods for which there is a greater market. Remember from equation (3.2) that the law of demand implies that a change in relative market sizes simultaneously leads to a price effect. Technology externalities in production reinforce the net effect of the price- and market size effects, but leave the net effect ambiguous for now.

To investigate the relative strength of the price-and market size effects, we follow Acemoglu by substituting the relative price of both goods, equation (3.2), into equation (3.8):

$$\frac{V_Y}{V_X} = \frac{\theta_Y^Z}{\theta_X^Z}\left(\frac{\theta_W^X}{\theta_W^Y}\right)^{\frac{1}{-\sigma_W}} \frac{p_X^Z}{p_Y^Z}\left(\frac{Y_Y}{Y_X}\right)^{\frac{1-\sigma_W}{-\sigma_W}} \tag{3.9}$$

This equation shows that the elasticity of substitution in consumption is an important determinant of the direction of technical change as it regulates the relative strength of the price- and market size effects. The less substitutable goods are, the more scarcity commands higher prices and the more powerful the price effect gets relative to the market-size effect. If both goods are gross complements ($\sigma_W < 1$), we expect a decrease in the relative supply of a good to increase its relative price and profitability so that the price effect dominates. If both goods are gross substitutes ($\sigma_W > 1$) we expect a decrease in the relative supply of a good to decrease its profitability so that the market-size effect dominates. If goods have unitary substitution elasticity, we expect both effects to balance.

In addition to showing the relative strength of the price- and market-size effect, equation (3.8) reveals a new term capturing consequences of the substitution effect in consumption for the relative profitability of technical change. Substitution of one good for the other in consumption increases demand for the substituting good and hence the profitability of manufacturing knowledge capital goods that are appropriate for production of the substituting good, *ceteris paribus*, as shown by the fact that V_i is increasing in θ_i^W.

In sum, we identify the substitution elasticity in consumption as well as the technology externalities as key determinants of the direction of technical change. What the direction precisely amounts to is what we turn to in Section 3.3.

3.3 Simulations

We now illustrate the key determinants while showing how the DOTIS model can be used to study directed technical change. We do so by testing the model to see if it is able to project the direction of technical change following the oil shock in the late 1970's in the Netherlands. More specifically, we study three simulations. In the first simulation, we assume limited substitution possibilities between goods in the economy ($\sigma_W < 1$). We think of the goods as energy and other products. This simulation highlights the response of the whole economy to the oil shock. The second simulation extends the first by differentiating between energy from oil and energy from non-oil resources such as coal and renewables, in which we assume more substitution possibilities between energy from oil and non-oil $(\sigma_W > 1)$ than between energy and other products $(\sigma_W < 1)$. In addition, the second simulation extends the first by allowing for the technology externalities and shows their effects on the direction of technical change. We exclude the possibility of *e.g.* negative spillovers or 'organizational forgetting' by restricting the externalities to take on positive values only. This simulation highlights the response of energy users to the oil shock. Finally, the third simulation extends the second by allowing oil producers to shift production between heavy oil products and light oil products. Heavy oil products include fuel oil whereas light oil products include gasoline, naphtha and diesel. This simulation highlights the response of energy producers to the oil shock.

In each simulation, we compare model results to the reference case where we report variables in percentage changes relative to the reference case. We compare outcomes with respect to (i) the rate and direction of technical change as indicated by production levels of knowledge capital goods in each intermediate sector, (ii) the structure of the economy as measured by consumption- or production levels of goods, and (iii) welfare of the representative consumer as measured by her intratemporal utility (Hicksian equivalent variation).

Data and parameters

In absence of detailed data for the 1970's, we use illustrative data as reported in Table 3B.1 in Appendix 3B, where we use recent *National Accounts* from Statistics Netherlands (2000) to approximate intra- and inter-industry flows and where we use information from IEA's *Energy Balances* to determine shares of heavy- and light oil products in the oil industry's output. We arbitrarily assume that knowledge capital goods account for 10 percent of a firm's cost price.

Turning to model parameters, we use general parameter values that are standard in the literature (see Table 3A.5 in Appendix 3A). Regarding technology-related parameters, we assume that there are close substitutes available for each variety of knowledge capital $(\sigma^{KC} = 5)$, which translates into a mark up over marginal costs of manufacturing knowledge capital goods of 20 percent. Further, we use a 25 percent depreciation rate for knowledge capital. Pakes and Schankerman (1979) study patent renewals in the 1930's 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 the lifespan of applied R&D expenditures, which suggests an average service life of four to five years. More recently, Jorgenson and Stiroh (2000) have estimated a geometric depreciation rate for computer equipment and software of 31.5 percent. Furthermore, we base the coefficient value for the knowledge spillovers in production on Coe and Helpman (1995), who estimate the elasticities of R&D stocks on domestic total factor productivity at 9 percent for non-G7 countries. Moreover, we assume a coefficient value of 15 percent for delayed technology externalities in innovation. To the best of our knowledge, patent citation studies offer the only evidence of delayed technology externalities in innovation.[4] Results by Trajtenberg *et al.* (1997), for example, imply that there are such externalities at the industry level.

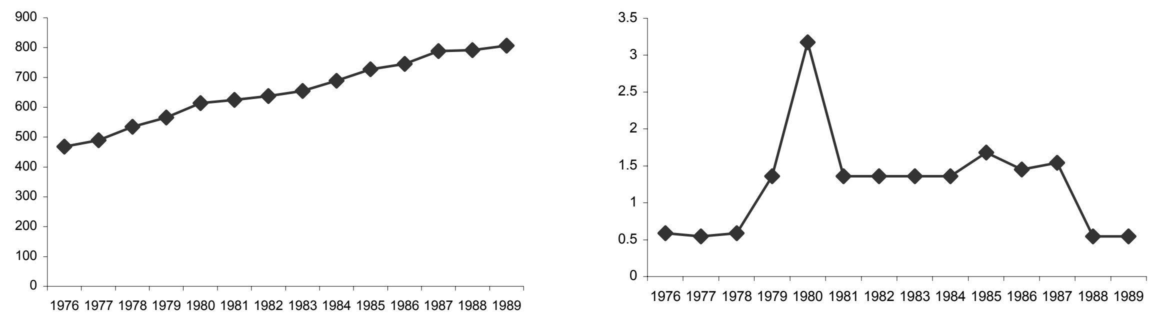
Regarding the substitution elasticities, we use a value of 1 for the substitution possibilities between inputs in production. Exceptions are the substitution elasticity between energy and other products, which we set at 0.25 to reflect their complementary character, and the substitution elasticity between energy from oil and non-oil, which we set at 4 to reflect the relatively many substitution possibilities between energy carriers.

Finally, we consider a 15-year time horizon, defined over the years 1976 through 1990, where the oil shock takes the form of a 16 percent supply reduction in 1980 relative to the reference case (IEA, 2004). We calibrate this stylized version of the model to a steady state rate of growth of 1 percent that serves as the reference case.

Simulation 1: Energy versus rest of the economy

The oil shocks in the 1970's drove up world oil prices and slowed productivity growth in many countries for several years to come. It has been argued that part of this productivity slow-down has been due to energy-biased technical change (Jorgenson, 1987). Figure 3.2 shows that public R&D expenditures on oil- and gas technologies in the Netherlands, for example, grew faster than total public R&D expenditures in the years 1979 and 1980. How can we explain this energy bias of technical change?

Figure 3.2 Public R&D expenditures in the Netherlands (mln. €)



(a) Total (b) Oil and gas technologies

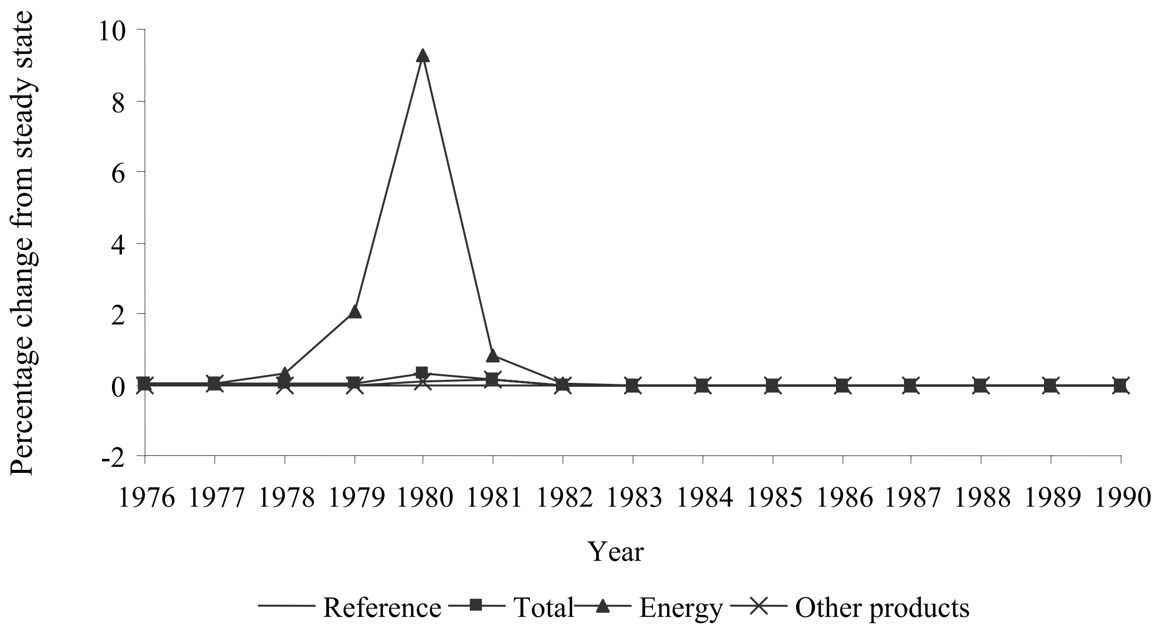
Sources: Statistics Netherlands *Statline* (a) and IEA *Energy Technology R&D Database* (b)

[4] Patent-citation studies investigate where and when existing patents are cited in the application of new patents (see *e.g.,* Caballero and Jaffe, 1993; and Jaffe *et al.*, 1993; 2000). By following these paper trails, patent citation studies inform us about the influence of past innovations on the development of new ones.

To explain this energy bias, we specify the energy sector and the rest of the economy as the two sectors in the economy that produce respectively energy and other products. There is a limited possibility to substitute more energy-efficient products for energy where energy production requires the energy resource as input. We think of the energy resource as crude oil.

Figure 3.3 shows the effects of the oil shock on production levels of knowledge capital goods in each sector. Aggregate demand for knowledge capital goods increases slightly during the oil shock because of the substitution effect in production. The stock of knowledge capital in the economy is still high relative to its new equilibrium level causing knowledge capital goods to be a relatively cheap input to production, *ceteris paribus*. However, aggregate demand for knowledge capital goods slightly falls as soon as knowledge capital depreciates and the stock approaches its new equilibrium level.

Figure 3.3 Effects of oil shock on production levels of knowledge capital goods



With respect to the energy bias of technical change, we find the various effects identified in equation (3.9) working in both directions. On the one hand, we find that the oil shock indirectly changes the relative scarcity of both products, leading to the price- and market-size effects discussed in Section 3.2. Limited substitution possibilities between energy and other products ensure that it now becomes more profitable to manufacture knowledge capital goods appropriate for production of relatively scarce energy causing the price effect to outweigh the market size effect, *ceteris paribus*. On the other hand, however, we find that the substitution effect in consumption reinforces the market size effect. The representative consumer, for example, shifts some consumption away from energy toward more energy-efficient products, which leaves manufacturers of other products with an incentive to adopt more knowledge capital goods to increase their productivity as to meet this increased demand for more energy-efficient products. This effect is relatively small, however, as substitution possibilities are limited. We therefore find a bias toward the scarce energy goods. Thus, the higher cost of crude oil implies that especially energy producers are induced to invest in energy-saving technology.

Figure 3.4 shows that the oil shock leaves the representative consumer worse off in terms of welfare. The reason is that the oil shock entails a deadweight welfare loss while the representative consumer's possibility to substitute final goods in consumption is limited.

Figure 3.4 Intratemporal utility in each simulation

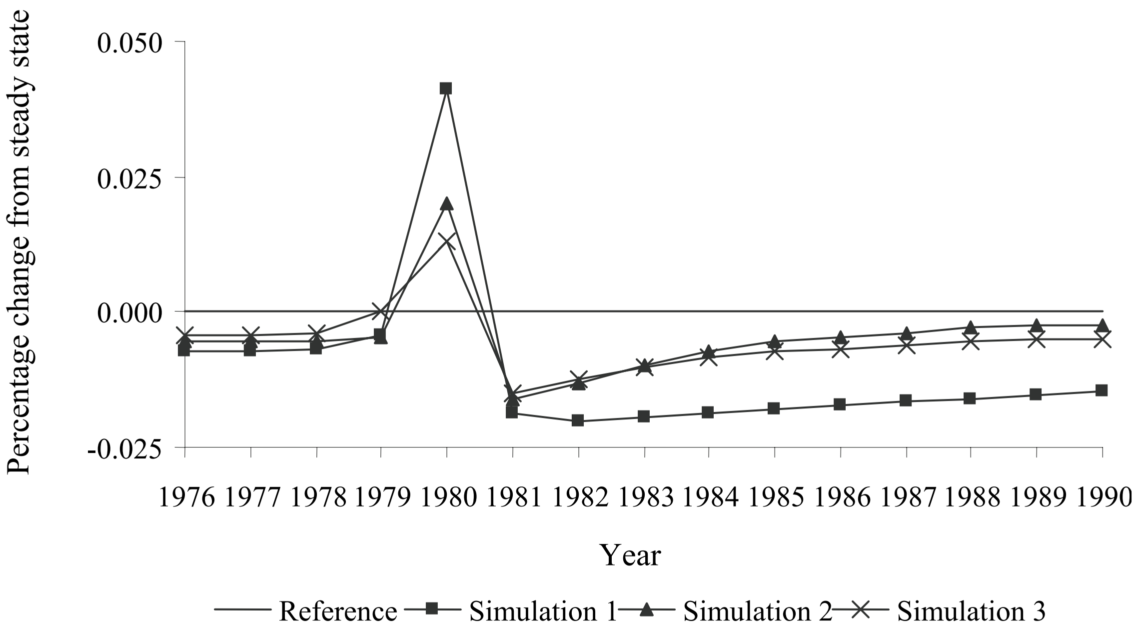
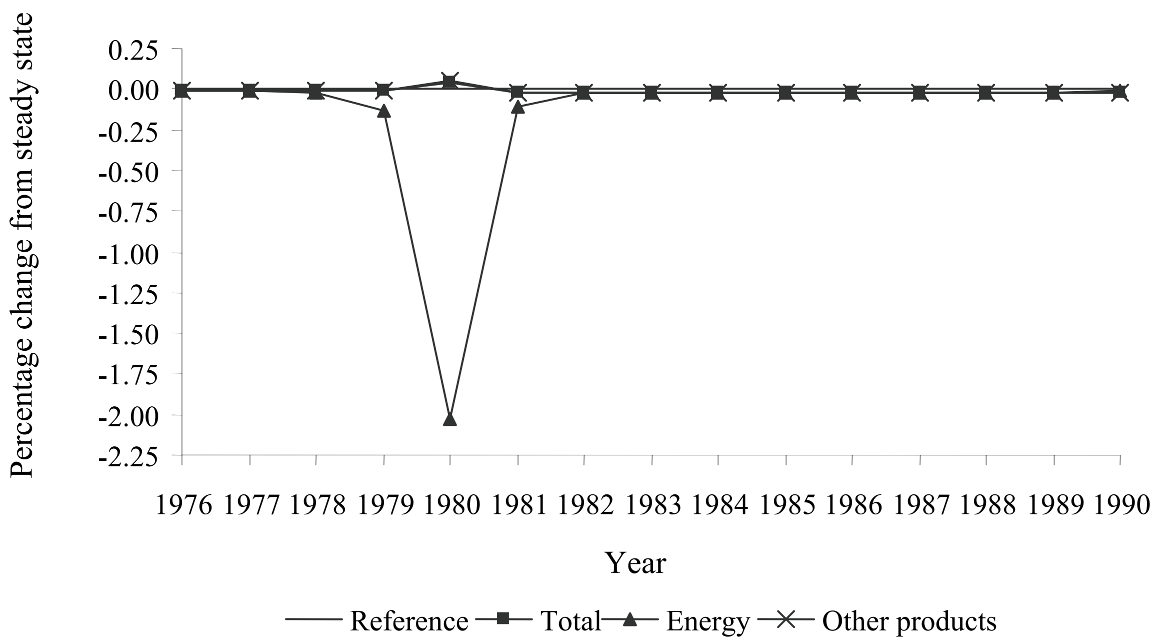


Figure 3.5 shows that the welfare loss translates into a concomitant drop in aggregate consumption levels, relative to the reference case. Further, consumption levels of energy drop sharply during the oil shock as the representative consumer substitutes a limited amount of other products for energy.

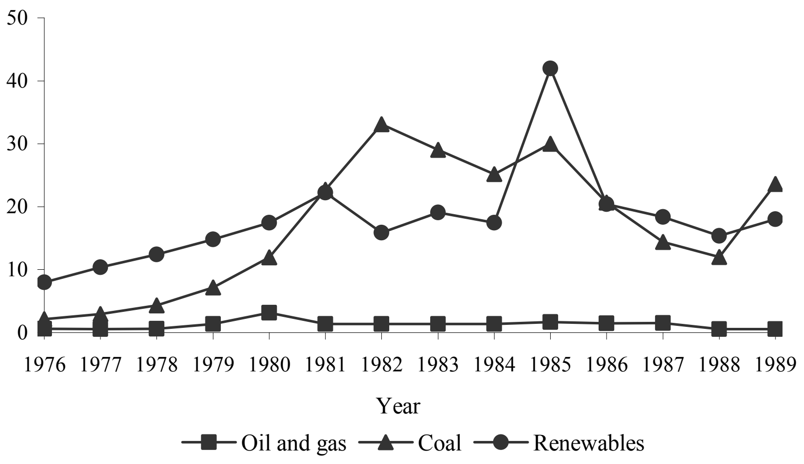
Figure 3.5 Effects of oil shock on consumption levels of final goods



Simulation 2: Differentiating the energy sector

Within the energy sector, technical change got directed away from oil toward non-oil energy resources during and shortly after the oil shocks of the 1970's. Figure 3.6 shows that public R&D expenditures on coal- and renewable-energy technologies in the Netherlands, for example, grew faster than public R&D expenditures on oil- and gas technologies in the period between 1979 and 1981. How can we explain this energy bias of technical change?

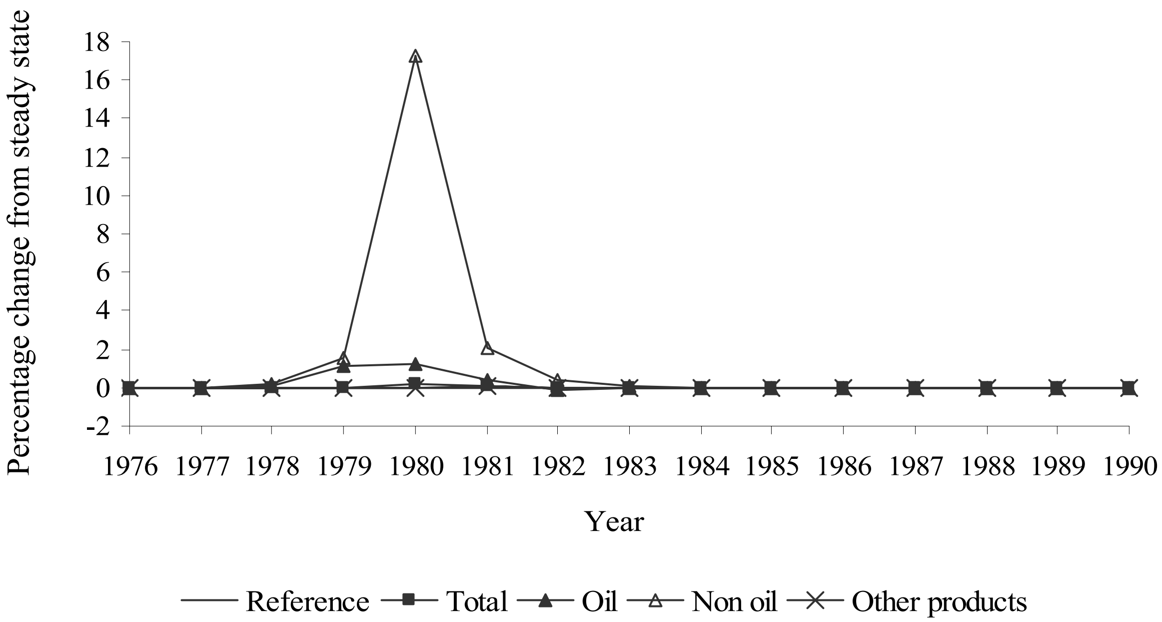
Figure 3.6 Public R&D expenditures in the Netherlands (mln. €)



Sources: Statistics Netherlands *Statline* and IEA *Energy Technology R&D Database*

To explain this energy bias, we specify the oil industry, the rest of the energy sector and the rest of the economy as the three sectors in the economy that produce respectively energy from oil, energy from non-oil energy carriers such as coal, gas, and renewables, and other products. There still is a limited possibility to substitute more energy-efficient products for energy whereas the homogeneous nature of energy ensures that there are many possibilities to substitute among energy carriers. The production of oil requires crude oil as input.

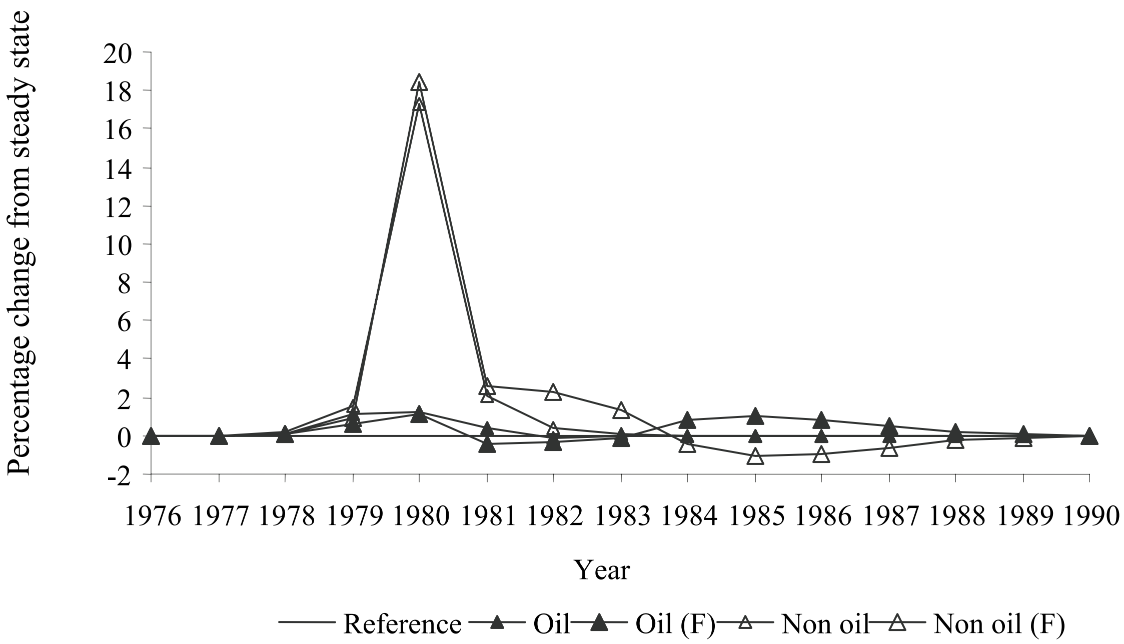
Figure 3.7 Effects of oil shock on production levels of knowledge capital goods



As in the previous simulation, the rate of aggregate technical change slightly increases during the oil shock and technical change is directed toward energy as shown in Figure 3.7. Within the energy sector, however, we find a bias in technical change away from oil toward non-oil energy carriers. We again find the various effects identified in equation (3.9) at play. The many possibilities to substitute non-oil energy for energy from oil cause the market-size effect to outweigh the price effect as well as strengthen the substitution effect in consumption– more of the non-oil energy is substituted for the relatively scarce energy from oil– that in turn translates into a relatively higher demand for knowledge capital goods appropriate for production of non-oil energy, *ceteris paribus*. Producers of energy using coal, for example, are especially induced to adopt more knowledge capital goods as to meet the increased demand for energy from coal.

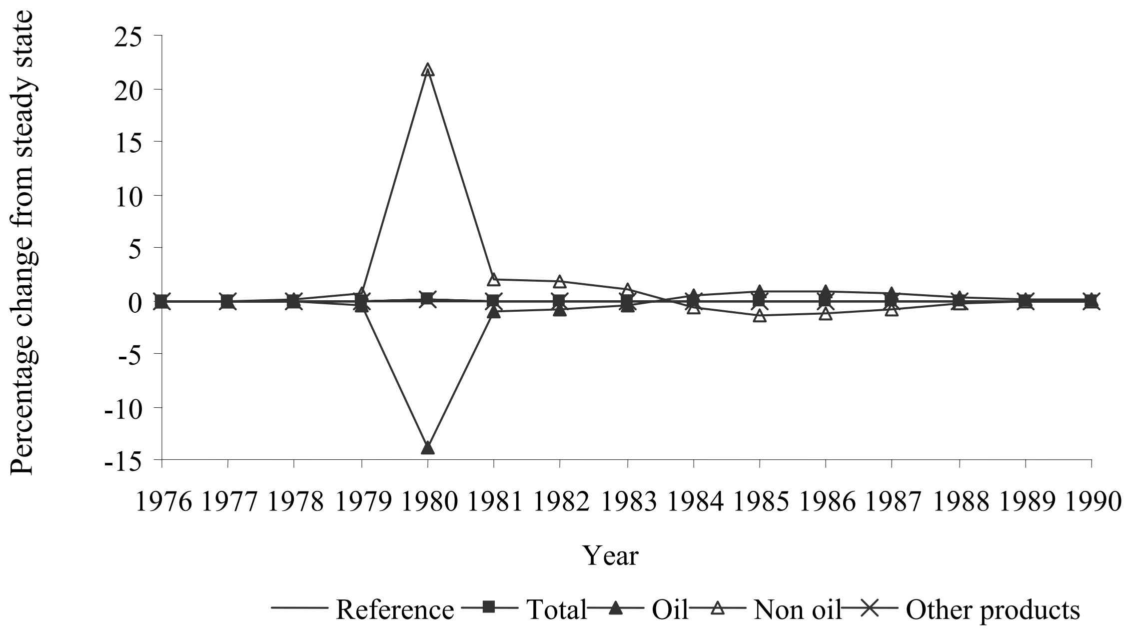
Figure 3.8 shows the effect of the technology externalities on the direction of technical change in the energy sector. The externalities make the economy more elastic in that a given shock leads to magnified adjustments in the economy, as originally pointed out by Arthur (1989). As a result, the bias in technical change toward non-oil energy is stronger if there are technology externalities. In addition, the delayed technology externalities in innovation cause the convergence to the steady state to oscillate, which is a characteristic pattern of behavior in models with system-dynamic elements.

Figure 3.8 Effects of oil shock on production levels of knowledge capital goods in the energy sector, with and without technology externalities (F)



Welfare levels are higher relative to the previous simulation because of the positive value of the technology externalities and because the increased substitution possibility allows the representative consumer to better adjust to the oil shock (see Figure 3.4). As a result, aggregate consumption levels slightly increase, relative to the previous simulation. Moreover, the possibility to substitute non-oil energy for energy from oil is reflected in significantly higher consumption levels of non-oil energy relative to energy from oil and other products (see Figure 3.9).

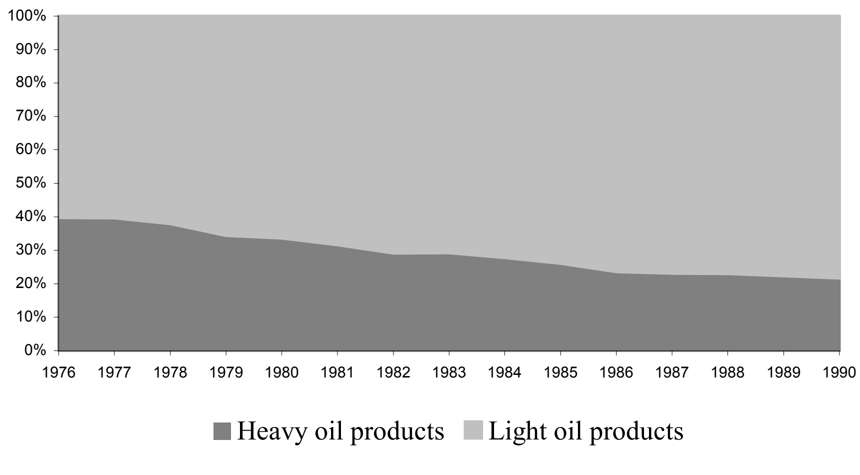
Figure 3.9 Effects of oil shock on consumption levels of final goods



Simulation 3: Introducing product differentiation in the oil industry

Within the oil industry, more energy-efficient technologies were installed during and after the oil shocks. Most notably, new refinery processes were installed that allowed for a different product mix comprising less of the heavy fuels and more of the light fuels. Figure 3.10 shows this change in the product mix for the Netherlands between 1976 and 1990. How can we explain this change in the product mix?

Figure 3.10 Production of heavy- and light oil products in the Netherlands (shares in %)



Source: *Energy Balances* (IEA, 2004)

To explain this change, we now allow the oil industry to differentiate between energy from heavy- and light oil instead of producing a homogeneous oil product. Substitution possibilities between more energy-efficient products and energy are still limited whereas there are more substitution possibilities among energy carriers. More specifically, there are many substitution possibilities between non-oil energy, such as coal, and energy from heavy oil while there are less substitution possibilities between energy from light oil and the aggregate of non-oil energy and energy from heavy oil.

Figure 3.11 Effects of oil shock on production levels of goods

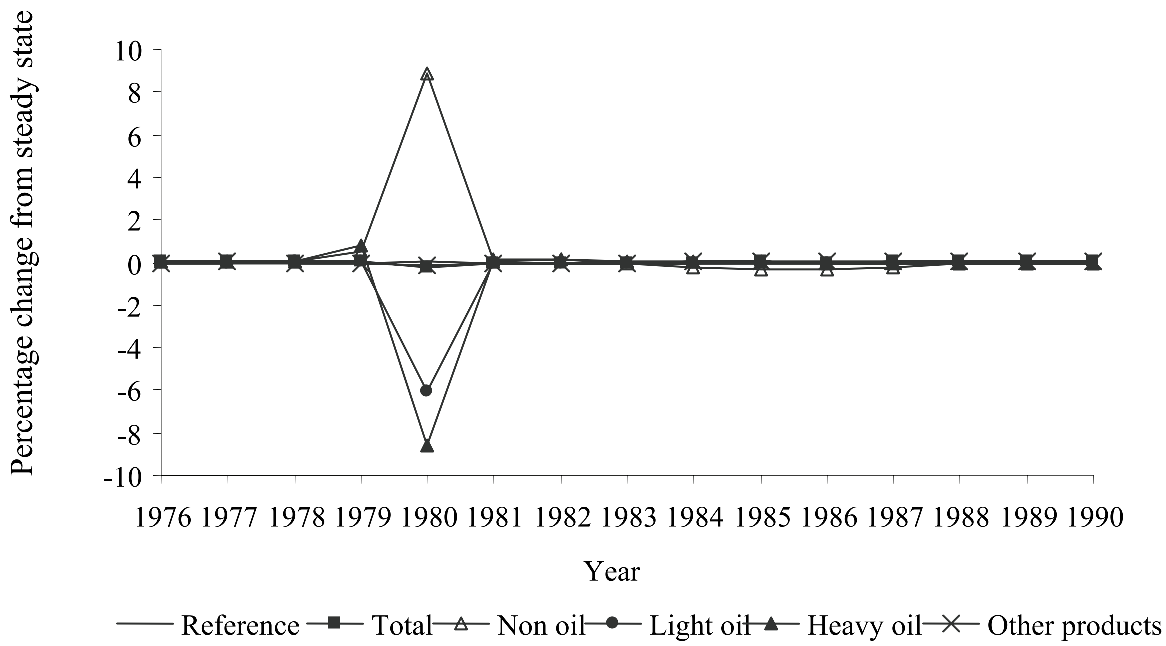


Figure 3.11 shows the effect of the oil shock on the production structure. Aggregate production falls slightly following the oil shock because less energy is demanded as intermediate input in production. As a result of the substitution possibilities between the various energy carriers, demand for and production of non-oil energy increases relative to the reference case, whereas demand for and production of energy from oil decreases relative to the reference case. Now that the oil industry can differentiate between energy from heavy- and light oil, we find that the oil industry shifts some production away from energy from heavy oil toward energy from lighter oil. Given that the market segment of heavy oil is now under relatively strong competitive pressure because of availability of energy that does not need crude oil as resource while the market segment of light oil products is not, the oil industry finds it profitable to shift some production from the former market segment to the latter.

Multiple equilibria

Because it is not possible to exclude existence of multiple equilibria in general equilibrium models with imperfect competition or increasing returns to scale, we test for the existence of multiple equilibria (Mercenier, 1995). It remains difficult, however, to locate multiple equilibria in a systematic manner because of the absence of an 'all-solutions' algorithm. We proceed by heuristically searching for equilibria making use of random starting values for the variables that we draw from uniform distributions with varying ranges. We do so for both the reference case and the three simulations.

We confirm existence of multiple equilibria if we allow for a wide range of *e.g.* 50 percent (calibrated starting values minus 25% through plus 25%). This is not surprising given that we created in effect widely different economies by using such a wide range. Narrowing the range to more realistic percentages sharply reduces the number of equilibria or even yields a unique equilibrium. Allowing for a range of 20 percent, for example, yields two additional equilibria in the second simulation, which are corner solutions that entail no investments in knowledge capital appropriate for energy production from respectively oil and non-oil in the last periods in order to increase welfare. Allowing for a range of 10 percent or smaller yields a unique equilibrium.

Sensitivity analysis

To gain further understanding of the model, we perform 'piecemeal' sensitivity analyses. We use central parameter values in all simulations (see Table 3A.6) except for the parameter subject to analysis. We report effects on the relative profitability of knowledge capital goods in each sector in present values, as defined in equations (3.7) through (3.9). Table 3.1 presents the results.

Halving the substitution elasticity between knowledge capital goods and other inputs in production (σ^Z) directly translates into a weak substitution effect in production and lowers the relative profitability of investing in knowledge capital goods appropriate for production of the scarce good X. The opposite holds if we double this substitution elasticity.

Doubling the substitution elasticity between varieties of knowledge capital goods (σ^{KC}) makes their markets more competitive and therefore reduces the profitability for firms to enter the intermediate sectors. Because demand for knowledge capital goods appropriate for production of the scarce good X is already lower relative to those appropriate for production for the abundant good Y, the decrease in profitability is stronger for the former type of knowledge capital goods. Consequently, technical change gets directed even more toward the sector producing the relatively abundant good Y. The opposite holds if we halve this substitution elasticity between varieties. This effect on the direction of technical change, however, is small in size.

Table 3.1 Piecemeal sensitivity analysis

			Relative profitability of technical change: V_Y/V_X		
			Simulation		
			1	2	3
Regular simulation			0.996	1.013	1.003
σ^Z	Substitution elasticity of knowledge capital goods in production	halved	1.000	1.016	1.009
		doubled	0.987	1.011	0.994
σ^{KC}	Substitution elasticity of varieties of knowledge capital goods	halved	0.996	1.013	1.002
		doubled	0.996	1.013	1.004
δ^H	Depreciation rate of knowledge capital	halved	0.995	1.013	1.003
		doubled	0.997	1.015	1.004
γ	Coefficient of technology externalities in production	halved		1.012	1.003
		doubled		1.013	1.004
ξ	Coefficient of technology externalities in innovation	halved		1.012	1.003
		doubled		1.015	1.004

Notes: All numbers are indices relative to the reference case. Simulation 1 refers to the rest of the economy (*Y*) versus energy (*X*); simulation 2 extends simulation 1 by differentiating the energy sector where results are for energy from non-oil (*Y*) versus energy from oil (*X*); simulation 3 extends simulation 2 by introducing product differentiation in the oil industry, where results are again for energy from non-oil versus energy from oil.

Doubling the depreciation rate on knowledge capital (δ^H) raises the opportunity costs of resources devoted to investments in knowledge capital and leads to a smaller stock of knowledge capital. Consequently, marginal costs of manufacturing knowledge capital costs are higher and profitability of manufacturing knowledge capital goods is lower. Again, the decrease in profitability is stronger for the knowledge capital goods appropriate for production of the relatively scarce good *X* and technical change is directed even more toward the sector producing the relatively abundant good *Y*. The opposite holds if we halve the depreciation rate.

Finally, doubling either the coefficient of technology externalities in production (γ) or innovation (ξ) increases the profitability of investing in knowledge capital and as a result, technical change gets even more directed toward the sector producing the relatively abundant good *Y*. The opposite holds if we halve these parameter values.

3.4 Conclusions

In this chapter, we presented a stylized version of the DOTIS model that explicitly captures links between energy, the rate and direction of technical change, and the economy. We incorporated Acemoglu's (2002) framework on directed technical change and derived its determinants in our model. At the same time, we showed how our model can be used to study directed technical change by testing the model to see if it is able to project the direction of technical change following the oil shock in the late 1970's in the Netherlands.

We find that technology externalities and substitution possibilities in consumption are key determinants of the direction of technical change. We confirm Acemoglu's finding that technical change is directed toward the relatively abundant good (not intensive in its use of the energy resource) if the final goods are gross substitutes and that technical change is directed toward the relatively scarce good (intensive in its use of the energy resource) if the final goods are gross complements. The direction toward the non-energy intensive good is more pronounced if there are technology externalities.

All this is of public concern. The more substitution possibilities exist between goods, the less an energy price increase reduces the rate of technical change and welfare, whether it is because of an interruption in the energy supply or because of environmental policy. Finally, a case for technology policy arises as the technology externalities cause a divergence between the social- and private returns to knowledge capital. We believe that the model presented in this chapter offers a useful framework to study questions related to the rate and direction of technical change, the economy and policy intervention.

Appendix 3A Structure of the stylized DOTIS model

This appendix provides an algebraic summary of the stylized version of the DOTIS 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), CET (constant elasticity of transformation), 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. We choose the price of intertemporal utility as the numeraire and report all prices in present values. Tables 3A.1 through 3A.6 list the nomenclature.

Zero profit conditions

Production of goods:

$$\Pi^Y_{i,t} \equiv \overline{H}^{-\gamma}_{i,t}\ CES\left(p^{Z^A}_{i,t}, p^{KLEM}_{i,t}; \sigma^Z\right) - p_{i,t} \geq 0 \qquad \perp Y_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad (3A.1)$$

where in the first simulation:

$$p^{KLEM}_{i,t} = CES\left(r^K_t, w_t, p^E_{t\ t}, p_{ROE,t}; \sigma^{KLEM}\right) \qquad i = NRG$$

$$p^{KLEM}_{i,t} = CES\left(p_{NRG,t}, CES\left(r^K_t, w_t; \sigma^{KLEM}\right); \sigma^{NRG}\right) \qquad i = ROE$$

and where in the second simulation:

$$p^{KLEM}_{i,t} = CES\left(r^K_t, w_t, p^E_t, p_{ROE,t}; \sigma^{KLEM}\right) \qquad i = OIL$$

$$p^{KLEM}_{i,t} = CES\left(r^K_t, w_t, p_{ROE,t}; \sigma^{KLEM}\right) \qquad i = NOIL$$

$$p_{i,t}^{KLEM} = \left(CES\left(p_{OIL,t}, p_{NOIL,t}; \sigma^{OIL} \right), CES\left(r_t^K, w_t; \sigma^{KLEM} \right); \sigma^{NRG} \right) \qquad i = ROE$$

and additionally in the third simulation:

$$p_{i,t} = CET\left(p_{HOIL,t}, p_{LOIL,t}; \eta \right) \qquad i = OIL$$

$$\begin{aligned} p_{i,t}^{KLEM} = &\left(CES\left(p_{LOIL,t}, CES\left(p_{HOIL,t}, p_{NOIL,t}; \sigma^{OIL} \right); \sigma^{LOIL} \right), \right. \\ &\left. CES\left(r_t^K, w_t; \sigma^{KLEM} \right); \sigma^{NRG} \right) \end{aligned} \qquad i = ROE$$

Aggregate production of knowledge capital goods:

$$\left(H_{i,t}\ p_{i,t}^{Z\,1-\sigma^{KC}} \right)^{\frac{1}{1-\sigma^{KC}}} = p_{i,t}^{Z^A} \qquad \perp Z_{i,t}^A \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad (3A.2)$$

Production of varieties of knowledge capital goods:

$$\begin{aligned} \Pi_{i,t}^Z \equiv\ & CES\left(r_t^K, w_t; \sigma^{KLEM} \right) \\ & - p_{i,t}^Z \left(1 - 1/\sigma^{KC} \right) \geq 0 \end{aligned} \qquad \perp Z_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad (3A.3)$$

Stock of knowledge capital:

$$p_{i,t}^H = r_{i,t}^H + \left(1 - \delta^H \right) p_{i,t+1}^H \qquad \perp H_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T-1 \qquad (3A.4)$$

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

Investments in knowledge capital:

$$\Pi_{i,t}^R \equiv \overline{R}_{i,t-1}^{-\xi}\ p_{i,t} = p_{i,t+1}^H \qquad \perp R_{i,t} \qquad i = 1,..,I\ ;\ t = 1,..,T-1 \qquad (3A.5)$$

$$\Pi_{i,T}^R \equiv \overline{R}_{i,T-1}^{-\xi}\ p_{i,T} = p_i^{TH} \qquad \perp R_{i,T} \qquad i = 1,..,I$$

Stock of physical capital:

$$p_t^K = r_t^K + \left(1 - \delta^K \right) p_{t+1}^K \qquad \perp K_t \qquad t = 1,..,T-1 \qquad (3A.6)$$

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

Investments in physical capital:

$$\Pi_t^I \equiv LT\left(p_{j,t}\right) = p_{t+1}^K \qquad \perp I_t \qquad t = 1,..,T-1 \qquad (3A.7)$$

$$\Pi_T^I \equiv LT\left(p_{j,T}\right) = p^{TK} \qquad \perp I_T$$

Intratemporal utility:

$$\Pi_t^W \equiv CES\left(p_{NRG,t}, p_{ROE,t}; \sigma_W^{NRG}\right) - p_t^W \geq 0 \qquad \perp W_t \qquad t = 1,..,T \qquad (3A.8)$$

where in the second simulation:

$$p_{NRG,t} = CES\left(p_{OIL,t}, p_{NOIL,t}; \sigma_W^{OIL}\right)$$

and where in the third simulation:

$$p_{NRG,t} = CES\left(p_{LOIL,t}, CES\left(p_{HOIL,t}, p_{NOIL,t}; \sigma_W^{OIL}\right); \sigma_W^{LOIL}\right)$$

Intertemporal utility:

$$\Pi^U \equiv CES\left(p_{t\ \ t}^W; \rho\right) - p^U = 0 \qquad \perp U \qquad (3A.9)$$

Market clearing conditions

Goods:

$$Y_{j,t} = \frac{\partial \Pi_t^I}{\partial p_{j,t}} I_t + \frac{\partial \Pi_{j,t}^R}{\partial p_{j,t}} R_{j,t} + \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial p_{j,t}} Y_{i,t} + C_{j,t} \qquad \perp p_{j,t} \qquad j = 1,..,J;\ t = 1,..,T \qquad (3A.10)$$

in which:

$$C_{j,t} = \frac{\partial \Pi_t^W}{\partial p_{j,t}} W_t$$

Varieties of knowledge capital goods:

$$Z_{i,t} = \frac{\partial \Pi_{i,t}^Y}{\partial p_{i,t}^{Z^A}} H_{i,t}^{\frac{1}{1-\sigma_i^{KC}}}\ Y_{i,t} \qquad \perp p_{i,t}^Z \qquad i = 1,..,I;\ t = 1,..,T \qquad (3A.11)$$

Knowledge capital (in stock):

$$H_{i,t=1} = H_{0i} \qquad \perp p_{i,t=1}^H \qquad i = 1,..,I \qquad (3A.12)$$

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

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

Knowledge capital (in monopolistic competitive market: free-entry condition):

$$Z_{i,t} \frac{1}{\sigma^{KC}-1} = \theta_i^R Z_{i,t} \qquad \perp r_{i,t}^H \qquad i=1,..,I\ ;\ t=1,..,T \tag{3A.13}$$

Physical capital (in market):

$$\frac{r_t^K K_t}{r+\delta^K} = \sum_i \left(\frac{\partial \Pi_{i,t}^Y}{\partial r_t^K} Y_{i,t} + \frac{\partial \Pi_{i,t}^Z}{\partial r_t^K} H_{i,t} Z_{i,t} \right) \qquad \perp r_t^K \qquad t=1,..,T \tag{3A.14}$$

Physical capital (in stock):

$$K_{t=1} = K_0 \qquad \perp p_{t=1}^K \tag{3A.15}$$

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

$$TK = \left(1-\delta^K\right) K_T + I_T \qquad \perp p^{TK}$$

Labor:

$$L_t = \sum_i \left(\frac{\partial \Pi_{i,t}^Y}{\partial w_t} Y_{i,t} + \frac{\partial \Pi_{i,t}^Z}{\partial w_t} H_{i,t} Z_{i,t} \right) \qquad \perp w_t \qquad t=1,..,T \tag{3A.16}$$

Energy resource:

$$E_t = \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial p_t^E} Y_{i,t} \qquad \perp p_t^E \qquad t=1,..,T \tag{3A.17}$$

Intratemporal utility:

$$W_t = \frac{\partial \Pi^U}{\partial p_t^W} U \qquad \perp p_t^W \qquad t=1,..,T \tag{3A.18}$$

Intertemporal utility:

$$U = \prod_j d_U^j \frac{B}{p^U} \qquad \perp p^U \tag{3A.19}$$

Income balance

$$B = \sum_{t=1}^{T} \left(w_t L_t + p_t^E E_t \right) + p_{t=1}^K K_0 - p^{TK} TK \tag{3A.20}$$

Coefficients

Supply of the energy resource:

$$E_t = \left(1+g\right)^{t-1} E_0 \left(1 - shock_t\right) \qquad t = 1,..,T \tag{3A.21}$$

Supply of labor:

$$L_t = \left(1+g\right)^{t-1} L_0 \qquad t = 1,..,T \tag{3A.22}$$

Degree of homogeneity in the production of knowledge capital goods:

$$d_j^Z = \frac{\sigma^{KC}}{\sigma^{KC}-1} \qquad j = 1,..,J \tag{3A.23}$$

Degree of homogeneity in intertemporal utility:

$$d_U^j = \left(d_j^Z\right)^{\left(\frac{\sigma^Z}{\sigma^Z-1}\right)\left(\frac{\sigma_W^{NRG}}{\sigma_W^{NRG}-1}\right)\left(\frac{\rho}{\rho-1}\right)} \qquad j = 1,..,J \tag{3A.24}$$

where in the second simulation:

$$d_U^j = \left(d_j^Z\right)^{\left(\frac{\sigma^Z}{\sigma^Z-1}\right)\left(\frac{\sigma_W^{OIL}}{\sigma_W^{OIL}-1}\right)\left(\frac{\sigma_W^{NRG}}{\sigma_W^{NRG}-1}\right)\left(\frac{\rho}{\rho-1}\right)} \qquad j = OIL, NOIL$$

and where in the third simulation:

$$d_U^j = \left(d_j^Z\right)^{\left(\frac{\sigma^Z}{\sigma^Z-1}\right)\left(\frac{\sigma_W^{LOIL}}{\sigma_W^{LOIL}-1}\right)\left(\frac{\sigma_W^{NRG}}{\sigma_W^{NRG}-1}\right)\left(\frac{\rho}{\rho-1}\right)} \qquad j = LOIL$$

$$d_U^j = \left(d_j^Z\right)^{\left(\frac{\sigma^Z}{\sigma^Z-1}\right)\left(\frac{\sigma_W^{OIL}}{\sigma_W^{OIL}-1}\right)\left(\frac{\sigma_W^{LOIL}}{\sigma_W^{LOIL}-1}\right)\left(\frac{\sigma_W^{NRG}}{\sigma_W^{NRG}-1}\right)\left(\frac{\rho}{\rho-1}\right)} \qquad j = HOIL, NOIL$$

Terminal constraints

We solve the model for a finite number of time periods. To avoid that the complete stocks of physical capital and knowledge capital will be consumed in the last period, transversality conditions are necessary. We follow Lau *et al.*, (2002) by constraining 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 transversality conditions is that they impose balanced growth but neither specific stocks nor specific growth rates in the last period. This condition therefore suits models in which growth rates are endogenously specified.

$$\frac{I_T}{I_{T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TK \qquad (3A.25)$$

$$\frac{R_{i,T}}{R_{i,T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TH_i \qquad (3A.26)$$

Nomenclature

Table 3A.1 Sets and indices

i	$ROE, NRG, OIL, NOIL$	Sectors and industries
j	$ROE, NRG, OIL, LOIL, HOIL, NOIL$	Goods
t	$1,..,T$	Time periods

Table 3A.2 Activity variables

$Y_{i,t}$	Production of goods in sector i at time t
$Z^A_{i,t}$	Aggregate production of knowledge capital goods in intermediate sector i at time t
$Z_{i,t}$	Production of varieties of knowledge capital goods in intermediate sector i at time t
$H_{i,t}$	Stock of knowledge capital in intermediate sector i at time t
$\overline{H}_{i,t}$	Knowledge spillovers in production sector i at time t
TH_i	Terminal stock of knowledge capital in intermediate sector i
$R_{i,t}$	Investments in knowledge capital in intermediate sector i at time t
$\overline{R}_{i,t}$	Delayed technology externalities in intermediate sector i from 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
$C_{j,t}$	Consumption of final goods j at time t
$M_{i,j,t}$	Demand for intermediate goods j in production sector i at time t
W_t	Intratemporal utility at time t
U	Intertemporal utility

Table 3A.3 Income- and endowment variables

B	Budget of the representative agent
H_{0i}	Initial stock of knowledge capital in intermediate sector i
K_0	Initial stock of physical capital
L_t	Endowment of labor at time t
L_0	Initial endowment of labor
E_t	Endowment of the energy resource at time t

E_0	Initial endowment of the energy resource
d_j^Z	Degree of homogeneity in the aggregate production of knowledge capital goods
d_U^j	Degree of homogeneity in intertemporal utility

Table 3A.4 Price variables (in present values)

$p_{j,t}$	Price of goods *j* at time *t*
$p_{i,t}^{KLEM}$	Price of aggregated inputs in sector *i* at time *t*
r_t^K	Rental rate of physical capital at time *t* (in market)
p_t^K	Price of physical capital at time *t* (in stock)
p^{TK}	Price of physical capital (in terminal stock)
$p_{i.t}^{Z^A}$	Price of aggregate knowledge capital goods in intermediate sector *i* at time *t*
$p_{i,t}^Z$	Price of varieties of knowledge capital goods in intermediate sector *i* at time *t*
$r_{i,t}^H$	Rental rate of knowledge capital in intermediate sector *i* at time *t* (in monopolistic
$p_{i,t}^H$	Price of knowledge capital in intermediate sector *i* at time *t* (in stock)
p_i^{TH}	Price of knowledge capital in intermediate sector *i* (in terminal stock)
w_t	Wage rate at time *t*
p_t^E	Price of the energy resource at time *t*
p_t^W	Price of intratemporal utility at time *t*
p^U	Price of intertemporal utility

Table 3A.5 Cost shares

$\theta_{i,t}^Z$	Share of knowledge capital goods in production sector *i* at time *t*
$\theta_{Y_{i,t}}^K$	Share of physical capital in production sector *i* at time *t*
$\theta_{i,t}^L$	Share of labor in production sector *i* at time *t*
$\theta_{i,t}^E$	Share of the energy resource in production sector *i* at time *t*
$\theta_{i,t}^{OIL}$	Share of oil in production sector *i* at time *t*
$\theta_{i,t}^{HOIL}$	Share of heavy oil in production sector *i* at time *t*
$\theta_{i,t}^{LOIL}$	Share of light oil in production sector *i* at time *t*
$\theta_{i,t}^j$	Share of intermediate good *j* in production sector *i* at time *t*
$\theta_{Z_{i,t}}^K$	Share of physical capital in intermediate sector *i* at time *t*
θ_i^R	Knowledge capital investment share in intermediate sector *i*
θ_i^I	Physical capital investment share of sector *i* at time *t*
θ_W^j	Share of good *j* in intratemporal utility

Table 3A.6 Elasticities and coefficients

Description		Value in each simulation 1	2	3
Elasticity of substitution in intertemporal utility				
ρ	Between time periods	0.50	0.50	0.50
Elasticities of substitution in consumption				
σ_W^{NRG}	Between energy and other products	0.25	0.25	0.25
σ_W^{OIL}	Between energy carriers		4	4
σ_W^{LOIL}	Between light oil and other energy carriers			1
Elasticities of substitution in production				
σ^{Z}	Between knowledge capital goods and remaining inputs	1	1	1
σ^{NRG}	Between energy and remaining inputs	0.25	0.25	0.25
σ^{KLEM}	Between remaining inputs	1	1	1
σ^{OIL}	Between energy carriers		4	4
σ^{LOIL}	Between light oil and other energy carriers			1
Elasticity of transformation in production				
η	Between energy from light- and heavy oil			1
Elasticity of substitution in production of knowledge capital goods				
σ^{KC}	Between varieties of knowledge capital goods	5	5	5
g	Growth rate	0.01	0.01	0.01
r	Interest rate	0.05	0.05	0.05
δ^{K}	Depreciation rate of physical capital	0.05	0.05	0.05
δ^{H}	Depreciation rate of knowledge capital	0.25	0.25	0.25
γ	Coefficient of technology externalities in production		0.09	0.09
ξ	Coefficient of technology externalities in innovation		0.15	0.15
$shock_t$	Energy resource shock at time *t=1980*	0.16	0.16	0.16

Note: Simulation 1 refers to energy versus the rest of the economy; simulation 2 extends simulation 1 by differentiating the energy sector; simulation 3 extends simulation 2 by introducing product differentiation in the oil industry.

Appendix 3B National accounting matrices

Table 3B.1 *National accounting matrices (mln. €)*

	Energy sector	Intermediate sector	Investments in knowledge capital	Rest of the economy	Intermediate sector	Investments in knowledge capital	Consumption	Investments in physical capital	Income
Energy	10		-0.18	-6			-1.30	-2.52	
Knowledge goods	-1	1		-35					
Knowledge capital		-0.20	0.20						
Other products	-1			350		-6.30	-226.50	-116.20	
Knowledge goods					35				
Knowledge capital					-7	7			
Labor	-1	-0.20		-150	-21				172.20
Physical capital	-3	-0.60		-159	-7				169.60
Crude oil	-4								4.00
Expenditures							227.80	118.72	-346.52

(a) Simulation 1: Energy versus rest of the economy

	Rest of the energy sector	Intermediate sector	Investments in knowledge capital	Oil industry	Intermediate sector	Investments in knowledge capital	Rest of the economy	Intermediate sector	Investments in knowledge capital	Consumption	Investments in physical capital	Income
Energy from non oil	2.50		-0.045				-1			-0.475	-0.98	
Knowledge goods	-0.25	0.25										
Knowledge capital		-0.05	0.05									
Energy from oil				7.50		-0.135	-5			-0.825	-1.54	
Knowledge goods				-0.75	0.75							
Knowledge capital					-0.15	0.15						
Other products	-0.50			-0.50			350		-6.30	-226.50	-116.20	
Knowledge goods							-35	35				
Knowledge capital								-7	7			
Labor	-0.50	-0.05		-0.50	-0.15		-150	-21				172.20
Physical capital	-1.25	-0.15		-1.75	-0.45		-159	-7				169.60
Crude oil				-4.00								4.00
Expenditures										227.80	118.72	-346.52

(b) Simulation 2: Differentiating the energy sector

	Rest of the energy sector	Intermediate sector	Investments in knowledge capital	Oil industry	Intermediate sector	Investments in knowledge capital	Rest of the economy	Intermediate sector	Investments in knowledge capital	Consumption	Investments in physical capital	Income
Energy from non oil	2.50		-0.045				-1			-0.475	-0.98	
Knowledge goods	-0.25	0.25										
Knowledge capital		-0.05	0.05									
Energy from light oil				4.25			-3			-1.25		
Energy from heavy oil				3.25		-0.135	-2			0.425	-1.54	
Knowledge goods				-0.75	0.75							
Knowledge capital					-0.15	0.15						
Other products	-0.50			-0.50			350		-6.30	-226.50	-116.20	
Knowledge goods							-35	35				
Knowledge capital								-7	7			
Labor	-0.50	-0.05		-0.50	-0.15		-150	-21				172.20
Physical capital	-1.25	-0.15		-1.75	-0.45		-159	-7				169.60
Crude oil				-4.00								4.00
Expenditures										227.80	118.72	-346.52

(c) Simulation 3: Introducing product differentiation in the oil industry

Sources: Statistics Netherlands (2000), IEA's *Energy Balances*, and authors' own calculations.

Chapter 4 Estimating feedback effect in technical change: A frontier approach*

4.1 Introduction

Treatment of technical change in economic literature can be traced back to Schumpeter (1942) whose ideas on the process of technical change comprising three phases of invention, innovation, and diffusion led to the first systematic economic theory on this topic. It is becoming increasingly clear, however, that delayed feedback occurs between these phases. That is, today's technical change depends on yesterday's technical change. Arthur (1994) refers to this phenomenon as 'path dependency' and shows its importance for the process of technical change. Path dependency is also identified as a key determinant for technical change and economic growth in recent growth models in which innovation is specified endogenously (most notably, Acemoglu, 2002). All this is of public concern. To the extent that such feedback is external to agents' decision-making processes, social returns to research and development (R&D) diverge from the private returns and a case for policy intervention arises.

To our knowledge, patent citation studies offer the only empirical evidence of feedback in technical change. These studies have investigated where and when existing patents are cited in the application of new patents (see *e.g.* Caballero and Jaffe, 1993; and Jaffe *et al.*, 1993; 2000). By following these paper trails, patent citation studies inform us about the influence of past innovations on the development of new ones. Yet, these studies have some drawbacks. One is that they are only available for a limited range of sectors and industries. Another is that they suffer from measurement problems associated with the use of patents as measure of innovation (Griliches, 1979). Because of the importance of delayed feedback for the process of technical change, and hence for productivity growth, we believe it merits further investigation.

In this chapter, we explore an alternative route for empirical analysis of feedback in technical change based on the literature of productive efficiency analysis, in particular the Malmquist productivity index (Caves *et al.*, 1982). This index can be decomposed into an *efficiency change* index and a *technical change* index, which measure the extent to which productivity changes are due to changes in efficiency and technology respectively (see *e.g.* Färe *et al.*, 1994a; 1994b; and Kumar and Russell, 2002). We argue that the technical change component of the Malmquist index is a useful measure for the purposes of feedback estimation

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because it represents the impact of technical change on productivity. It therefore captures the quality and effectiveness of R&D activities as well as spontaneously arising technical change through *e.g.* learning-by-doing. This measure can therefore overcome several measurement problems associated with the use of patents as measure for technical change. Other advantages of this measure include its capability to handle multiple-input multiple-output technologies and biased technical change.

In general, the proposed Malmquist approach is applicable at any level of aggregation from firm-level studies to cross-country comparisons. In this chapter we focus on empirical estimation of the feedback effect at the macro level using cross-country panel data, but the approach is easily adapted to an industry- or firm-level analysis. Our data set covers aggregate production data of 25 OECD countries for the years 1980 through 1997. We apply a two-stage estimation procedure which combines the bootstrap approach recommended by Simar and Wilson (2003) with the Generalized Method of Moments (GMM) approach suggested by Zengfei and Oude Lansink (2006). More specifically, we first estimate the technical change component of the Malmquist index by nonparametric data envelopment analysis, and apply the Simar-Wilson bootstrap procedure to correct for small sample bias in the efficiency estimators. We subsequently use the obtained estimates in a panel data model with finite distributed lag structure and use the Arellano and Bond (1991) GMM estimator to obtain estimates of the delayed feedback effect.

This chapter is organized as follows. In Section 4.2, we present the theoretical framework that underlies our feedback estimation. Section 4.3 outlines the computation of the Malmquist productivity index and its component indices. Section 4.4 presents the regression model to be estimated and discusses related econometric issues. Section 4.5 describes the application to the 25 OECD countries and Section 4.6 concludes. Finally, Appendix 4A outlines the construction of our dataset.

4.2 Theoretical framework

This section presents the theoretical framework that forms the foundation for the feedback estimation in Section 4.4. Given the vast number of economic theories on technical change, a comprehensive review is beyond the scope of this study. Instead, we restrict ourselves to a generally accepted macroeconomic framework that is directly applicable in Section 4.4. To keep discussion focused, we first summarize the general model specification formally, and then interpret and motivate it.

The process of technical change generally depends on R&D expenditures, past changes in technology and certain other variables. Let $TC_{n,t}$ denote the rate of technical change in country n ($n = 1,..,N$) in time period t ($t = 1,..,T$). We denote a country's expenditure on research and development by $R\&D_{n,t}$, and $\mathbf{X}_{n,t}$ represents a vector of country-specific control variables. The functional relationship between these variables can be generally expressed as

$$TC_{n,t} = f\left(TC_{n,t-j}, R\&D_{n,t}, \mathbf{X}_{n,t}\right) \quad (n=1,..,N),\ (t=1,..,T),\ j \in (1,..,T-1) \qquad (4.1)$$

in which index *j* denotes the delay of the feedback effect.

The main theoretical rationale of this equation draws from the endogenous growth model by Rivera-Batiz and Romer (1991). First, we capture the essence of what they refer to as the 'lab equipment' specification by specifying technical change as a function of expenditures on R&D, in which we assume the effect of R&D on the rate of technical change to be positive (*i.e.* $f'_{R\&D} > 0$). Second, we capture the essence of their 'knowledge-based' specification by allowing for delayed feedback in technical change.[1] That is, yesterday's technical change can have an effect on today's technical change. As for the sign of this effect, it is often argued that current innovations allow researchers to develop further innovations, that is, researchers 'stand on the shoulders' of their predecessors implying $f'_{TC} > 0$. Practical examples of causes of such delayed feedback include learning-by-doing, learning-by-using, network externalities, and knowledge spillovers.[2]

With respect to the control variables, we follow studies that emphasize the role of complementary inputs in technical change by allowing technical change in country *n* to be a function of country *n*'s distance from the production possibilities frontier (*e.g.* Rosenberg, 1972). The higher the quality of a country's complementary inputs is, the better able this country is to develop and implement inventions. Griffith *et al.* (2003) present an endogenous growth model that explicitly incorporates this consideration by allowing the size of innovations to be a function of the distance from a meta production possibilities frontier. We also draw from studies that stress the importance of international knowledge spillovers for domestic productivity levels and specify technical change in country *n* as a function of these spillovers (Coe and Helpman, 1995). As we also discuss in Section 4.3, productivity levels reflect a country's ability to innovate or to adopt new technologies.

The lag structure of the regressors warrants particular attention. First, we follow patent citation studies and include multiple lags of the dependent variable as regressors in the model, in which we set $J \geq 3$. For example, Caballero and Jaffe (1993) find a modal lag of three years for patent citations in the USA, whereas Jaffe and Trajtenberg (1999) report a five-year lag for the G5 countries. Second, we follow studies that focus on research productivity and include up to

[1] Rivera-Batiz and Romer (1991) refer to the 'lab-equipment' specification because of its emphasis on physical inputs and refer to the 'knowledge-based' specification because of its emphasis on non-physical inputs.

[2] Yet, it can also be argued that, as more and more innovations are developed, the more difficult and costly it becomes to develop an innovation that improves upon the previous ones because the easiest discoveries are usually made first. This 'fishing out effect' would imply $f'_{TC} < 0$. Popp (2005) finds that such diminishing returns apply to R&D at the industry level rather than aggregate R&D. As expected returns to R&D within any industry decreases, profit maximizing researchers and developers are expected to shift resources to more profitable industries.

three lags of the R&D regressor as well. R&D takes time and it typically takes several years before R&D expenditures affect the growth rate of productivity (see Griliches, 1979, for a description of various lags involved). Hall *et al.* (1986) find that the average lag between R&D expenditures and patent application is short although it still takes a few years before a patent application translates into productivity growth. They find no conclusive evidence, however, on the precise form of the lag structure. Third, we follow Coe and Helpman (1995) in including knowledge spillovers as a one period lagged regressor. Before we can move from theory to estimation, however, we need to obtain estimates for the rate of technical change.

4.3 Estimating technical change

Traditionally, technical change is approximated by the Solow (1957) residual or by a variable representing inputs or outputs of the R&D process. The Solow residual is what is left over of economic growth after it has been accounted for changes in aggregate inputs. It thereby proxies total factor productivity growth that shifts the production possibility frontier. The quality of this approximation, however, depends largely on the validity of the assumptions on perfect competition and constant returns to scale. In case of imperfect competition, for example, the Solow residual comprises not only technical change but also efficiency improvements. For this reason, later studies have extended Solow's contribution to the case of imperfect competition and increasing returns, although this comes at the cost of imposing additional structure on the production function (see *e.g.* Hall, 1988b).

One could also use inputs and outputs of R&D activities as proxy variables for technical change. R&D input variables include R&D expenditures and numbers of engineers and scientists, whereas R&D output variables typically include the depreciated sum of past innovations and numbers of patents. Yet, these measures are prone to several measurement problems (Howitt, 1996). One well known problem relates to knowledge as an input: Intangible inputs such as informal exchange of information are difficult to measure and, hence, R&D input variables tend to underestimate the real inputs. Likewise, intangible outputs are also difficult to measure and R&D is not the only driver behind changes in technology; technical change also occurs spontaneously without R&D efforts. Yet another problem relates to quality improvements: R&D output variables underestimate real outputs because of practical difficulties of dealing with quality improvements in constructing price indices. For these reasons, we next consider an alternative approach originating from the production frontier literature.

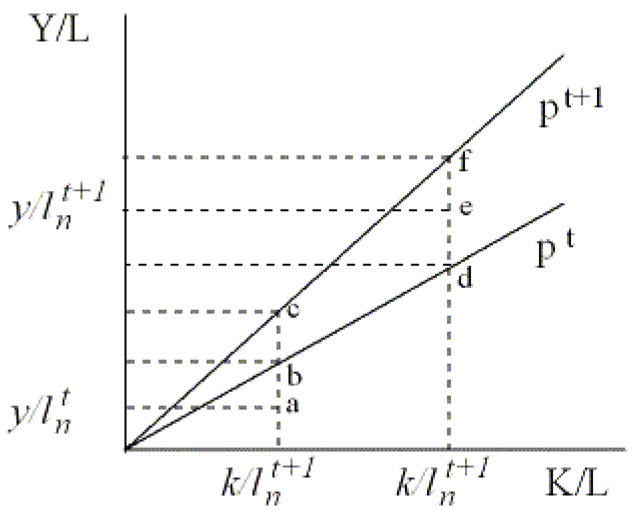
Malmquist productivity index

For simplicity, we focus on a single-output, two-input technology in which k represents the capital input, l the labor input, and y the output.[3] Let the production technology of period t be characterized by the Shephard (1953) output distance function

$$D^t(k,l,y) \equiv \inf_\theta \left\{ \theta \in R_+ \,\middle|\, \text{inputs } (k,l) \in R_+^2 \text{ can produce output } y/\theta \in R_+ \right\} \tag{4.2}$$

Output distance functions measure (the inverse of) the maximum output expansion potential at a given input level and thus provide a complete characterization of a technology.[4] In theory, this maximum corresponds to the best technology that is available whereas in empirical work it corresponds to the best practiced technology.

Figure 4.1 Decomposition of the Malmquist productivity index



The Malmquist productivity index (MI) is defined in terms of the distance function as

$$MI(k^{t,t+1}, l^{t,t+1}, y^{t,t+1}) \equiv \left[\frac{D^t(k^{t+1}, l^{t+1}, y^{t+1})}{D^t(k^t, l^t, y^t)} \cdot \frac{D^{t+1}(k^{t+1}, l^{t+1}, y^{t+1})}{D^{t+1}(k^t, l^t, y^t)} \right]^{\frac{1}{2}} \qquad (t = 1,..,T) \tag{4.3}$$

(Caves *et al.*, 1982; Färe *et al.*, 1994a; 1994b). It measures productivity change in terms of the change in the output augmentation potential relative to a fixed production possibility frontier so that index values MI > 1 indicate productivity growth and MI < 1 productivity decline. Taking the base period t frontier as the benchmark, the change of productivity is measured by the distance function ratio $\frac{D^t(k^{t+1}, l^{t+1}, y^{t+1})}{D^t(k^t, l^t, y^t)}$. Alternatively, we could take the target period t+1

[3] The approach can be directly generalized to multi-input multi-output settings that are of interest at the firm level (see *e.g.* Färe *et al.*, 1994b). This can be seen as one advantage of the approach.

[4] If function F denotes the production function that characterizes the production possibility frontier, then $F(k,l) = D(k,l,y) \cdot y$.

frontier as the benchmark and use the distance function ratio $\dfrac{D^{t+1}(k^{t+1},l^{t+1},y^{t+1})}{D^{t+1}(k^{t},l^{t},y^{t})}$. Since we have no particular reason to prefer the base period frontier to the target period frontier (or vice versa), we calculate the index number as the geometric mean of these two distance function ratios. Figure 4.1 illustrates the Malmquist index and its two distance function ratios. Period *t* distance function ratio is given by *(e/d)/(a/b)*. Period *t*+1 ratio is *(e/f)/(a/c)*.

The main rationale for considering the Malmquist index here is that it explicitly allows for inefficiency and that it therefore lends itself naturally for estimating technical change. Stated otherwise, the MI can be decomposed into two mutually exclusive and exhaustive components: technical change (TC) and efficiency change (EC) (Färe *et al*., 1994a). Formally,

$$MI^{t}(k^{t,t+1},l^{t,t+1},y^{t,t+1}) = TC\cdot EC \qquad (t=1,..,T-1) \tag{4.4}$$

in which

$$EC \equiv \frac{D^{t+1}(k^{t+1},l^{t+1},y^{t+1})}{D^{t}(k^{t},l^{t},y^{t})} \qquad (t=1,..,T-1) \tag{4.5}$$

and

$$TC \equiv \left[\frac{D^{t}(k^{t+1},l^{t+1},y^{t+1})}{D^{t+1}(k^{t+1},l^{t+1},y^{t+1})}\cdot\frac{D^{t}(k^{t},l^{t},y^{t})}{D^{t+1}(k^{t},l^{t},y^{t})}\right]^{\frac{1}{2}} \qquad (t=1,..,T-1) \tag{4.6}$$

Values greater than one indicate progress in technical efficiency or technical possibilities whereas values less than one indicate regress. The EC component can be interpreted as a relative shift of a country towards or away from the production possibilities frontier. In Figure 4.1, the EC index corresponds to *(e/f)/(a/b)*. On the other hand, the TC component corresponds to a shift of the frontier, as perceived from a fixed input-output combination as the benchmark. Similar to the MI, we calculate the TC index as the geometric mean of distance function ratios referring to input-output observations from periods *t+1* and *t* as benchmarks. In Figure 4.1, the TC index corresponds to a geometric mean of (*e*/*d*)/(*e*/*f*) and (*a*/*b*)/(*a*/*c*).

Following Nishimizu and Page (1982) and Färe *et al*. (1994a), we interpret the TC component as measure of technical change and the EC component as measure of catching up. In empirical context, the TC component represents change of the best practice technology, while the EC component represents adoption of best practices. Yet, these TC components have to be interpreted broadly in our application below as to encompass, among others, disembodied technical change and differences in economic structures.

Using the TC component of MI as measure of technical change can overcome several of the measurement problems that R&D variables suffer from. This index measures technical change in terms of its overall effect on total factor productivity, which encompasses both R&D efforts and spontaneous technical change. Thus, this index enables us to overcome the knowledge input problem because inputs do not have to be ascribed to R&D. It does not matter, for example, whether machines are used in a laboratory or in a production facility as long as these machines generate productivity growth. Similarly, changes in the characteristics of machines are irrelevant as long as these new characteristics generate productivity benefits, in effect overcoming the quality improvement problem.

The Malmquist index offers a general framework that is based on the microeconomic theory of the firm (see *e.g.* Färe *et al*., 1994b). The approach extends to a firm- or industry-level analysis in a straightforward fashion. It does not require restrictive assumptions about the structure of the production technology or the rate and direction of technical change. For example, the Malmquist approach does not require the assumption of Hicks neutral technical change as the traditional Solow residual does (see *e.g.* Färe *et al*., 1997).

Some caveats should be noted though. Besides capturing changes in technology and technical efficiency, measures of productivity growth (and MI is no exception here) also typically comprise the effects of: (i) measurement error, (ii) economies of scale due to widespread imperfect competition and increasing returns, and (iii) procyclical fluctuations (Basu and Fernald, 2000). Productivity is procyclical mainly because of variable utilization of inputs and reallocations of resources. The former effect can be seen as a type of measurement error: True inputs are more cyclical than measured inputs and, hence, productivity measures are downward biased in economic downturns. The latter effect arises from reallocation of inputs to sectors with higher marginal products yielding more output per input and, therefore, higher productivity.[5] If one is interested in productivity because of its index value for welfare, one does not need to be concerned about these effects; if productivity and technology differ, then it is productivity that most closely indexes welfare (*c.f.* Basu and Fernald, 2000). But since we are interested in productivity because of its index value for technical change, we need to correct for these effects. We return to the various corrections in further detail in subsequent sections.

Data envelopment analysis

In empirical studies, production possibility frontiers or distance functions are not known *a priori*, but must be estimated from empirical data. A common approach in the frontier estimation literature is to use a nonparametric programming technique known as data envelopment analysis (DEA) to calculate the distance functions underlying the Malmquist index.[6] This technique does not require any parametric specification of the functional form of the distance function or the distribution of inefficiencies. Neither are assumptions about market

[5] To be complete, Basu and Fernald (2000) also identify procyclical technology shocks, and scale economies due to imperfect competition and increasing returns as reasons why productivity is procyclical.

[6] See Färe *et al*. (1994b) or Charnes *et al*. (1994) for general expositions of this technique. Stochastic Frontier Analysis (SFA) is another popular approach; see Bauer (1990) for a review.

structure nor firm behavior required. Distance functions are estimated relative to the minimal extrapolation envelopment, which is the minimal set that contains all observed data and satisfies the maintained regularity conditions. The minimal extrapolation envelopment is essentially the smallest set enveloping the data where the upper boundary is the 'best-practice' production possibilities frontier.

In our application, we use macroeconomic variables: aggregate labor- and capital inputs and aggregate output. We calculate the values of distance function relative to a (global, contemporaneous) production possibility frontier exhibiting constant returns to scale. Under the usual set of regularity conditions of free disposability, convexity, and constant returns to scale, the empirical distance function value $\hat{D}^s(k_n^t, l_n^t, y_n^t)$ of country *n* observed in period *t*, measured relative to period *s* technology ($s = t-1, t, t+1$), can be computed as the optimal solution to the linear programming problem[7]:

$$\hat{D}^s(k_n^t, l_n^t, y_n^t)^{-1} = \max_{\theta,\lambda} \theta \quad \textit{subject to} \tag{4.7}$$

$$k_n^t \geq \sum_{m=1}^{M} k_m^s \cdot \lambda_m \tag{4.8}$$

$$l_n^t \geq \sum_{m=1}^{M} l_m^s \cdot \lambda_m \tag{4.9}$$

$$\theta y_n^t \leq \sum_{m=1}^{M} y_m^s \cdot \lambda_m \tag{4.10}$$

$$\lambda_m \geq 0 \tag{4.11}$$

in which *m* is an alias of *n*. This problem calculates the output distance from the input-output vector of country *n* to the best-practice frontier constructed as a linear combination of observed input-output vectors. Multipliers λ_m denote the weight of country *m* in the benchmark (frontier) input-output vector that represents the maximum output for country *n*. The constructed reference technology is a convex cone and its isoquants are piecewise linear.

The EC component captures the effects of scale economies on productivity growth. Färe *et al*. (1994a) present an extended decomposition, in which they further decompose the EC component into pure efficiency changes, calculated relative to a variable-returns-to-scale

[7] Note that we need four different distance function values to calculate the Malmquist index, corresponding to (*t,s*=*t*), (*t*+1,*s*=*t*), (*t,s*=*t*+1), and (*t*+1,*s*=*t*+1).

frontier, and a scale component that captures the deviations between the variable- and constant-returns-to-scale frontiers.[8] Besides capturing scale economies, we expect this scale component to also capture (at least partly) the effects of resource reallocations on productivity growth given that these reallocations, as well as their effects, are related to increasing returns (Basu and Fernald, 2000). Increasing returns and imperfect competition cause marginal products to differ across firms or industries, which in turn leads to some reallocation of resources across these firms or industries. Moreover, resource reallocations appear as increasing returns: output increases without proportional increases of the inputs.

The statistical properties of the nonparametric distance function estimators are nowadays relatively well known (see Simar and Wilson, 2000). Nonparametric statistical inference generally suffers from '*curse of dimensionality*', and DEA is no exception. More specifically, the empirical distance function estimates based on finite samples exhibit downward statistical bias because we do not observe the true maximum output but approximate it by linear interpolation of the frontier. The problem is severe especially in small samples. To obtain unbiased estimates, it is advisable to complement the estimation procedure with nonparametric bootstrap techniques (see Simar and Wilson, 2000, for further details). There is another important reason for eliminating the sampling bias: Besides distorting the MI and its components, it would cause problems of endogeneity and serial correlation in the regression analysis that follows.[9] The sensitivity analysis in Section 4.5 aptly reveals the importance of the correction for the sampling bias.

4.4 Estimating feedback effect in technical change

Having estimated the rates of technical change, we next proceed to estimation of the feedback effect. This section discusses some general econometric issues related to such feedback estimation, and suggests a procedure based on GMM. Equation (4.1) is our starting point in moving from theory to estimation. As the estimation of the Malmquist index requires panel data, the estimation of equation (4.1) essentially boils down to a panel data model with a finite distributed lag structure. Following the macro-economic growth literature, we assume a constant-elasticity-of-substitution specification for function *f* and take logarithms on both sides to get the regression equation

[8] The decomposition by Färe *et al*. (1994a) measures technical change with respect to the constant returns to scale reference technology, which we interpret as a 'global' benchmark for productivity improving technical progress. Ray and Desli (1997) proposed an alternative decomposition which measures technical change by means of a variable returns to scale benchmark technology (see also Grosskopf, 2003; and Lovell, 2003 for critical discussion).

[9] We refer to Simar and Wilson (2003) and Zengfei and Oude Lansink (2006) for further discussion about econometric issues in two-stage semiparametric models.

$$\ln TC_{n,t} = \sum_{j=1}^{J} \alpha_j \ln TC_{n,t-j} + \beta \ln R\&D_{n,t-3} + \boldsymbol{\chi} \ln \mathbf{X}_{n,t} + u_{n,t} \qquad (n = 1,..,N),\ (t = 1,..,T) \qquad (4.12)$$

Coefficients α_j represent elasticities of the current rate of technical change with respect to previous rates of technical change, henceforth referred to as the delayed feedback effect. Similarly, coefficient β is the R&D elasticity, and $\boldsymbol{\chi}$ represents elasticities of the control variables. We assume the substitution elasticities to be homogeneous for the cross-sectional units. The composite error term $u_{n,t} \equiv \gamma_n + \tau_t + \varepsilon_{n,t}$ comprises three effects. A fixed effect (γ_n) controls for unobserved time-invariant heterogeneity in the cross section that can be correlated with any regressor. In our application below, sources of heterogeneity include cross-country differences in, for example, culture, geography, and accumulated stocks of knowledge from past R&D. The error term also includes a time trend (τ_t) to represent any systematic component of the unmeasured factors. Finally, $\varepsilon_{n,t}$ is the idiosyncratic error term.

Estimation of equation (4.12) is complicated by the fact that we cannot assume all regressors to be strictly exogenous conditional on the unobserved effect. The inclusion of lagged dependent variables in the set of regressors violates this assumption by definition. Instead, we assume the regressors to be predetermined conditional on the unobserved effect.[10] In other words, we now allow $\ln TC_{n,t}$ to affect future values of our regressors after all current and past values of the regressors and the fixed effect are controlled for. These current and past values are still restricted to be uncorrelated with the idiosyncratic error term. This sequential moment restriction would be violated if, for example, the delay in the feedback in technical change were actually longer than we have specified it in equation (4.12) and violations would be reflected in serial correlation of the idiosyncratic error term $\varepsilon_{n,t}$. One therefore has to test for serial correlation when applying this specification. To obtain consistent coefficient estimates, one can use instrumental variables and a transformation to remove the fixed effects. It can be shown that under a sequential moment restriction and some dependence over time, first differencing is an attractive transformation because it not only removes the fixed effects (*i.e.* γ_n), but also allows for the use of lagged levels of the regressors as instruments (Anderson and Hsiao, 1982). In our application below, we follow Arellano and Bond (1991) and use such lagged levels in a GMM procedure (see also Zengfei and Oude Lansink, 2006). To preserve finite sample properties, we include only two lags of each predetermined regressor as instrument. This particular GMM estimator is robust to heteroskedasticity of arbitrary form and is the most efficient GMM estimator.[11] Because the consistency of this estimator hinges critically on absence of serial

[10] The only regressor for which we can maintain the strict exogeneity assumption is the knowledge spillover variable as future spillovers cannot affect today's innovations.

[11] Note that all least squares estimators belong to this class of estimators.

correlation in the idiosyncratic error term, we assure ourselves that this is indeed the case by reporting tests of the LM statistic next to the Sargan statistic in our results below.[12]

As a final note, we observe that many of the variables we are interested in tend to correlate with each other, which makes it difficult to isolate the specific contribution of each variable with precision. This especially concerns the lag structure of the TC variables on the right hand side of equation (4.12). We treat each of these years as a separate variable although they are correlated from year to year. There is no easy solution to this problem. We should therefore limit attention on broader trends revealed by the data and not expect the model to answer detailed questions regarding the exact magnitude of the feedback effect.

4.5 Application

Aggregate production functions remain the workhorse of macroeconomics despite the recurring criticism (see *e.g.* Colacchio and Soci, 2003).[13] We next estimate the feedback effect at the aggregate level focusing attention on a sample of 25 OECD countries over the period of 1980 through 1997 (see Appendix 4A for details and sources).[14] We first construct our global, contemporaneous production possibility frontier and estimate the Malmquist productivity indices and their components to capture changes in technology and technical efficiency. We correct the Malmquist indices for the effects of sampling error, scale economies, reallocations of resources, variable utilization of inputs over time, as well as for quality differences in the labor input. This leaves us with the TC component as estimate of technical change and allows us to compare the technical performance of each country to the frontier over time. We finally use the obtained TC estimates in regression equation (4.12), which yields coefficient values of the delayed feedback effect.

Data

From the OECD *Annual National Accounts*, we obtain gross domestic product (GDP), which we use as our value-added measure of aggregate output. We approximate the aggregate capital input by the productive capital stock where we make the simplifying assumption that capital

[12] The Sargan (1958) statistic tests for correlation between the instruments and the idiosyncratic error term that would invalidate the instruments. An instrument would correlate with $\varepsilon_{n,t}$ if it were falsely omitted from the model. Not including a sufficient number of lagged dependent variables in equation (4.12), for example, would result in serially correlated $\varepsilon_{n,t}$ and correlation between $\varepsilon_{n,t}$ and any falsely omitted lagged dependent variables as instruments.

[13] It is worth to point out the recent study by Zelenyuk (2005), which shows that consistent aggregation of Malmquist indices from the micro units to the macro level is possible. We should also re-emphasize that the approach presented above applies equally well to micro-level analysis of technical change in firms.

[14] Countries for which data was available for the entire time period include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Great Britain, Germany, Greece, Iceland, Ireland, Italy, Japan, South-Korea, Mexico, the Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, and USA.

assets are fully efficient until their retirement. Assuming that capital assets are quasi-fixed, we subsequently multiply the capital stock with its utilization rate to account for variability in its utilization. We obtain data for the productive capital stock from the OECD *Annual National Accounts* and the utilization rate from the OECD *Business Tendency Survey*. We measure the aggregate labor input by total number of persons employed and multiply this employment measure with the average number of hours actually worked to account for variable utilization of labor. To control for quality differences in the aggregate labor input, we differentiate between production- and non-production workers. This is a crude distinction, but the only one available for a large sample of countries over time. In addition, it has been found that these occupational proportions correlate highly with other measures of human capital like education (Berman *et al*., 1998). We obtain number of persons employed from the OECD *Economic Outlook*, the average hours actually worked from the OECD *International Sectoral Database* and numbers of both types of workers from the UN *Industrial Statistics Database*. We express both aggregate output and the aggregate capital input in US dollars (at purchasing power parity (PPP) adjusted prices of 1995), whereas we express the aggregate labor input in hours worked. The use of different measurement units does not pose a problem because the MI is an index number measure. Table 4.1 presents average growth rates of the inputs and output for each country in the sample.

Table 4.1 Average annual growth rates of inputs and output for G7 countries between 1980 and 1997

Country	GDP	Capital	Labor
Canada	1.025	1.033	1.011
France	1.019	1.022	0.994
Great Britain	1.024	1.025	1.001
Germany	1.019	1.022	1.011
Italy	1.019	1.011	0.996
Japan	1.031	1.042	1.003
USA	1.030	1.032	1.017

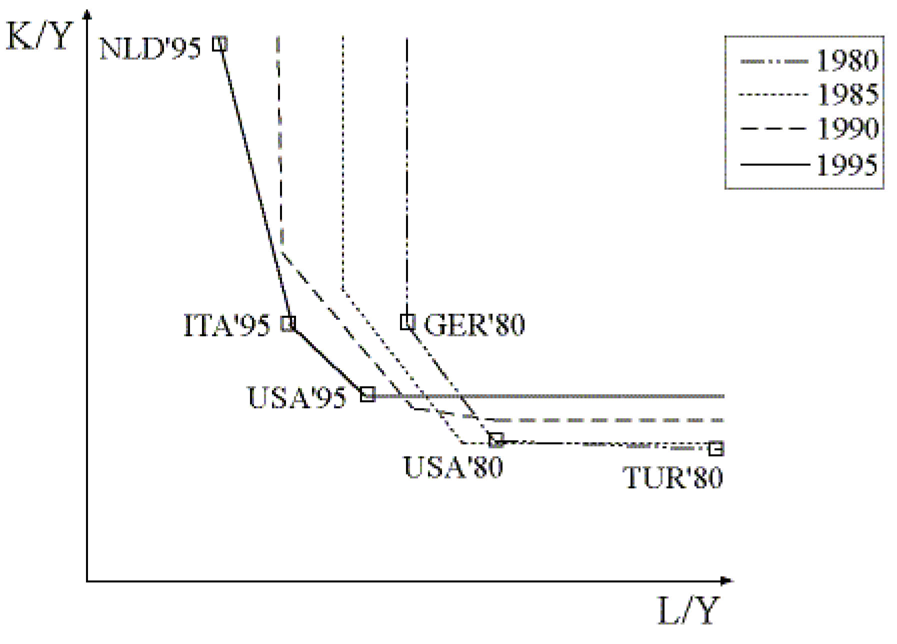
Note: Average values are indices and are geometrically calculated.

In the subsequent regression analysis we use gross expenditures on R&D (expressed in 1995 PPP adjusted prices) as our R&D measure. We obtain this variable from the OECD *Main Science and Technology Indicators* where it should be noted that, unfortunately, the data coverage of this variable is relatively incomplete for our sample. We use country-specific distance function values as our estimate of country n's distance from the production possibilities frontier in period t.[15] A distance function with value one translates into a country spanning the frontier. Finally, in the absence of data for our sample, we approximate international knowledge spillovers by a variable that measures a country's openness to trade. We follow Coe and Helpman (1995) and define a country's openness to trade as the value share of imports in total value added, all expressed in 1995 PPP adjusted prices. We obtain the import variable from the *Economic Outlook* of the OECD.

Estimates of technical change

Figure 4.2 illustrates the shape of the DEA production frontiers and their biased shift over time by means of an isoquant map. The isoquants represents the combinations of inputs that can produce one unit of value added; the horizontal axis represents the labor input per GDP and the vertical axis the capital input per GDP. In year 1980, Germany, USA, and Turkey defined the efficient frontier. Germany had the highest labor productivity (y/l), Turkey had the highest capital productivity (y/k), while the USA performed well on both criteria. We construct the frontier as the linear combination of these observed points in the input space.

Figure 4.2 Isoquant map of DEA frontiers



Since 1980, the capital intensity of production increased in all countries. USA and Germany span the frontiers of 1985 and 1990, as they did in 1980, so in Figure 4.2 we can follow their

[15] Contrary to what one might expect, inclusion of this control variable next to the lagged dependent variables does not lead to multicollinearity problems, even though distance functions are used for calculating the TC index. Note that this particular distance function is merely one of the four distance functions underlying the TC component, and thus this distance function need not be correlated with the TC component.

development in three different points of time. In the 1990s, the Netherlands begins to shift the highly capital intensive end of the frontier outwards as illustrated by its observation in 1995. The German unification shows up in the productivity figures since 1993, and Italy took over its relative position as the frontier shifting country. USA preserved its relative position until 1996, but the relatively labor intensive Ireland emerged to dominate it in 1997.

In Figure 4.2 we observe that the input isoquants shift northwest over time, which means that a given value added could be produced with less labor, while more capital was needed. A similar pattern of biased technical change has been noted in other studies; see *e.g.* Kumar and Russell (2002). The figure in fact indicates technical regress for labor intensive countries like Turkey. A naïve interpretation of the figure would suggest that production techniques have been forgotten; for example, USA could not have produced the output of 1995 with input levels of 1980. Sampling bias offers a more credible explanation: We simply do not observe countries that operate efficiently with a highly labor intensive technology in 1995. We apply the standard bootstrap procedure (see Simar and Wilson, 2000, for details) to alleviate this kind of sampling bias. Note that this figure represents the initial frontiers prior to the bootstrap.

Table 4.2 Decomposition of the Malmquist productivity index for G7 countries

	Average annual changes from 1980 through 1997		
Country	Malmquist index (MI)	Technical change (TC)	Efficiency change (EC)
Canada	0.993	1.007	0.987
France	1.009	1.001	1.007
Great Britain	0.999	1.002	0.997
Germany	0.996	0.998	0.998
Italy	1.006	1.004	1.002
Japan	1.006	1.004	1.002
USA	1.000	0.997	1.003

Note: Average values are geometrically calculated.

We next calculate the Malmquist index and its technical- and efficiency change components relative to the frontiers for every country in all time periods, generating a total of 1350 (=18·25·3) indices. To provide intuition concerning the results, Table 4.2 reports the geometric averages of the bootstrapped indices for each country in our sample throughout the study period. The first column of the table reports change in total factor productivity, as measured by the Malmquist index. According to our analysis, the productivity growth in OECD countries was relatively modest during the study period, confirming the phenomenon known as 'productivity paradox' (see *e.g.* Lee and Barua, 1999). Specifically, the great capital investments that took place in the study period, in particular in the information- and communication technology sector, did not appear to contribute to the output growth (the so-called dot.com boom occurred only after the study period). The productivity growth was highest in South Korea, Norway, and France, with average annual productivity growth rates of 2.16, 1.38, and 0.86 percents, respectively. Many countries (12 out of 25) experienced small productivity decline. Turkey, Switzerland, and Portugal were associated with the greatest average productivity decline of 1.85, 1.35, and 1.31 percents, respectively.

The TC component, reported in the second column of Table 4.2, represents the productivity growth ascribed to technical change. Note that a high value of TC component does not necessarily imply that the country has been highly innovative. Rather, the TC component measures the productivity growth potential at the given resource endowment of the country; whether or not the country can realize this potential depends on its relative distance to the frontier. The rate of technical change was relatively slow for most countries. Countries with the highest TC component were highly capital intensive countries like the Netherlands and Switzerland. For relatively labor-intensive countries such as Spain, Turkey, and Mexico, the average figures suggest technical regress, though less than 0.5 percentage points for all countries.

The third column of Table 4.2 reports the EC component, which represents catching up to the frontier. For the majority of countries (16 out of 25), the average EC component was negative, thereby suggesting a lagging behind. Switzerland and Greece experienced the largest declines in relative efficiency (lagging behind of the Netherlands and Italy, respectively). On the other hand, South Korea showed impressive catching up, with average efficiency increase of 2.09 percent per year.

Overall, our results seem to be consistent with other cross-country comparisons of total factor productivity (*e.g.* Färe *et al.*, 1994a; and Kumar and Russell, 2002). We observe biased technical progress that has improved the labor productivity, while the capital productivity has declined in line with the productivity paradox that attracted a lot of debate in the late 1990s.

Estimates of the feedback effect in technical change

We now turn to the results of our distributed lag model. Model 1 of Table 4.3 presents the main results where we applied the bootstrap and have made the input adjustments as discussed in Section 4.3.

We find evidence for delayed feedback up to eight years. Coefficients of the eight lagged dependent variables included as regressors are jointly significant at the five-percent level and five of these coefficients are individually significant at the 5% level as well. All significant coefficients have a positive sign confirming results of patent citation studies, which find similar evidence (see *e.g.* Figure 4.1 in Jaffe *et al.*, 1993, and Figures 2 through 6 in Jaffe and

Trajtenberg, 1999). Moreover, our results suggest not only that yesterday's change in technology contribute to today's technical change but, most importantly that technologies developed several years ago are significant in developing today's technology. For example, having generated a one percent increase in productivity with technical change six years ago results in slightly less than a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*. Thus, these findings support the argument that researchers 'stand on the shoulders of giants' at the aggregate level of the economy.

Regarding the other estimates, the coefficient of the lagged R&D variable has a sign opposite of what one would expect from the analytical framework presented above, but is statistically insignificant. It is likely that the lagged R&D variable correlates with the skill content of the labor force, which we control for when estimating the TC component of the Malmquist index; both variables depend on the unobserved amount of human capital in the economy. Coefficients of the two control variables are signed as anticipated and are significant at the one percent level. Being ten percent closer to the frontier is predicted to generate a three percent increase in productivity due to technical change, *ceteris paribus*. This implies that countries that are closer to the frontier are more innovative than countries that lag behind, or are more capable to use the innovations they have already developed, or both. Further, the negative sign of the proxy for international knowledge spillovers confirms that domestic innovations are less important an explanation for productivity changes the more open an economy is. This finding is consistent with the result of Coe and Helpman (1995) who find that knowledge spillovers explain more of domestic productivity changes the more open an economy is. Lastly, the trend coefficient approximates zero and is insignificant indicating that there is no systematic component left to control for (*i.e.* macroeconomic shocks that equally affect technologies in all countries over time).

Conditional on the covariates, we find no evidence of serial correlation in the idiosyncratic error terms. First, the Sargan test statistic implies that we can accept the null hypothesis of no correlation between our set of instruments and the idiosyncratic error term. Second, the LM test statistic implies that we can accept the null hypothesis of no second-order serial correlation in the idiosyncratic error terms.[16]

The estimated lag structure also suggests that private- and social returns to R&D diverge to the extent that agents do not internalize delayed feedback. Once R&D expenditures have caused productivity to grow because of induced changes in technology, these technical changes contribute to further changes in technology and productivity while concomitant rents are not

[16] Since we take first differences of serially uncorrelated $\varepsilon_{n,t}$ in equation (4.12), the $\Delta\varepsilon_{n,t}$ typically are serially correlated. Arellano and Bond (1991) show that the consistency of the GMM estimators therefore hinges on the assumption that there is no second-order serial correlation in the $\varepsilon_{n,t}$.

necessarily appropriated. The nonrival nature of innovations and associated knowledge implies that this is likely to be the case.

Table 4.3 Estimated coefficients of the distributed lag model

	Model			
	(1)	(2)	(3)	(4)
$\ln TC_{t-1}$	0.323*	0.271*	0.389*	0.139
	(0.000)	(0.006)	(0.000)	(0.172)
$\ln TC_{t-2}$	-0.279	-0.335*	-0.699*	0.753*
	(0.127)	(0.003)	(0.004)	(0.000)
$\ln TC_{t-3}$	0.369*	-0.058	0.432*	-0.190*
	(0.017)	(0.664)	(0.041)	(0.041)
$\ln TC_{t-4}$	-0.232	-0.433*	-0.398	0.118
	(0.272)	(0.006)	(0.076)	(0.708)
$\ln TC_{t-5}$	0.177	0.129	0.245	-0.012
	(0.242)	(0.430)	(0.230)	(0.914)
$\ln TC_{t-6}$	0.468*	0.702*	0.194	0.340
	(0.003)	(0.000)	(0.224)	(0.321)
$\ln TC_{t-7}$	0.243*	0.360*	0.371*	-0.776*
	(0.004)	(0.000)	(0.001)	(0.000)
$\ln TC_{t-8}$	0.438*	0.553*	0.603*	-0.751*
	(0.000)	(0.000)	(0.000)	(0.007)
$\ln RD_{t-3}$	-0.009	0.003	-0.032*	-0.047*
	(0.505)	(0.868)	(0.000)	(0.017)
$\ln D_t$	0.301*	0.113*	0.102	0.363*
	(0.000)	(0.018)	(0.212)	(0.007)
$\ln OPEN_{t-1}$	-0.037*	0.021	0.019	0.099*
	(0.002)	(0.109)	(0.207)	(0.000)
$trend_t$	0.001	0.003*	0.003*	0.004*
	(0.488)	(0.006)	(0.005)	(0.017)
Sargan test (p)	1.000	1.000	1.000	1.000
LM test (p)	0.167	0.003	0.305	0.031
Bootstrap	yes	no	yes	yes
Adjustment of labor input	yes	yes	no	yes
Adjustment of capital input	yes	yes	yes	no

Notes: Dependent variable is $\ln TC_{i,t}$. Coefficients are constant elasticities and values in parentheses are *p* values. Coefficient values marked by an asterisk are statistically significant at the 5% level. Instruments include *T-J-2* lagged levels of the dependent variable, *T-lag-1* lagged levels of the predetermined variables, and differences of the strictly exogenous variables (Arellano and Bond, 1991). To preserve finite sample properties, we restrict ourselves to only two lags of each predetermined regressor as instrument. Model (1) is our preferred model.

Sensitivity analysis

In model 2 of Table 4.3, we assess the sensitivity of our results to the bootstrapping of the data envelopment analysis described above. Conditional on the covariates, we find evidence for serial correlation in the idiosyncratic error terms when we fail to apply the bootstrap. We reject the null hypothesis of no serial correlation at the one-percent significance level, thereby invalidating our instruments. Consequently, the Arellano-Bond estimator no longer yields consistent estimates. In our interpretation, this finding suggests that the bootstrap is successful in accounting for the sampling bias in the distance functions that would otherwise be captured by the error terms.

Model 3 of Table 4.3 tests for the robustness of our results to the skill adjustment of the labor input in the data envelopment analysis. When we fail to adjust this labor input for its skill content, we find an overall change in coefficient values. Most notably, the trend coefficient becomes significant implying that we now are omitting a regressor that is relatively common for all countries but varies over time, namely the skill content of the labor force. The absolute magnitudes of most of the estimated coefficients of the lagged dependent variables are larger, as these variables now also account for feedback in technical change augmenting the human capital stock. In addition, the coefficient of the lagged R&D variable now becomes statistically significant since this variable no longer correlates with the skill content of the labor force, though maintaining a sign opposite to economic priors. Coefficients of the two control variables are rendered statistically insignificant as human capital plays a crucial role in a country's ability to transform domestic- and foreign technical change into productivity growth. Lastly, we find no evidence of serially correlated error terms conditional on the covariates.

Model 4 summarizes the robustness of our results to the adjustment of the capital input for variable capacity utilization. In this model, we test our adjustment with the OECD data on capacity utilization by omitting this adjustment. Comparing models 4 and 1, we find that omitting this adjustment results in serially correlated error terms, *ceteris paribus*. This suggests that our direct adjustment is important in accounting for variable utilization of inputs. At least a part of the variability now ends up in the error terms in which it correlates over time. Coefficients are now inconsistent and cannot be relied upon. In sum, we find that our estimation results are sensitive to the various adjustments discussed in previous sections. Although not desirable from a practical point of view, it underscores the need to correct productivity indices for disturbances if one is interested in productivity because of its index value for technical change.

4.6 Conclusions

In this study, we examine whether today's technical change depends on yesterday's technical change; *i.e.* whether there is delayed feedback in technical change. Learning-by-doing, learning-by-using, knowledge spillovers and network externalities, among others, can underlie such delayed feedback. We propose to investigate this feedback effect by using the TC component of the Malmquist productivity index to measure the impact of technical change on productivity. This approach has the virtue of being able to overcome some problems in the alternative patent citation approaches. Specifically, this component represents the impact of technical change on productivity, and therefore captures the quality and effectiveness of R&D activities as well as spontaneously arising technical change through, for example, learning-by-doing. Other advantages of this measure include its applicability at any level of aggregation from firm level studies to cross-country comparisons, and its capacity to handle multiple-input multiple-output technologies and biased technical change. However, this approach is not a panacea: The various adjustments described above as well as econometric problems such as endogeneity of the regressors complicate estimation of the feedback effect. We therefore see the frontier approach as a complement rather than a substitute to the patent citation approach.

We applied the proposed frontier approach to estimate the feedback effect from aggregate production data of 25 OECD countries for 1980 through 1997. Our model yields conclusive evidence on positive feedback in technical change with delays up to eight years. The feedback effect is strong: Predicting a one percent increase in productivity with technical change six years ago, for example, still results in slightly less than a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*. These findings are consistent with patent citation studies.

The evidence of delayed feedback in technical change is interesting from the policy perspective. Many existing studies on research productivity neglect delayed feedback in technical change and, hence, underestimate the social returns to R&D. If social returns to R&D diverge from the private returns, a case for policy intervention arises. In this respect, we hope that our approach can bring us closer to a full measure of the magnitude and duration of social returns to R&D.

Appendix 4A Data

Aggregate output

We use gross domestic product as our 'value-added' measure of aggregate output expressed in 1995 PPP adjusted prices. We obtain this variable from the OECD *Annual National Accounts*.

Aggregate capital input

Services derived from capital assets are very difficult to observe directly. Therefore, we approximate the aggregate capital input by the productive capital stock, assuming capital services to be proportional to the productive capital stock and make a 'one hoss shay' assumption on the efficiency profile of the capital stock (OECD, 2001). That is, we assume capital assets to be fully efficient until their retirement, when their productive capacity drops to zero. We construct initial capital stocks by dividing initial investments by their equilibrium rental price, which is the sum of the interest rate at which capital can be invested and a mark up to recover depreciation. We compute stocks in subsequent periods using the perpetual inventory method:

$$\begin{aligned} K_{n,t} &= \frac{I_{n,t}}{r_{n,t}+\delta_{n,t}} \qquad (n=1,..,25),\ (t=1960) \\ K_{n,t} &= K_{n,t-1}-D_{n,t-1}+I_{n,t} \qquad (n=1,..,25),\ (t=1961,..,1997) \end{aligned} \tag{4A.1}$$

in which I is investment in fixed capital, D is depreciation of fixed capital, and δ is the depreciation rate of fixed capital. r is the interest- or opportunity cost, depending on whether the asset is financed by a loan or by equity, and is also called the nominal rate of return. Together with δ, r measures the marginal cost of financing capital assets. We construct the capital stock from 1960 onward so that by 1980 most of the initial stock has fully depreciated. This minimizes bias in our aggregate capital measure potentially arising from the approximation of the initial stock. Finally, we multiply the capital stock measure with the utilization rate to account for variability in its utilization across countries and over time.

We use 'gross fixed capital formation' as our measure of investment and 'consumption of fixed capital' as our measure of depreciation.[17] We subsequently express these measures in 1995 PPP adjusted prices to facilitate calculation of the productive capital stock. We obtain these measures from the OECD *Annual National Accounts*. We obtain the deflators from the OECD *Economic Outlook*. With respect to the nominal rate of return, theory provides no specific

[17] Note that consumption of fixed capital (CFC) is relatively broadly defined as the loss in value of an asset over an accounting period. CFC comprises thus not only the effects of ageing, *i.e.* wear and tear, but also the effects of obsolescence, *i.e.* capital gains or losses.

guidance as to its measurement. We take the usual approach and use the interest rate as measure of the nominal rate of return. More specifically, we use the ‘bank rate’ as reported in the IMF *International Financial Statistics*. To minimize bias in our capital stock measure potentially arising from year specific shocks to the bank rates, we average rates of 1959 through 1961. We assume a six percent depreciation rate for fixed capital for 1960. This rate is comparable to rates found in the productivity literature. Although differences in the depreciation rate may exist among countries, there is little evidence that this is the case. We therefore make the usual assumption that the depreciation rate is the same in all the countries in our sample. Further, from the OECD *Business Tendency Survey* we obtain the ‘capacity utilization’ variable. Finally, we interpolate or extrapolate values that are missing for certain years and take average values across the countries in the sample for missing country values.

Aggregate labor input

We measure the aggregate labor input in total number of hours worked and adjust this measure for quality differences. We divide employment in each country into production- and non-production workers. This is a crude distinction, but the only one available for multiple countries over time. In addition, it has been found that these occupational proportions correlate highly with other measures of human capital like education (Berman *et al*., 1998). Following Jorgenson and Fraumeni (1995), we express the aggregate labor input as a translog function of the two types of labor. We obtain ‘total employment’ numbers from the OECD *Economic Outlook* and the ‘average annual hours actually worked per person in employment’ variable from the OECD *International Sectoral Database*. From the *General Industrial Statistics* of the UN *Industrial Statistics Database*, we obtain data on the numbers of both types of workers in the industrial sectors as well as of their wage shares. We assume this occupational split to be similar in other sectors of the economy. These three variables are available for the period 1980 through 1990 only. For this reason, we extrapolate these series until 1997. We take average values across the countries in the sample for missing country values.

Chapter 5 Directed technical change and climate policy*

5.1 Introduction

There is an increasing consensus that growing emissions of greenhouse gases such as carbon dioxide (CO_2) pose a serious threat to the world. One strategy for addressing this threat is to use environmental policy such as a trading scheme to constrain emissions; the approach envisioned in the Kyoto Protocol of the Framework Convention on Climate Change that has entered into force and will be implemented in most industrial nations beginning in 2008. The use of a trading scheme in this agreement was seen as a success of economic reasoning by many, because such schemes are widely heralded as generating a given level of abatement in the most cost-effective manner. The Bush Administration has taken the United States out of the Kyoto Protocol and instead adopted a technology policy that includes support for research and development (R&D) as an alternative strategy, with the idea that without technical options to reduce greenhouse gases an emission constraint will mostly punish the economy by slowing economic growth. While such a punishment seems mostly exaggerated for 'small' reductions in emissions the ultimate goal of the Framework Convention, stabilization of greenhouse gas concentrations, requires that the world economy reduces emissions by 90 to 95% from best projections of where it otherwise would be. This is untested territory, and thus the need for new technology is real if these stabilization goals are to be met. However, even recognizing that new technology is needed, one might believe that appropriate environmental policy instruments—the right CO_2-trading scheme or tax—would induce new technologies.

We study the cost effectiveness of these different strategies. If emissions are priced will that induce technical change? Can R&D subsidies achieve emission reductions, and is this strategy cheaper than using emission trading schemes? Are the two strategies complementary as climate policies? Can one improve on uniform climate policy by differentiating it toward relatively dirty technologies? Previous investigations of the two strategies include Jaffe *et al.* (2005) and the general equilibrium analyses of Goulder and Schneider (1999) and Popp (2004a), who show that carbon taxes are cost effective when they are complemented by a R&D subsidy. In a cost-minimization setting, Rosendahl (2004) and Bramoullé and Olson (2005) demonstrate theoretically that technology externalities call for differentiation of pollution taxes. We proceed

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by empirically studying these different strategies in which we pay specific attention to their differentiation.

For this purpose, we develop the 'Dynamics of Technology Interaction for Sustainability' (DOTIS) model. DOTIS is an intertemporal dynamic computable general equilibrium (CGE) model that captures empirical links between CO_2 emissions associated with energy use, directed technical change and the economy. We draw on endogenous growth models of Rivera-Batiz and Romer (1991) and Acemoglu (2002) and specify technologies as stocks of knowledge capital that are sector-specific investment goods, which have associated positive externalities. We calibrate the model to the Dutch economy, where availability of investment data for knowledge capital that is consistent with the national accounting framework allows us to pay special attention to its representation in the benchmark data. We construct simulations to reveal cost effective combinations of CO_2 trading schemes and R&D subsidies, including the desirability of differentiating these instruments among clean and dirty sectors.

This chapter is organized as follows. Section 5.2 describes the key specifications of the DOTIS model. In Section 5.3 we outline the calibration procedure, in which we pay special attention to the knowledge capital accounting. Section 5.4 presents the results that we obtain with the policy simulations and discusses their macro-economic implications. Section 5.5 concludes. Finally, Appendix 5A offers a full model description and Appendix 5B presents the underlying data.

5.2 Basic features of the model

We specify a representative consumer and producers in the following sectors: 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), where the energy sector comprises the oil- and gas industries. Agents behave rationally and have perfect foresight.

The representative consumer maximizes intertemporal utility subject to the intertemporal budget constraint. Intertemporal utility is a function of the discounted sum of consumption over the time horizon. Environmental quality does not enter the utility function, implying independence of the demand functions for goods with respect to environmental quality.

Producers maximize profits over time subject to their production-possibility frontiers, which are determined by nested constant-elasticity-of-substitution functions of knowledge capital, physical capital, labor, and intermediate inputs. In addition, imported coal is used in the production of CO_2-intensive goods and –electricity. Intermediate usage of oil, gas, and coal entail CO_2 emissions, which might be subject to quantity constraints, *i.e.* CO_2 trading schemes.

Technical change is characterized by innovation possibility frontiers, which describe investment in knowledge capital in the sectors. Knowledge capital is sector specific (*c.f.* Basu and Weil, 1998). Further, technical change is a deterministic process and aggregate innovation possibility frontiers are continuous, which allows us to avoid problems due to uncertainty or integer variables.[1] Investments in knowledge capital merely involve final goods as input. In addition, there is a delayed technology externality in innovation in that previous investments in knowledge capital have a positive external effect on the efficiency of current investments.[2] Knowledge spillovers and network effects, among others, underlie this technology externality. We specify this technology externality to exist within each sector only but relax this assumption in the sensitivity analysis. Finally, knowledge-capital investments accumulate into stocks, which give rise to an additional technology externality in sectoral production. The rationale for this externality is that, while producers can prevent others from using their knowledge capital by means of patent protection, they cannot completely prevent knowledge embodied in patents from spilling over to other producers in their sector. These two types of technology externalities lead to the result that profit maximizing firms underinvest in R&D and thus there exists a rationale to subsidize investments in knowledge capital (henceforth referred to as R&D subsidies).

Regarding international trade, domestically produced goods and physical capital are allocated between domestic- and export markets. Goods traded on domestic markets are combined with imported goods into an Armington (1969) aggregate, which satisfies demand for intermediate- and final goods. An exception is coal imports, which are directly used in certain CO_2-intensive industries and the CO_2-intensive electricity sector. Domestic investment in physical capital is combined with foreign investment into an Armington aggregate as well, satisfying investment demand for physical capital. We do not model international trade in knowledge capital. As a small open economy, it is potentially easy to meet CO_2-reduction targets by specializing in non-CO_2 intensive sectors so that the implied emissions occur outside the economy. While that might be a realistic response for a small economy independently pursuing a climate policy, if it succeeds only by increasing emissions elsewhere there is little or no real climate benefit. The Armington specification, as opposed to a Heckscher-Ohlin formulation, closes international trade in a way that limits this leakage effect.

Equilibrium and growth

Each agent solves its optimization problem. When markets clear at all points in time, the output- price- and income paths constitute an equilibrium. Markets for production factors and final

[1] Even though indivisibility of knowledge capital and uncertainty related to R&D processes are facts of life, averaging out makes these facts matter less at aggregate levels (Romer, 1990).

[2] Rivera-Batiz and Romer (1991) dub this specification 'knowledge-based' in contrast to the former specification, which they dub 'lab-equipment' for its emphasis on physical inputs.

goods are perfectly competitive but there initially is no market for CO_2 emissions associated with energy use. The technology externalities support nonconvexities in the 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. Growth rates of both capital stocks stem from endogenous saving- and investment behavior. The economy achieves balanced growth over time with the stocks of physical- and knowledge capital growing at the same rate as the labor supply.

5.3 Calibration

In this section, we describe the calibration of the DOTIS model in which we pay special attention to the accounting of knowledge capital. Accounting for knowledge capital in CGE models is relatively new and, when undertaken, is typically done in a rudimentary fashion because of absence of detailed information. Because of the availability of investment data for knowledge capital in the Netherlands that is consistent with the national accounting framework, we calibrate the model to the Dutch economy. We choose 1999 as the benchmark year.

Accounting for knowledge capital

To account for knowledge capital, we identify and capitalize flows associated with knowledge and subsequently incorporate these in the national accounting matrix (Statistics Netherlands, 2000). We follow de Haan and Rooijen-Horsten (2004) and identify expenditures on R&D, expenditures on education (EDU) and investments in information- and communication infrastructure (ICT) as knowledge flows.[3] We include ICT because of its role in disseminating and storing knowledge and ICT is therefore an important part of the infrastructure required for knowledge capital to be productive.

To capitalize these knowledge flows, we take the following two steps. First, we create an additional (column) account registering investments in the stock of knowledge capital and an additional (row) account registering services derived from the stock. Investment in ICT is reported as investment and expenditures on R&D and education are reported as derived services. We assume the Dutch economy to be in 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 gives us the total column- and row accounts for knowledge capital as a result of the three knowledge flows. Second, we debit the national accounting matrix

[3] We are aware that this identification entails to a certain degree unavoidable randomness. There are many types of knowledge and knowledge may be embedded not only in software and books but also in *e.g.* people and traditions. It therefore is difficult to comprehensively measure and aggregate knowledge. Yet, it is not altogether different from aggregating physical capital goods. The main difference is, of course, that it is difficult to attach a value to knowledge capital (Griliches, 1979).

to avoid double counting. Given that investments in ICT are originally reported as investments in physical capital, we debit the investment (column) account with the amounts of investment in ICT. Expenditures on R&D and education are originally reported as intermediate consumption requiring us to debit the intermediate goods matrix. We follow Terleckyj (1974) and assume that knowledge is embodied in tangible goods and services, which allows us to debit each sector's expenditures on education and R&D from the sector's consumption of intermediate goods proportionally to its sector of origin. We balance the national accounting matrix by adjusting the (row) account for labor.

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 for both types of electricity generation (Böhringer *et al.*, 2003). Table 5B.1 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). We classify CO_2-intensive industries, trade and transport, energy and CO_2-intensive electricity as CO_2-intensive sectors and agriculture, non-CO_2 intensive industry and services and non-CO_2 intensive electricity as non-CO_2 intensive sectors. Table 5B.2 presents the complete industry classification, Table 5B.3 presents the national accounting matrix and Table 5B.4 reports factor- and CO_2 intensities.

Turning to model parameters, we use general parameter values that are standard in the literature (see Tables 5A5 and 5A.6). Regarding international trade, however, we assume unitary substitution elasticity between domestic and foreign commodities, which is lower than is often used. This limits the leakage effect discussed above. Many of the largest trading partners of the Netherlands are implementing similar environmental policies, such as the EU Greenhouse Gas Emission Trading Scheme, which limits effects of international trade on relative factor shares. Regarding technology-related parameters, we use a 25 percent depreciation rate for knowledge capital.[4] Pakes 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 lifespans of applied R&D expenditures, which suggests an average service life of four to five years. More recently, Jorgenson and Stiroh (2000) have

[4] Alternatively, one can take the view that knowledge does not depreciate at all. This assumption is likely to be valid if the sector or industry under study is narrowly defined and its stock of knowledge capital changes only slowly (Griliches, 1988). This assumption is less likely to be valid, however, if one defines sectors more broadly or for periods in which one might suspect more rapid obsolescence of knowledge capital such as the decades following the ICT boom.

estimated a geometric depreciation rate for computer equipment and software of 31.5 percent. Further, we assume a coefficient value of 20 percent for delayed technology externalities in innovation 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 the latter has been estimated around 50 percent (see *e.g.* Baumol, 2002, or Chapter 4, in which a positive feedback effect is estimated of 45 percent with delays up till eight years). We base the coefficient value for the knowledge spillover in production 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.

Finally, we consider a 27-year time horizon, defined over the years 1999 through 2025, and calibrate the model to a steady state rate of growth of two percent that serves as a reference case.

5.4 Simulations

We analyze cost-effectiveness of both environmental- and technology policy to reduce cumulative CO_2 emissions in production over the time horizon of the model by 10 percent relative to the reference case. We differentiate both policies between CO_2 intensive- and non-CO_2 intensive sectors. Environmental policy takes the form of CO_2 trading schemes and technology policy takes the form of R&D subsidies. To avoid leakage of CO_2 emissions to consumption in all simulations, we also reduce these emissions by 10 percent relative to the reference case using a separate quantity constraint.

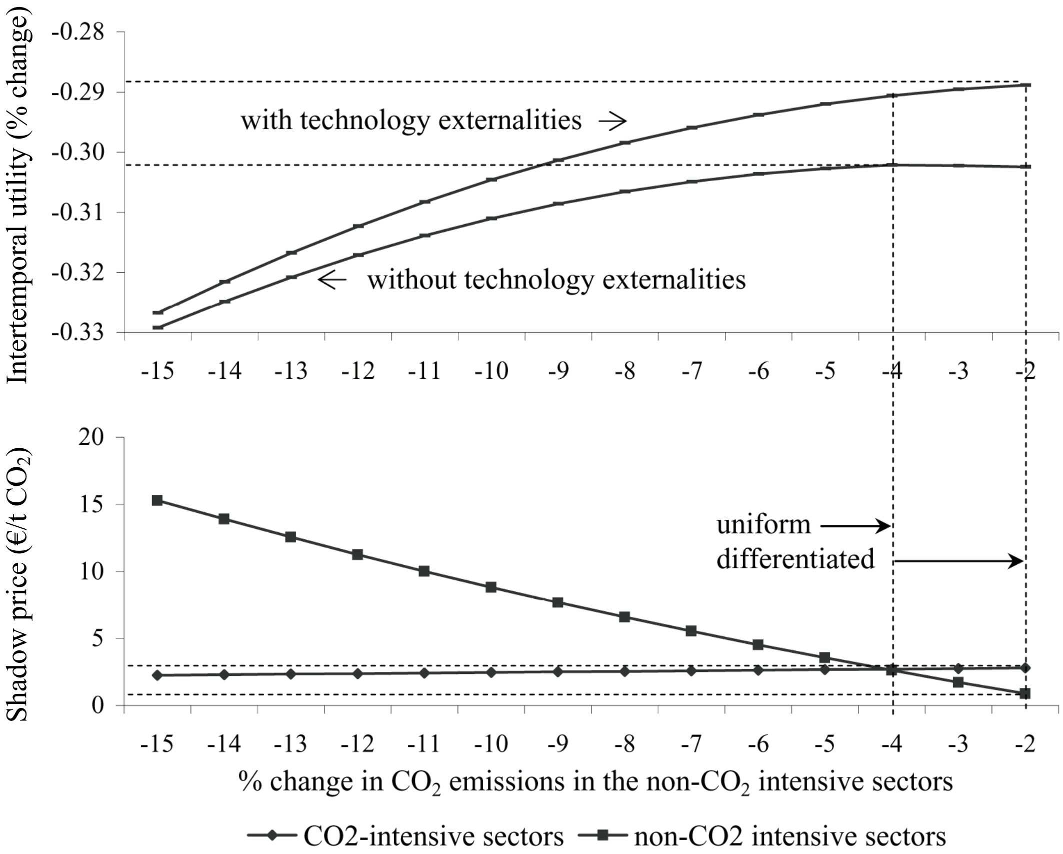
Simulation 1: Differentiated CO_2-trading schemes

Figure 5.1 shows effects of the various possibilities to differentiate the CO_2-trading schemes between CO_2 intensive- and non-CO_2 intensive sectors on shadow prices of CO_2 emissions in the sectors (lower graph) and discounted welfare as measured by intertemporal utility (upper graph). We explain this figure in several steps, starting with the horizontal axes that list percentage changes in CO_2 emissions of the non-CO_2 intensive sectors. As a first step, we set these percentage changes exogenously and calculate the CO_2-reduction target for the CO_2-intensive sectors necessary for total emissions in production to be reduced by 10 percent. Second, we use the model to calculate the general equilibrium result associated with each differentiation of both CO_2-trading schemes. The lower graph maps the corresponding sets of shadow prices for CO_2 emissions required to meet the sectoral reduction targets. In general, technology externalities positively affect the shadow prices. In this simulation, however, we find the shadow prices with technology externalities to exhibit negligible differences from those without technology externalities.[5] For this reason, we present only one curve for each sector in

[5] The difference between shadow prices with and without technology externalities is difficult to graphically detect in this simulation. Technology externalities have a positive effect on the shadow price of CO_2 emissions because of their positive effect on welfare and hence

this graph. Yet, the technology externalities have a noticeable effect on welfare. As a last step, therefore, we map the changes to intertemporal utility that correspond with each differentiation of the CO_2-trading schemes in the upper graph. Utility indices smaller than one imply discounted welfare losses relative to the reference case. The upper curve shows the discounted welfare loss if there are technology externalities whereas the lower curve shows the discounted welfare loss if there are none. The left dashed vertical line represents the set of uniform shadow prices, which is the cost-effective (highest welfare) set if there are no technology externalities. The right dashed vertical line represents the set of differentiated shadow prices, which is the cost-effective set if there are technology externalities.

Figure 5.1 Effects of differentiated CO_2-trading schemes on discounted welfare



Note: CO_2 emissions in the CO_2-intensive sectors change to the extent that overall CO_2 emissions in production are reduced by 10 percent.

overall demand for energy and concomitant CO_2 emissions. Yet, this effect is limited in this simulation because of the deadweight losses associated with the CO_2 emission constraints.

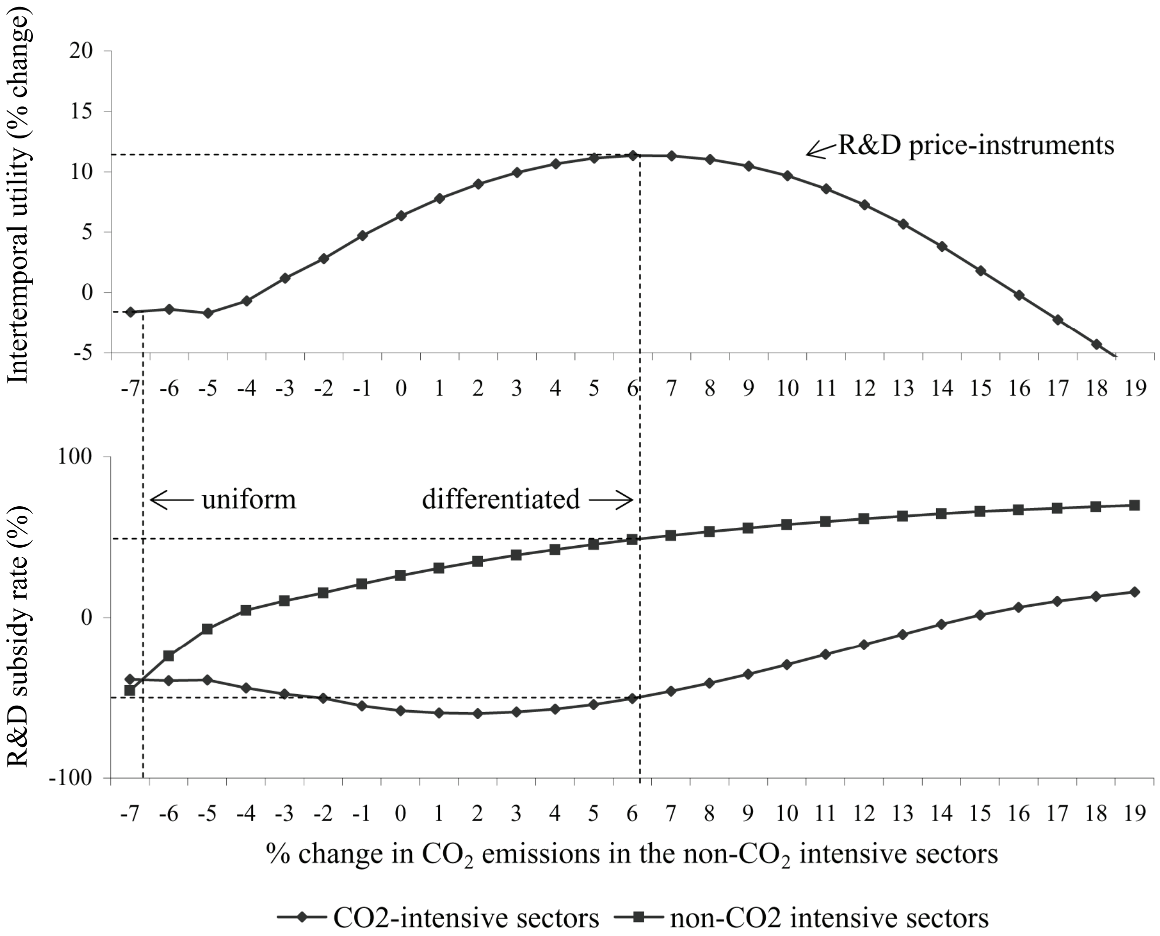
We find that the conventional result of uniform shadow prices across sectors being cost effective holds if there are no technology externalities. The 10 percent emission reduction in production entails a welfare loss of 0.30 percent over the time period and results in a shadow price of €2.70 per ton CO_2 in all sectors. When there are technology externalities, however, we find that welfare is higher for all differentiations of the CO_2-trading schemes. If the constraints can be set at different levels, we find it cost effective to differentiate the trading schemes toward the CO_2-intensive sectors. The 10 percent emission reduction in production now entails a welfare loss of 0.28 percent over the time period and results in shadow prices of €2.80 per ton CO_2 in the CO_2-intensive sectors and €0.10 per ton CO_2 in the non-CO_2 intensive sectors. CO_2-trading schemes direct technical change toward non-CO_2 intensive sectors yielding relatively more technology externalities in these sectors and therefore raising their opportunity cost of abatement. The electricity sector, for example, redirects its R&D toward biomass- and wind technologies resulting in relatively more knowledge spilling over from the development of these technologies than fossil-fuel electricity technologies. Thus, it is cheaper to shift some abatement toward CO_2-intensive technologies and -sectors.

The direction of technical change can be best understood with help of the general framework presented by Acemoglu (2002) or the framework applied to energy technologies in Chapter 3. On the supply side of the economy, CO_2-trading schemes give rise to a price effect as there is an incentive to develop knowledge capital that can be used in the production of CO_2-intensive goods, which are now relatively expensive. At the same time, however, there is a market-size effect as there is also an incentive to develop knowledge capital that can be used in the production of non-CO_2 intensive goods, for which there ultimately is a bigger market. On the demand side of the economy, CO_2-trading schemes give rise to a substitution effect in consumption as consumers shift toward non-CO_2 intensive goods raising the profitability of investing in knowledge capital in the non-CO_2 intensive sectors. When introducing CO_2-trading schemes, we find the demand side to be relatively important as substitution in consumption is necessary for cost-effective emission reduction. Technology externalities reinforce the direction.

Simulation 2: Differentiated R&D subsidies

We now study R&D subsidies as our instrument to reduce overall CO_2 emissions in production by 10 percent relative to the reference case. Figure 5.2 shows effects of the various possibilities to differentiate the CO_2-emission reduction between CO_2 intensive- and non-CO_2 intensive sectors on required R&D subsidies (lower graph) and discounted welfare as measured by intertemporal utility (upper graph). We obtain Figure 5.2 in a similar fashion as Figure 5.1 except that we now compute R&D subsidy rates instead of shadow prices of CO_2 emissions in general equilibrium. Finally, the left dashed vertical line represents the set of uniform R&D subsidies and the right dashed vertical line represents the set of differentiated R&D subsidies.

Figure 5.2 Effects of differentiated R&D subsidies on discounted welfare



Note: CO_2 emissions in the CO_2-intensive sectors change to the extent that overall CO_2 emissions in production are reduced by 10 percent.

We find that R&D subsidies can also achieve the 10 percent emission reduction in production. In fact, differentiating R&D subsidies toward non-CO_2 intensive sectors not only can reduce emissions but also increases welfare compared to the reference case. Table 5.1 shows that compared to the hypothetical reference case, however, using R&D subsidies to achieve the emission reduction always entails a welfare loss as R&D subsidies are a first-best instrument to internalize technology externalities but a second-best instrument to reduce emissions.

Table 5.1 Effects of policies on discounted welfare (% change from reference)

	Original reference	Hypothetical reference
Reference cases		
Original	0.00	-28.35
Hypothetical with correction for technology externalities	28.35	0.00
Simulations		
Differentiated CO_2-trading schemes	-0.28	-28.63
Differentiated R&D subsidies to reduce CO_2 emissions	11.30	-17.05
Combinations of differentiated CO_2-trading schemes and differentiated R&D subsidies	27.10	-1.25

The cost-effective set of R&D subsidies yields a welfare gain of 11.3 percent over the time period and comprises an R&D subsidy of 48 percent in the non-CO_2 intensive sectors and an R&D *tax* of 50 percent in the CO_2-intensive sectors. Although the introduction of an R&D subsidy in the non-CO_2 intensive sectors has a negative effect on CO_2 emissions because of substitution effects in production and consumption, the R&D subsidy also gives rise to a strong rebound effect that offsets the substitution effects. As the R&D subsidy lowers the marginal costs of non-CO_2 intensive goods, it indirectly increases demand for these goods and concomitant demand for energy and CO_2 emissions. More importantly, by internalizing some of the technology externalities as well, the R&D subsidy increases welfare leading to an overall higher demand for energy and CO_2 emissions that strengthens the rebound effect. If R&D subsidies are the sole instruments of choice, an R&D *tax* in CO_2-intensive sectors is thus preferred in the cost-effective solution to keep overall emissions within bounds.[6] Essentially, the policy is one of supporting growth of non-CO_2 intensive sectors while slowing it in CO_2-intensive sectors. Introducing R&D subsidies in all sectors is feasible albeit cost ineffective in achieving the emission reduction.

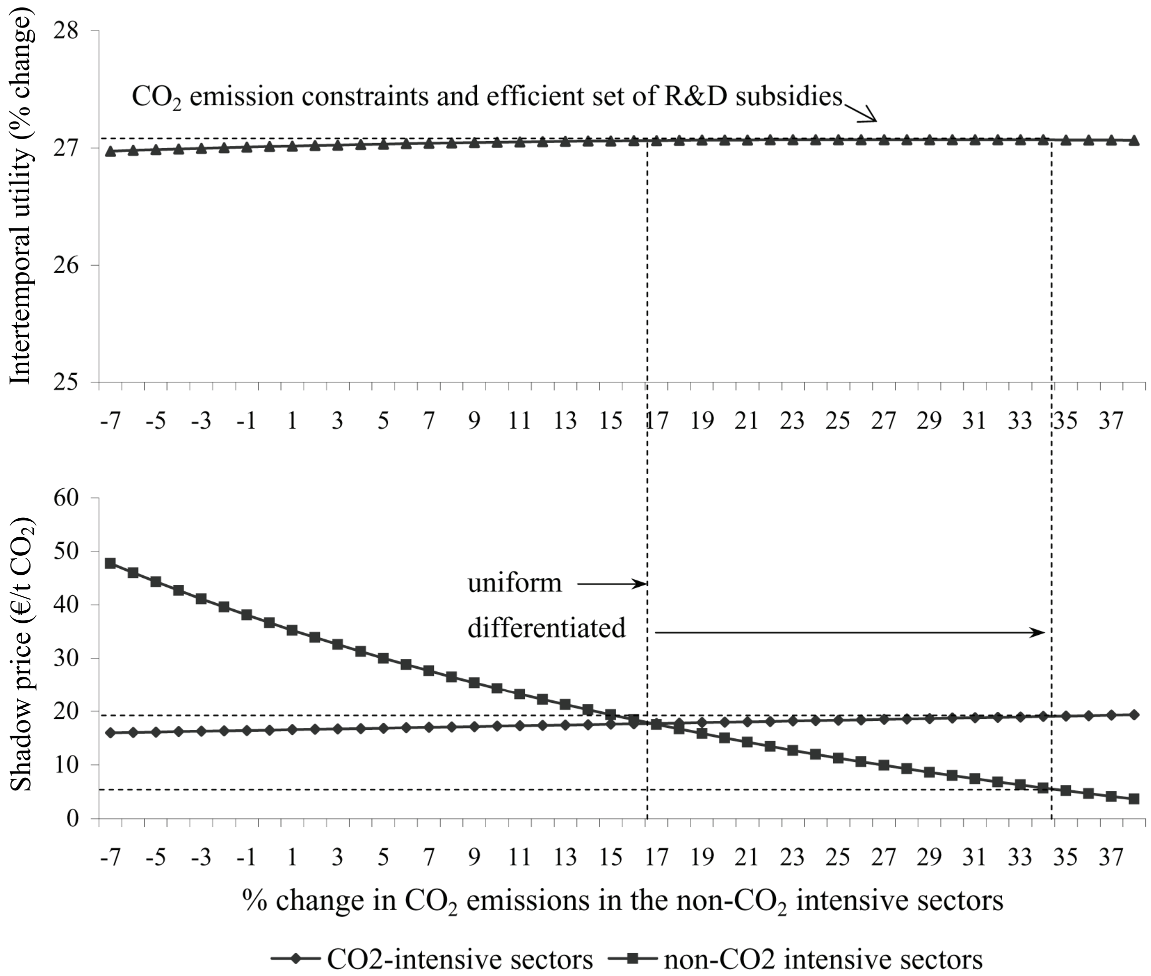
Simulation 3: Combinations of differentiated CO_2-trading schemes and differentiated R&D subsidies

We next study combinations of CO_2-trading schemes and R&D subsidies as our instruments to abate CO_2 emissions in production by 10 percent relative to the reference case. For this purpose, we augment the first simulation by introducing combinations of differentiated R&D subsidies before computing the general equilibrium associated with each differentiation of the CO_2-trading schemes. This way we can identify both the cost-effective set of differentiated CO_2-

[6] This finding is in line with other studies. Popp (2004a), for example, finds that subsidizing energy R&D yields significant increases in energy technology but nevertheless has little effect on CO_2 emissions.

trading schemes and the efficient set of differentiated R&D subsidies. Figure 5.3 shows effects of the various possibilities to differentiate the CO_2-trading schemes between CO_2 intensive- and non-CO_2 intensive sectors on shadow prices of CO_2 emissions in the sectors (lower graph) and discounted welfare as measured by intertemporal utility (upper graph) when the efficient set of R&D subsidies is introduced next to the CO_2-trading schemes.

Figure 5.3 Effects of cost-effective set of differentiated CO_2-trading schemes and differentiated R&D subsidies on discounted welfare



Note: CO_2 emissions in the CO_2-intensive sectors change to the extent that overall CO_2 emissions in production are reduced by 10 percent.

Emission reduction is cost effective if R&D subsidies complement rather than substitute for CO_2-trading schemes. The cost-effective set of instruments yields a welfare gain of 27.1 percent over the time period and comprises R&D subsidies of 62 percent and 53 percent in the CO_2 intensive- and non-CO_2 intensive sectors as well as shadow prices of €18.60 and €9.30 per ton CO_2 in the respective sectors. Of course, the emission reduction still comes at a cost when compared to the hypothetical reference case in which we would already correct for the technology externalities (see Table 5.1). Compared with this hypothetical case, welfare falls by 1.25 percent over the time period, which is significantly more than the 0.28 percent welfare loss in the case in which we do not yet make such a correction (see first simulation). The CO_2-trading schemes are more binding when the technology externalities are already corrected and hence they entail a bigger deadweight loss.

Regarding differentiation of the policy instruments, we find that continued differentiation remains a feature of the cost-effective policy in this simulation because of interacting policy effects. The CO_2 trading schemes are principally introduced to reduce emissions but also induce technical change and concomitant technology externalities. Similarly, R&D subsidies correct for the technology externalities but at the same time affect CO_2 emissions. The R&D subsidies are now differentiated toward CO_2-intensive sectors, as they are in the hypothetical reference case in which we just correct technology externalities without regard for emission reduction, and subsequently direct technical change toward these sectors. CO_2 shadow prices remain differentiated in this simulation as technology externalities, and hence the opportunity costs of abatement, remain higher in non-CO_2 intensive sectors because of their initial size and knowledge intensity. Compared to the first simulation though, the relative difference in shadow prices narrows while shadow prices increase in magnitude because of the CO_2-trading schemes being more binding.

Macro-economic effects

Besides having different welfare implications, Tables 5.2 and 5.3 show that the three simulations have different macro-economic effects as well. Contracted growth characterizes the first simulation with CO_2-trading schemes. Total output growth is negative relative to the reference case, where CO_2-intensive sectors decrease their production relatively more as they are subject to the more stringent CO_2-trading scheme. Exceptions are non-CO_2 intensive industries and services and non-CO_2 intensive electricity, which slightly increase their production. Similarly, CO_2-intensive sectors reduce their CO_2 emissions more than the non-CO_2 intensive sectors. With respect to inputs to production, substitution effects in production increase marginal returns to factors other than energy, where the marginal return to physical capital increases to the extent that investments in physical capital actually increase slightly relative to the reference case. Foreign investment changes accordingly. International trade in goods falls proportionally to domestic trade as we assume trading partners of the Netherlands to introduce similar CO_2 emissions abatement policies.

Table 5.2 Effects of climate policies on the Dutch economy (percentage changes)

		Simulation								
		1			2			3		
		2005	2015	2025	2005	2015	2025	2005	2015	2025
Production	Total	-0.4	-0.6	-0.9	31.0	43.8	44.8	48.1	78.9	98.4
CO_2 intensive	IND	-0.8	-1.5	-2.3	-9.6	-11.0	-29.5	85.9	133.1	161.9
	TT	-0.7	-1.3	-2.0	-10.1	-15.5	-39.8	35.3	60.3	74.2
	NRG	-3.5	-5.4	-8.2	-11.6	-9.3	-29.7	10.6	36.6	44.8
	CIE	-2.6	-4.2	-6.5	-12.1	-8.6	-16.0	36.3	47.6	36.3
Non-CO_2 intensive	AGR	-0.6	-1.1	-1.6	15.2	16.3	-15.3	18.5	56.6	80.3
	SER	0.1	0.2	0.2	51.8	73.2	88.6	52.3	78.6	101.6
	NCIE	3.1	5.0	8.1	88.4	105.5	74.5	25.4	119.7	258.0
Investments in knowledge capital	Total	-0.3	-0.4	-0.6	246.6	275.3	310.3	346.7	510.4	625.2
CO_2 intensive	IND	-1.0	-1.7	-2.5	-44.0	-49.5	-59.1	632.5	935.5	1156.4
	TT	-0.9	-1.6	-2.3	-43.1	-53.7	-66.7	355.9	535.9	628.3
	NRG	-4.1	-6.3	-9.0	-47.2	-48.6	-59.8	208.2	418.8	481.0
	CIE	-2.7	-4.2	-6.2	-48.3	-45.6	-48.8	361.3	478.7	447.8
Non-CO_2 intensive	AGR	-0.8	-1.3	-1.9	166.6	155.2	58.8	166.4	362.8	471.5
	SER	0.0	0.1	0.1	324.6	363.8	414.7	318.8	462.0	568.4
	NCIE	5.7	7.7	12.3	458.0	481.3	338.5	181.2	700.6	1455.5
Investments in physical capital		0.9	1.3	1.7	38.7	88.8	126.0	38.6	42.7	51.4
Exports of goods		-0.8	-1.5	-2.4	0.3	-6.3	-41.3	29.7	57.2	74.1
Imports of goods		-0.6	-1.0	-1.5	3.4	9.6	3.0	31.0	56.0	70.0
Foreign investment		0.7	1.1	1.2	12.8	52.5	79.2	38.2	43.2	51.5
Shadow price of CO_2	CI	2.8	2.8	2.8				18.6	18.6	18.6
emissions	NCI	0.1	0.1	0.1				9.3	9.3	9.3
Subsidy on investments	CI				-0.50	-0.50	-0.50	0.62	0.62	0.62
in knowledge capital	NCI				0.48	0.48	0.48	0.53	0.53	0.53

Notes: Shadow prices of CO_2 emissions are in €/t CO_2. AGR is agriculture, IND is CO_2-intensive industry, TT is the trade and transport sector, SER is non-CO_2 intensive industry and services, NRG is the energy sector, CIE is CO_2-intensive electricity and NCIE is non-CO_2 intensive electricity. CI refers to CO_2-intensive sectors and NCI to non-CO_2 intensive sectors.

Table 5.3 Effects of climate policies on CO_2 emission patterns in the Netherlands (percentage changes)

		Simulation								
		1			2			3		
		2005	2015	2025	2005	2015	2025	2005	2015	2025
CO_2 emissions	Total	-6.6	-10.3	-15.6	-7.3	-5.8	-24.4	1.3	-9.2	-28.6
CO_2 intensive sectors	IND	-4.6	-7.4	-11.4	-2.0	-4.5	-24.1	30.4	15.7	-8.2
	TT	-5.5	-8.8	-13.4	-8.1	-11.8	-36.6	6.6	-7.0	-28.6
	NRG	-8.9	-13.8	-20.6	-10.9	-7.6	-27.9	-14.0	-27.4	-48.2
	CIE	-2.5	-4.0	-6.2	-0.8	-1.5	-7.1	19.1	19.1	5.4
Non-CO_2 intensive	AGR	-2.2	-3.6	-5.7	-1.0	-0.1	-20.7	28.0	44.1	41.9
sectors	SER	-1.7	-2.7	-4.2	6.6	18.2	26.5	33.2	38.7	32.1

Notes: AGR is agriculture, IND is CO_2-intensive industry, TT is the trade and transport sector, SER is non-CO_2 intensive industry and services, NRG is the energy sector, and CIE is CO_2-intensive electricity. CI refers to CO_2-intensive sectors and NCI to non-CO_2 intensive sectors.

Biased growth characterizes the second simulation with R&D subsidies. By using R&D subsidies in non-CO_2 intensive sectors and R&D taxes in CO_2-intensive sectors, one speeds up growth in the former while slowing it in the latter. The production structure and emission pattern, for example, shift markedly from CO_2 intensive- to non-CO_2 intensive goods. Although increased welfare and limited substitution possibilities in the economy lessen the negative impact for the CO_2-intensive sectors for the first half of the model horizon, these sectors are hit hard afterwards when more substitution has been taking place and path dependency in technical change is strong. Further, more physical capital is required to expand the non-CO_2 intensive sectors and as a result investments in physical capital increase. Foreign investments change accordingly. Finally, more goods are now imported and fewer goods exported.

Enhanced growth characterizes the third simulation with both CO_2-trading schemes and R&D subsidies. Because of the introduction of R&D subsidies in all sectors, total factor productivity and hence production levels increase throughout the economy relative to the reference case. Nevertheless, the CO_2 emission reduction is achieved with the CO_2-intensive sectors bearing the abatement burden to the extent that non-CO_2 intensive sectors can even increase their emissions. As a result of the enhanced growth, demand for production factors increases as is reflected in, among others, increased investment in physical capital. Foreign investments and international trade in goods change accordingly.

Sensitivity analysis
Table 5.4 reports the sensitivity of our results to key parameter values. We use central parameter values in all sensitivity simulations (see Tables 5A.5 and 5A.6) except for the parameter subject to analysis. Given the importance of technical change for our findings, we focus on technology parameters, which simultaneously are a good proxy for the knowledge-capital accounting. We report effects as index values compared to the regular simulations.

The general result from Table 5.4 is that our findings are robust to the range of parameter values considered. The cost-effective set of instruments still includes R&D subsidies as complements to, rather than substitutes for, CO_2-trading schemes while the cost-effective differentiation remains unchanged (no index value changes sign).

Turning to the specific parameters subject to analysis, lowering the depreciation rate of knowledge capital (δ^H) by 25 percent has a negative effect on discounted welfare in all simulations as fewer investments in knowledge capital are required yielding less technology externalities in innovation.[7] The overall decrease of technology externalities reduces the relative opportunity cost of CO_2 abatement in the non-CO_2 intensive sectors and hence the cost-effective differentiation of the CO_2-trading schemes in the first and third simulation. In the second

[7] At the same time, lower depreciation rates lead to bigger stocks of knowledge capital yielding more knowledge spillovers in production. This positive welfare effect, however, is outweighed by the negative welfare effect of less technology externalities in innovation.

simulation, the gap between R&D subsidies widens as R&D subsidy rates fall relatively more in CO_2 intensive sectors. Bigger stocks of knowledge capital enhance total factor productivity and the rebound effect, *ceteris paribus*. It therefore is cost effective to further differentiate R&D subsidies to keep emissions within bounds. The opposite holds if we increase the depreciation rate of knowledge capital by 25 percent.

Table 5.4 Piecemeal sensitivity analysis

		Discounted welfare			Cost-effective differentiation of instruments			
		Simulation			Simulation			
		1	2	3	1	2	3	
		U	U	U	$p_{CI}^{EM} - p_{NCI}^{EM}$	$s_{CI} - s_{NCI}$	$p_{CI}^{EM} - p_{NCI}^{EM}$	$s_{CI} - s_{NCI}$
Regular simulation		1.00	1.00	1.00	1.00	1.00	1.00	1.00
δ^H	low	1.00	0.99	0.97	0.53	1.09	0.88	1.00
δ^H	high	1.00	1.01	1.02	1.00	0.92	1.09	1.00
ξ	low	1.00	0.95	0.93	1.00	0.91	0.90	1.11
ξ	high	1.00	1.09	1.13	1.00	1.09	1.16	0.78
ξ	uniform	1.00	0.99	1.00	0.69	1.52	0.92	0.89
σ^H	low	1.00	0.96	0.94	1.00	0.88	0.94	1.33
σ^H	high	1.00	1.05	1.07	1.00	1.31	1.02	0.67

Notes: We index all numbers to the regular simulation. Results in simulation 1 are robust at the 1 percent precision level. Simulation 1 refers to differentiated CO_2-trading schemes; simulation 2 to differentiated R&D subsidies; simulation 3 to combinations of differentiated CO_2-trading schemes and differentiated R&D subsidies. Low and high refer to 25 percent lower and higher parameter values than in the regular simulation and uniform refers to technology externalities in innovation existing across sectors. U denotes discounted welfare as measured by intertemporal utility, p^{EM} denotes the shadow prices of CO_2 emissions and s denotes the R&D subsidies in respectively the CO_2-intensive- and non-CO_2 intensive sectors.

Lowering the coefficient value of technology externalities in innovation (ξ) by 25 percent has a negative effect on discounted welfare in all simulations as fewer externalities are enjoyed. The decrease of technology externalities reduces the relative opportunity cost of CO_2 abatement in non-CO_2 intensive sectors and hence the cost-effective differentiation of R&D subsidies in the second simulation and of CO_2-trading schemes in the third simulation. As R&D subsidies fall relatively more in non-CO_2 intensive sectors in the third simulation, the gap between R&D subsidies widens. The opposite holds if we increase the coefficient value of technology externalities in innovation by 25 percent.

Specifying technology externalities in innovation to exist across rather than merely within sectors has a small negative effect on discounted welfare, especially in the second simulation, as the technology externalities in the non-CO_2 intensive sectors now also benefit CO_2-intensive sectors requiring a higher R&D tax in the latter to keep emissions within bounds. Consequently, the cost-effective differentiation of R&D subsidies widens in the second simulation. In the first and third simulations, however, the cost-effective differentiation of both policy instruments narrows as the technology externalities benefit all sectors while the policy instruments are used for their first-best purpose.

Finally, lowering the substitution elasticity between knowledge capital and other factors in production (σ^H) by 25 percent has a negative effect on discounted welfare in especially the second- and third simulations as substitution possibilities to adjust to the CO_2 abatement are limited. Moreover, the limited substitution possibilities translate into lower demands for knowledge capital and therefore fewer technology externalities. Consequently, changes in model results are similar to the analysis in which we changed the height of the technology externalities in innovation.

5.5 Conclusions

Recent interest has arisen with respect to the role of induced innovation in environmental policy, particularly regarding climate change. The Kyoto Protocol that many industrial countries are pursuing relies on a conventional trading scheme to constrain emissions. The USA has withdrawn and has instead adopted technology policy as an alternative strategy with the intent of directing R&D to reduce CO_2 emissions. The questions we addressed in this chapter are: Which strategy is preferred from a welfare perspective or does a combination of both strategies work better? Can one improve on uniform climate policy by differentiating policy toward CO_2-intensive sectors?

To answer these questions, we developed the DOTIS model that captures empirical links between CO_2 emissions associated with energy use, directed technical change and the economy. We specified technologies as knowledge capital, which are sector-specific investment goods and which empirical research has long found to cause positive technology externalities leading to underinvestment relative to what is socially optimal.

At this point, it is necessary to add some policy reality to the discussion. If policies can be designed to correct for technology externalities the economy can gain substantially. We show this to be the case, such that welfare in the Dutch economy under study can be improved by nearly 30 percent over our 27-year time span. We find that R&D subsidies that are optimally differentiated to achieve a 10 percent reduction in CO_2 emissions improve the economy by about 11 percent relative to the reference case in which technology externalities are not yet internalized. This appears to be a double-dividend world where CO_2 emissions are reduced while leaving the economy better off. The difficulty, however, is how to design such technology policy in reality. The unrealized 30 percent welfare gain from the technology externalities is evidence of the difficulty of correcting for them. Our best past efforts, patent protection and government funded R&D, leave us with significant underinvestment. To realize the emission reduction requires that we overcome the known limits of government funding and intellectual property rights protection and then direct technology policy toward non-CO_2 intensive sectors. Our results suggest that the differential policy to achieve the emission reduction needs to be very strong. Essentially, it means creating disincentives for R&D in CO_2-intensive sectors causing them to wither away, and creating large subsidies for non-CO_2 intensive sectors, accelerating their growth. If it is possible to ideally correct for the technology externalities, we find that the preferred policy is to do so in combination with CO_2 trading schemes. These schemes are costly to the economy relative to the case in which technology externalities are corrected for without reducing emissions, but a combination is much preferred to R&D subsidies alone or trading schemes alone.

Regardless of the particular instruments chosen, we find that technology externalities call for differentiation of instruments between non-CO_2 intensive- and CO_2-intensive sectors, such that the latter bear relatively more of the abatement burden. Essentially such differentiation partly corrects for the CO_2 implications of the technology externalities. The welfare gain for differentiated CO_2-trading schemes is relatively small compared with uniform schemes. The gain is large for the differentiation of R&D subsidies; in fact, uniform R&D subsidies are negative in all sectors, essentially slowing economic growth to achieve the emission reduction with highly negative welfare effects relative to the reference case or the cases involving CO_2-trading schemes.

Thus, is a true double dividend possible? In principle differentiated R&D subsidies with or without CO_2-trading schemes lead to that result, relative to the reference case. However, if we can design such precise incentives for technical change we might as well compare our situation to a reference case in which technology externalities are already corrected without regard to emission reduction. Compared to that reference case, CO_2-trading schemes entail a larger welfare loss than the trading scheme only case does relative to the reference case in which technology externalities are not yet corrected. So, the answer depends in part on perspective and in large part on the confidence one has that public policy can effectively direct technical change.

Appendix 5A Structure and parameter values of the DOTIS model

This appendix provides an algebraic summary of the DOTIS 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. We choose the price of intertemporal utility as numeraire and report all prices in present values. Tables 5A.1 through 5A.6 list the nomenclature.

Zero profit conditions

Production of goods:

$$\Pi^Y_{i,t} \equiv \overline{H}^{-\gamma}_{i,t}\ CES\left(r^H_{i,t}, p^{KLEM}_{i,t}; \sigma^H\right) - p_{i,t} \geq 0 \qquad \perp Y_{i,t} \qquad i = 1,..,I;\ t = 1,..,T \qquad (5A.1)$$

in which:

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

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

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

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

$$p^{FF}_{i,t} = CES\left(LT\left(p_{NRG,t}, p^{EM}_{CI}\right), LT\left(p^{COAL}_t, p^{EM}_{CI}\right); \sigma^{FF}_i\right) \qquad i = CII, CIE$$

Aggregate production of electricity:

$$\Pi_t^{EL} \equiv CES\left(p_{i,t};\sigma^{EL}\right) - p_t^{EL} \geq 0 \qquad \perp EL_t \qquad i \in EL\,;\; t=1,..,T \qquad (5A.2)$$

Investments in knowledge capital:

$$\Pi_{i,t}^{R} \equiv \overline{R}_{i,t-1}^{-\xi}\; p_{i,t}\left(1-s^c\right) - p_{i,t+1}^{H} = 0 \qquad \perp R_{i,t} \qquad i \in c\,;\; t=1,..,T-1 \qquad (5A.3)$$

$$\Pi_{i,T}^{R} \equiv \overline{R}_{i,T-1}^{-\xi}\; p_{i,T}\left(1-s^c\right) - p_{i}^{TH} = 0 \qquad \perp R_{i,T} \qquad i \in c$$

Stock of knowledge capital:

$$p_{i,t}^{H} = r_{i,t}^{H} + \left(1-\delta^H\right) p_{i,t+1}^{H} \qquad \perp H_{i,t} \qquad i=1,..,I\,;\; t=1,..,T-1 \qquad (5A.4)$$

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

Investments in physical capital:

$$\Pi_t^{I} \equiv CD\left(p_{i,t}, CES\left(r_t^K, p_t^{FDI};\sigma^A\right)\right) - p_{t+1}^{K} = 0 \qquad \perp I_t \qquad t=1,..,T-1 \qquad (5A.5)$$

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

Stock of physical capital:

$$p_t^{K} = r_t^{K} + \left(1-\delta^K\right) p_{t+1}^{K} \qquad \perp K_t \qquad t=1,..,T-1 \qquad (5A.6)$$

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

Armington aggregate:

$$\Pi_{i,t}^{A} \equiv CES\left(p_{i,t}^{IM}, CES\left(p_{j,t};\sigma_i^M\right);\sigma^A\right) - p_{i,t}^{A} \geq 0 \qquad \perp A_{i,t} \qquad \begin{cases} i=1,..,I;\, j \notin E; \\ t=1,..,T \end{cases} \qquad (5A.7)$$

Imports of goods:

$$\Pi_{i,t}^{IM^Y} \equiv p_t^{FX} - p_t^{IM} \geq 0 \qquad \perp IM_{i,t}^{Y} \qquad i=1,..,I\,;\; t=1,..,T \qquad (5A.8)$$

Imports of coal:

$$\Pi_t^{IM^{COAL}} \equiv p_t^{FX} - P_t^{COAL} \geq 0 \qquad \perp IM_t^{COAL} \quad t=1,..,T \tag{5A.9}$$

Foreign direct investment:

$$\Pi_t^{FDI} \equiv p_t^{FX} - p_t^{FDI} \geq 0 \qquad \perp FDI_t \quad t=1,..,T \tag{5A.10}$$

Exports of goods:

$$\Pi_t^{EX^Y} \equiv CD\left(p_t^{EL}, p_{i,t}\right) - p_t^{FX} \geq 0 \qquad \perp EX_t^Y \quad i \notin EL\,;\; t=1,..,T \tag{5A.11}$$

Exports of physical capital:

$$\Pi_t^{EX^K} \equiv r_t^K - p_t^{FX} \geq 0 \qquad \perp EX_t^K \quad t=1,..,T \tag{5A.12}$$

Intratemporal utility:

$$\Pi_t^W \equiv CES\left(p_t^{FX}, CES\left(p_t^Y, p_t^E; \sigma_W^{YE}\right); \sigma^A\right) - p_t^W \geq 0 \qquad \perp W_t \quad t=1,..,T \tag{5A.13}$$

in which:

$$p_t^Y = CES\left(p_{j,t}; \sigma_W^Y\right) \qquad j \notin E$$

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

Intertemporal utility:

$$\Pi^U \equiv CES\left(p_t^W; \rho\right) - p^U = 0 \qquad \perp U \tag{5A.14}$$

Market clearing conditions

Goods:

$$\begin{aligned} Y_{j,t} = {} & \frac{\partial \Pi_{i,t}^R}{\partial p_{j,t}} R_{j,t} + \frac{\partial \Pi_t^I}{\partial p_{j,t}} I_t + \sum_i \frac{\partial \Pi_{i,t}^A}{\partial p_{j,t}} A_{i,t} \\ & + \frac{\partial \Pi_t^W}{\partial p_{j,t}} W_t + \frac{\partial \Pi_t^{EX^Y}}{\partial p_{j,t}} EX_t^Y \end{aligned} \qquad \perp p_{j,t} \quad j \notin E\,;\; t=1,..,T \tag{5A.15}$$

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

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

Electricity:

$$EL_t = \sum_i \frac{\partial \Pi_{i,t}^{Y}}{\partial p_t^{EL}} Y_{i,t} + \frac{\partial \Pi_{t}^{EX^Y}}{\partial p_t^{EL}} EX_t^Y + \frac{\partial \Pi_{t}^{W}}{\partial p_t^{EL}} W_t \quad \perp p_t^{EL} \quad t = 1,..,T \tag{5A.16}$$

Knowledge capital (in market):

$$\frac{r_{i,t}^H H_{i,t}}{r + \delta^H} = \frac{\partial \Pi_{i,t}^{Y}}{\partial r_{i,t}^{H}} Y_{i,t} \quad \perp r_{i,t}^H \quad i = 1,..,I\,;\ t = 1,..,T \tag{5A.17}$$

Knowledge capital (in stock):

$$H_{i,t=1} = H_{0i} \quad \perp p_{i,t=1}^H \quad i = 1,..,I \tag{5A.18}$$

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

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

Physical capital (in market):

$$\frac{r_t^K K_t}{r + \delta^K} = \frac{\partial \Pi_{t}^{I}}{\partial r_t^{K}} I_t + \sum_i \frac{\partial \Pi_{i,t}^{Y}}{\partial r_t^{K}} Y_{i,t} + \frac{\partial \Pi_{t}^{EX^K}}{\partial r_t^{K}} EX_t^K \quad \perp r_t^K \quad t = 1,..,T \tag{5A.19}$$

Physical capital (in stock):

$$K_{t=1} = K_0 \quad \perp p_{t=1}^K \tag{5A.20}$$

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

$$TK = \left(1 - \delta^K\right) K_T + I_T \quad \perp p^{TK}$$

Labor:

$$L_t = \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial w_t} Y_{i,t} \qquad \perp w_t \qquad t = 1,..,T \qquad (5A.21)$$

Coal (imports):

$$IM_t^{COAL} = \sum_i \frac{\partial \Pi_{i,t}^Y}{\partial p_t^{COAL}} Y_{i,t} \qquad \perp p_t^{COAL} \qquad t = 1,..,T \qquad (5A.22)$$

Import aggregate:

$$IM_{i,t}^Y = \frac{\partial \Pi_{i,t}^A}{\partial p_{i,t}^{IM}} A_{i,t} \qquad \perp p_{i,t}^{IM} \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad (5A.23)$$

Armington aggregate:

$$A_{i,t} = \frac{\partial \Pi_{i,t}^Y}{\partial p_{i,t}^A} Y_{i,t} \qquad \perp p_{i,t}^A \qquad i = 1,..,I\ ;\ t = 1,..,T \qquad (5A.24)$$

Foreign investments:

$$FDI_t = \sum_i \frac{\partial \Pi_t^I}{\partial p_t^{FDI}} I_t \qquad \perp p_t^{FDI} \qquad t = 1,..,T \qquad (5A.25)$$

Foreign exchange:

$$\begin{aligned} BOP_t = & \frac{\partial \Pi_t^{EX^Y}}{\partial p_t^{FX}} EX_t^Y + \frac{\partial \Pi_t^{EX^K}}{\partial p_t^{FX}} EX_t^K - \sum_i \frac{\partial \Pi_{i,t}^{IM^Y}}{\partial p_t^{FX}} IM_{i,t}^Y \\ & - \frac{\partial \Pi_t^{IM^{COAL}}}{\partial p_t^{FX}} IM_t^{COAL} - \frac{\partial \Pi_t^{FDI}}{\partial p_t^{FX}} FDI_t - \frac{\partial \Pi_t^W}{\partial p_t^{FX}} W_t \end{aligned} \qquad \perp p_t^{FX} \qquad t = 1,..,T \qquad (5A.26)$$

CO_2 emissions in consumption:

$$EM_W = \sum_t \frac{\partial \Pi_t^W}{\partial p_W^{EM}} W_t \qquad \perp p_W^{EM} \qquad (5A.27)$$

CO_2 emissions in production:

$$EM_c = \sum_i \sum_t \frac{\partial \Pi_{i,t}^Y}{\partial p_c^{EM}} Y_{i,t} \qquad \perp p_c^{EM} \qquad c = CI, NCI \qquad (5A.28)$$

Intratemporal utility:

$$W_t = \frac{\partial \Pi^U}{\partial p_t^W} U \qquad \perp p_t^W \qquad t = 1,..,T \qquad (5A.29)$$

Intertemporal utility:

$$U = \frac{B}{p^U} \qquad \perp p^U \qquad (5A.30)$$

Income balance

$$\begin{aligned} B = & \sum_i \left(H_{i,0} - p_i^{TH} TH_i \right) + K_0 - p^{TK} TK + \sum_t w_t L_t + \sum_c p_c^{EM} EM_c \\ & - \sum_c \sum_t s^c \frac{\partial \Pi_{i,t}^R}{\partial p_{i,t}} R_{i,t} + \sum_t p_t^{FX} BOP_t \end{aligned} \qquad (5A.31)$$

Endowments

Supply of labor:

$$L_t = (1+g)^{t-1} L_0 \qquad t = 1,..,T \qquad (5A.32)$$

Balance of Payments:

$$BOP_t = (1+g)^{t-1} BOP_0 \qquad t = 1,..,T \qquad (5A.33)$$

Constraints

CO_2 emission constraint in consumption:

$$EM_W = (1-a) \sum_t (1+g)^{t-1} EM_{0W} \qquad (5A.34)$$

CO_2 emission constraints of the trading schemes in production in simulations 1 and 3:

$$EM_c = \left(1 - a^c\right) \sum_t (1+g)^{t-1} EM_{0c} \qquad c = CI, NCI \qquad (5A.35)$$

in which:

$$a\ EM = \sum_c EM_c$$

and in simulation 2:

$$EM_c = \sum_t (1+g)^{t-1} EM_{0c} \qquad c = CI, NCI$$

CO_2-emission constraints of the R&D subsidies in simulation 2:

$$\sum_i \sum_t \frac{\partial \Pi_{i,t}^{Y}}{\partial p_c^{EM}} Y_{i,t} \leq \left(1 - a^c\right) EM_c \qquad \perp s^c \qquad c = CI, NCI \tag{5A.36}$$

in which:

$$a\ EM = \sum_c \left(1 - a^c\right) EM_c$$

and in simulation 3:

$$\sum_i \sum_t \frac{\partial \Pi_{i,t}^{Y}}{\partial p_c^{EM}} Y_{i,t} \leq EM_c \qquad \perp s^c \qquad c = CI, NCI$$

Terminal condition for physical capital:

$$\frac{I_T}{I_{T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TK \tag{5A.37}$$

Terminal condition for physical capital:

$$\frac{R_{i,T}}{R_{i,T-1}} = \frac{W_T}{W_{T-1}} \qquad \perp TH_i \tag{5A.38}$$

Nomenclature

Table 5A.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	$CI: IND, TT, NRG, CIE$	Sectors according to CO_2 intensity
t	$1,..,T$	Time periods

Table 5A.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*
$\overline{H}_{i,t}$	Knowledge spillover 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*
$\overline{R}_{i,t}$	Delayed technology externalities in innovation in sector *i* from 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
$IM_{i,t}^{Y}$	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

Table 5A.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	Initial allowances of CO_2 emissions
EM	Overall allowances of CO_2 emissions

Table 5A.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
s^c	Subsidy on investments in knowledge capital in sectors c
r_t	Rental rate of capital at time t
w_t	Wage rate at time t

Table 5A.5 Parameters

Description		Value
a	Abatement of CO_2 emissions	0.10
γ	Coefficient of knowledge spillover in production	0.09
ξ	Coefficient of delayed technology externalities in innovation	0.20
g	Growth rate	0.02
r	Interest rate	0.05
δ^K	Depreciation rate of physical capital	0.05
δ^H	Depreciation rate of knowledge capital	0.25

Table 5A.6 Elasticities

Description		Value
Elasticity of substitution in intertemporal utility		
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	0.9
σ_W^{Y}	Between other goods	0.7
Elasticities of substitution in international trade		
σ^{A}	Between domestic and foreign commodities	1.0
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 sector		AGR	IND	TT	SER	NRG	CIE	NCIE
σ^{H}	Between knowledge capital and remaining inputs	1.0	1.0	1.0	1.0	1.0	1.0	1.0
σ_i^{KLEM}	Between intermediate inputs and remaining inputs	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	0.2	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: The substitution elasticities in intratemporal utility are assumed. The substitution elasticity in intertemporal utility lies between smaller values typically found in time-series studies (*e.g.* Hall, 1988a) and larger values typically found in studies that also exploit cross-sectional data (*e.g.* Beaudry and Wincoop, 1996). The substitution elasticity in international trade is lower than usual to reflect introduction of similar climate policies by most of the trading partners of the Netherlands. We obtain the substitution elasticities in production from the TaxInc model (Statistics Netherlands, 1990), except for the substitution elasticity between knowledge capital and remaining inputs, which we obtain from Goulder and Schneider (1999), and except the substitution elasticity in aggregate electricity production, which is assumed.

Appendix 5B Data

Table 5B.1 Cost- and market shares of electricity technologies (%)

	Cost shares					Market share
	Physical capital	Labor	Energy	Intermediate inputs	Total	
CO_2 intensive						
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 5B.2 Classification of industries in the national accounting matrix

1. Agriculture
    - Arable farming
    - Horticulture
    - Cattle farming
    - Other agriculture
    - Gardening and agricultural services
    - Forestry
    - Fishery
    - Meat processing
    - Fish processing
    - Fruit and vegetable processing
    - Manufacturing of dairy products
    - Manufacturing of feedstock

2. CO_2-intensive industry
    - Pulp and paper
    - Printing and publishing
    - Chemistry
    - Inorganic chemistry
    - Petrochemistry
    - Fertilizers
    - Rubber and plastics
    - Construction materials
    - Metals

3. Trade and transport
    - Wholesale and retail
    - Transport

4. Non-CO2 intensive industry and services
    - Manufacturing of foods
    - Manufacturing of coffee and tea
    - Manufacturing of beverages
    - Tobacco processing
    - Mining
    - Textiles and apparel
    - Leather products
    - Wood products
    - Metal products
    - Machinery and equipment
    - Electronic equipment
    - Transport equipment
    - Other equipment
    - Other manufactures
    - Waste recycling
    - Water
    - Construction
    - Hotels, restaurants and cafes
    - Transport services
    - Communications
    - Real estate
    - Banking, insurance, financial services
    - Business services
    - Recreational and other services
    - Research and development
    - Public administration
    - Defense
    - Education
    - Health

5. Energy
    - Oil refineries
    - Gas production and distribution

Source: Statistics Netherlands (2000)

Table 5B.3 National accounting matrix for the Netherlands in 1999 (bln. €)

	Agriculture	CO_2-intensive industry	Trade and transport	Non-CO_2 intensive industry and services	Energy	CO_2-intensive electricity	Non-CO_2 intensive electricity	Exports	Consumption	Investments in physical capital	Investments in knowledge capital	Supply changes	Total
Agriculture	16.29	0.09	0.08	1.83	0.02		0.02	28.49	7.36	0.73	1.72	0.06	56.68
CO_2-intensive industry	0.87	4.92	1.43	8.63	0.14	0.05	0.07	34.66	3.96	0.28	7.31	0.01	62.31
Trade and transport	0.54	0.65	3.14	4.09	0.25	0.01	0.02	77.38	7.06	0.51	6.87	-0.01	100.50
Non-CO_2 intensive industry and services	4.23	4.71	14.64	67.09	1.16	0.64	0.08	34.45	160.94	89.36	60.46	0.16	437.92
Energy	0.99	1.08	1.50	1.23	4.31	0.83		11.42	5.38	0.07	1.07	0.08	27.97
Electricity	0.54	0.63	0.57	0.72	0.07	3.32	0.39	2.07	2.20	0.01	0.60	0.00	11.13
Imports	14.31	21.01	13.75	60.30	6.20	1.26			62.90	23.59		0.25	203.56
Taxes minus subsidies	-0.70	0.12	-0.98	4.18	4.60	0.38	0.06						7.66
Labor	5.97	10.90	33.23	133.54	1.34	0.76	0.09						185.84
Physical capital	11.72	10.09	25.52	89.12	8.69	2.16	0.31	0.56	16.96	3.50			168.63
Knowledge capital	1.92	8.12	7.63	67.18	1.19	0.60	0.07						86.71
Total	56.68	62.31	100.50	437.92	27.97	10.01	1.11	189.02	266.76	118.04	78.03	0.54	

Sources: Statistics Netherlands (2000), Böhringer *et al.* (2003), de Haan and Rooijen-Horsten (2004) and own calculations. Numbers are rounded.

Table 5B.4 Selected factor intensities of the Dutch economy in 1999 (% of gross sectoral output)

	Knowledge capital				Physical capital	Labor	CO_2
Sector	R&D	EDU	ICT	Total			
Production							
CO_2 intensive	3.3	4.8	0.7	8.7	23.1	23.0	0.07
CO_2-intensive industry	8.3	4.4	0.4	13.0	16.2	17.5	0.08
Trade and transport	0.8	6.2	0.6	7.6	25.4	33.1	0.04
Energy	1.8	1.3	1.3	4.3	31.1	4.8	0.04
CO_2-intensive electricity	1.3	2.4	2.3	6.0	21.6	7.6	0.41
Non-CO_2 intensive	3.7	8.7	1.5	14.0	20.4	28.2	<0.01
Agriculture	1.5	1.4	0.5	3.4	20.7	10.5	0.01
Non-CO_2 intensive industry and services	4.0	9.7	1.6	15.3	20.4	30.5	<0.01
Non-CO_2 intensive electricity	1.3	2.4	2.3	6.0	28.3	7.8	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. We obtain data on knowledge capital from de 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).

Chapter 6 Adoption of CO_2 abatement technology: A CGE analysis*

6.1 Introduction

The point has now been made a few times that environmental policy, such as a trading scheme to constrain carbon dioxide (CO_2) emissions, can induce technical change. Indeed, several pollution abatement technologies have been developed as a result of such environmental policy. One can think, for example, about scrubbers in exhaust pipes. Yet, these technologies are not necessarily adopted. Although non adoption itself is not a failure in the functioning of markets and therefore does not necessarily provide an economic rationale for technology policy, non adoption can signal underlying market failures. Technology externalities such as knowledge spillovers and network externalities are prime examples of such market failures. Technology policy aimed at these underlying market failures can also induce adoption of pollution abatement technology and in turn reduce pollution. Different policies have different effects on technical change and welfare, however, and it is hence unclear which policy is preferred *a priori*.

We take the differentiated CO_2-trading schemes from Chapter 5 as our starting point and study cost effectiveness of combining these schemes with different technology policies with respect to adoption of CO_2 abatement technology and ultimately with respect to abatement of CO_2 emissions. Is technology policy necessary in the first place? If yes, is it cheaper to use technology adoption subsidies or R&D subsidies directed to the CO_2 abatement technology? Do we also induce its adoption if we try to correct for all market failures associated with technical change throughout the economy?

Previous investigations of this issue include the econometric analyses of Jaffe and Stavins (1995) and Hassett and Metcalf (1995), who compare energy taxes with adoption subsidies regarding adoption of CO_2-abatement technology. Using theoretical models, Milliman and Prince (1989; 1992) and Jung *et al.* (1996), among others, compare CO_2-trading schemes with other environmental policy instruments regarding adoption of CO_2-abatement technology, although these studies do not include technology policy instruments in their comparisons. In a computable general equilibrium setting, Gerlagh and van der Zwaan (2006) compare various policy instruments regarding adoption of CO_2 capture and storage (CCS) as a CO_2 abatement

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* This chapter was written while Vincent Otto was visiting scholar at the Joint Program on the Science and Policy of Global Change at MIT and is based on the working paper Otto, V.M. and J. Reilly (2006), *Directed technical change and the adoption of CO_2 abatement technology: The case of CO_2 capture and storage*, Joint Program on the Science and Policy of Global Change Report No. 139, Massachusetts Institute of Technology, Cambridge, MA. We would like to thank Kay Damen, Jim McFarland, Sergej Paltsev, Andreas Löschel and John Parsons for helpful comments. The usual disclaimer applies.

technology, although their comparison is also limited to environmental policy instruments only. Popp (2004b) and Kverndokk *et al.* (2004) do not study adoption (of non-CO_2 intensive technology) per se but rather how adoption influences the cost effectiveness of carbon taxes and R&D subsidies with respect to CO_2 emission reduction.[1]

We combine these various approaches and compare CO_2-trading schemes, adoption subsidies, and R&D subsidies with respect to adoption of CO_2 abatement technology and ultimately with respect to cost effective abatement of CO_2 emissions. For this purpose, we use the DOTIS model as specified and calibrated in Chapter 5 but now add CCS as a discrete CO_2 abatement technology for gas-fired power plants (henceforth referred to as the gas CCS technology) in the CO_2-intensive electricity sector. We subsequently construct simulations to reveal the cost-effective policy combination. We explore the potential of CCS for coal-fired power plants (henceforth referred to as the coal CCS technology) in the sensitivity analysis.

This chapter is organized as follows. Section 6.2 describes how we account for the CCS technologies in the DOTIS model. In Section 6.3 we present the results that we obtain with the policy simulations and discus their effects on CO_2 emission patterns as well as their fiscal implications. Section 6.4 concludes.

6.2 Accounting for CO_2 capture and storage technology

CCS is a process consisting of the separation of CO_2 from industrial- or energy sources and the transport to a storage location where the CO_2 is isolated from the atmosphere (IPCC, 2005). Possible storage locations include geological formations such as saline aquifers or oil- and gas fields. The net reduction of CO_2 emissions depends on, among others, the fraction of CO_2 captured, the extent of efficiency loss in energy conversion and leakage during transport and storage. As such, CCS is expected to become part of the portfolio of mitigation options for stabilization of atmospheric CO_2 concentrations. Especially since the supply of primary energy will continue to be dominated by fossil fuels until at least the middle of this century. Although CCS can in principle be applied everywhere CO_2 is emitted in large quantities, energy- and economic models indicate that the major contribution of CCS to CO_2 mitigation will come from adoption in the electricity sector (IPCC, 2005). For this reason, we focus on adoption of CCS in the electricity sector in this thesis.

Electricity generation technologies fired by natural gas and coal are being used for respectively base- and mid-load electricity demand in the Netherlands. Table 6.1 shows the expected costs of these electricity generation technologies with CCS in the Netherlands (see Damen *et al.,* 2006), for a detailed comparison of the various CCS technology options).

[1] We refer to Jaffe *et al.* (2002a) for a survey of all previous studies and to Requate (2005) for a more recent survey of previous studies using theoretical models only.

Table 6.1 Cost of electricity with CO_2 capture and storage in the Netherlands (€ct/kWh)

	Without CCS	With CCS		
		NGCC	IGCC	PC
Electricity generation and CO_2 capture				
Capital		1.5	2.7	3.0
Fuel		3.0	1.5	1.6
Operation and maintenance		0.5	1.2	1.4
CO_2 storage		0.2	0.5	0.4
Transmission and distribution		2.9	2.9	2.9
Total	7.5	8.1	8.8	9.3
Markup (%)	0	8	17	24
CO_2 capture rate (%)	0	85	85	90

Notes: NGCC refers to natural gas combined cycle, IGCC refers to integrated coal gasification combined cycle and PC refers to pulverized coal. We base fuel costs of natural gas on 4€/GJ and fuel costs of coal on 1.5 €/GJ. We base storage costs 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.

The generation costs are based on natural-gas combined cycle (NGCC), pulverized-coal fired power plants (PC) and integrated coal gasification combined cycle (IGCC) and include cost estimates for CO_2 capture but not storage. Adding CCS to the PC technology results in a slightly higher CO_2 capture rate than when CCS is added to the other electricity technologies. Regarding storage, we use a cost estimate of 5 €/t CO_2 stored, which includes pipeline transport to and injection in the gas fields in the North Sea or the north of the Netherlands. Further, transmission and distribution costs must be incorporated to make a clean comparison with the cost of conventional electricity in the model. Overall, the CCS technology for NGCC is 8 percent more expensive than the cost of conventional electricity whereas the CCS technologies for IGCC and PC are 17 and 25 percent more expensive. These estimates of cost 'markup' correspond 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 CCS cannot be stated with certainty. Neither do we know the full potential of CCS with precision. We assume that all CO_2 captured in the Netherlands can also be stored and focus on subsequent adoption of the CCS technologies. For simplicity, we assume adoption can be immediate. Nevertheless, it is expected that further technical change will bring down costs or increase potential or both over time.

Regarding technical change, the CCS technologies use services derived from the same knowledge capital as the conventional technologies without CCS in the CO_2-intensive electricity sector. That is, we assume that engineers and scientists working in conventional power plants also work on the CCS technologies. Knowledge gained with the CCS technologies therefore spills over to the conventional electricity technologies as well. Investments in and services derived from this type of knowledge capital, however, can be ‘earmarked’ for the CCS technologies such that the services derived by conventional technologies without CCS are limited to only those services replacing obsolete services and all other services are derived by the CCS technologies.

6.3 Simulations

We analyze cost-effectiveness of differentiated CO_2-trading schemes, possibly combined with technology policy, to induce adoption of the gas CCS technology and ultimately to reduce CO_2 emissions in production by 40 percent relative to the reference case. This emission reduction approximates the stabilization of CO_2 emissions at 1990 levels for the Netherlands, as agreed upon in the Kyoto protocol while assuming similar post-Kyoto targets. Technology policy is aimed at the internalization of positive technology externalities that may underlie non-adoption of the CCS technology and takes the form of technology adoption subsidies or R&D subsidies. We direct R&D subsidies only to the development of the gas CCS technology or generally to the development of technologies throughout the economy. In the last case, we differentiate the subsidies between CO_2 intensive- and non-CO_2 intensive sectors as we do in Chapter 5. Specifically, we label agriculture, non-CO_2 intensive industries and services, and non-CO_2 intensive electricity as non-CO_2 intensive sectors and CO_2-intensive industries, trade and transport, energy, and CO_2-intensive electricity as CO_2-intensive sectors.

Table 6.2 Effects of policies on discounted welfare and adoption of the gas CCS technology

Simulation	Discounted welfare	Year of adoption
Reference	0.00 %	No
1 Differentiated CO_2-trading schemes	-1.46 %	2023
2 Combination of differentiated CO_2-trading schemes and an adoption subsidy	-0.75 %	2007
3 Combination of differentiated CO_2-trading schemes and a directed R&D subsidy	-1.19 %	2009
4 Combination of differentiated CO_2-trading schemes and differentiated R&D subsidies	13.84 %	2009

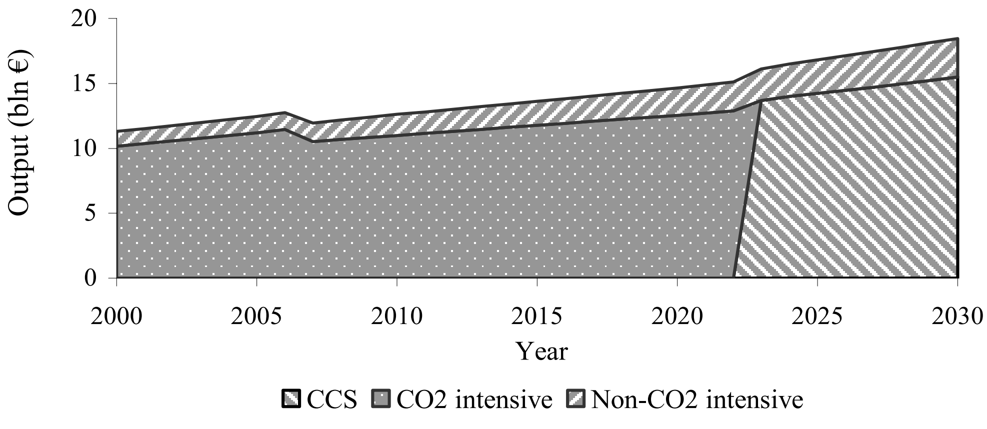
Note: Discounted welfare is measured as intertemporal utility and expressed in percentage changes relative to the reference case.

To avoid leakage of CO_2 emissions to consumption in all simulations, we also abate these emissions by 40 percent relative to the reference case using a separate quantity constraint.[2] We consider a 32-year time horizon, defined over the years 1999 through 2030, and calibrate the model to a steady state rate of growth of two percent that serves as the reference case. We introduce the policies from 2007 onward and evaluate their cost effectiveness by measuring the concomitant changes in discounted welfare (intertemporal utility) relative to the reference case. Table 6.2 summarizes the four simulations.

Simulation 1: Differentiated CO_2-trading schemes

Figure 6.1 shows effects of the cost-effective set of differentiated CO_2-trading schemes on electricity generation. The trading schemes yield a discounted welfare loss of 1.45 percent and entail shadow prices of €11.55 and €1.00 per ton CO_2 in respectively the CO_2 intensive- and non-CO_2 intensive sectors. By pricing CO_2 emissions, the trading schemes improve the competitiveness of the gas CCS technology and induce its adoption, albeit only from 2023 onward. In the meantime, CO_2 efficiency of the conventional electricity generation technologies improves instead, making it more difficult for the CCS technology to enter. Once the CCS technology has been adopted, however, large quantities of electricity can then be generated in a non-CO_2 intensive manner. As a result, electricity itself then gains market share as an energy carrier, further increasing output of the gas CCS technology.

Figure 6.1 Effects of the cost-effective set of differentiated CO_2-trading schemes on electricity generation per technology (bln. €)



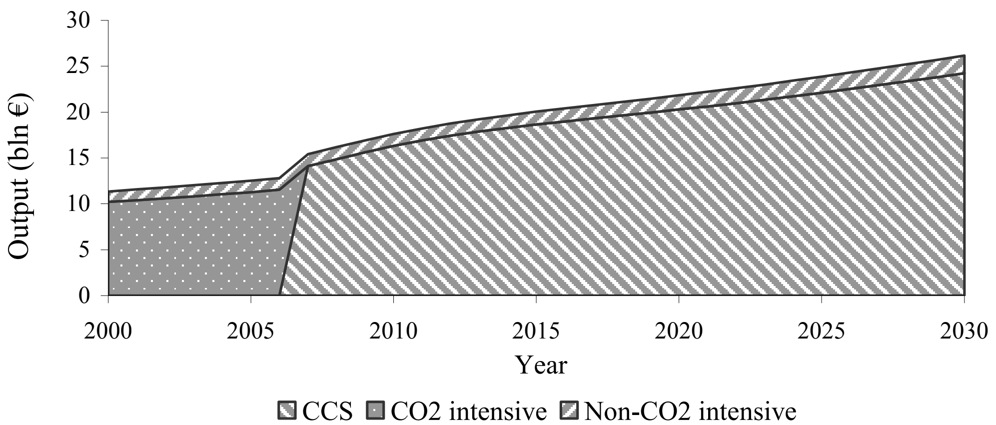
[2] Note that CO_2 emissions abroad can increase as we only investigate domestic abatement. Yet, the Armington specification, as opposed to the Heckscher-Ohlin formulation, closes international trade in a way that limits this leakage effect.

Simulation 2: Combination of differentiated CO_2-trading schemes and an adoption subsidy

Figure 6.2 shows that the cost-effective combination of differentiated CO_2-trading schemes with an adoption subsidy for the gas CCS technology is very effective in inducing its adoption. By directly compensating for the markup over the cost of conventional electricity, the CCS technology becomes competitive from the moment the adoption subsidy is introduced and immediately substitutes for the conventional technologies used in the CO_2-intensive electricity sector. This result is in line with empirical findings by Jaffe and Stavins (1995) and Hassett and Metcalf (1995) that show technology adoption subsidies to be more effective in inducing adoption of energy conservation technologies than energy taxes.

The cost-effective combination of instruments comprises shadow prices of €6.65 and €4.95 per ton CO_2 in the CO_2 intensive- and non-CO_2 intensive sectors and an adoption subsidy of 21 percent and entails a discounted welfare loss of 0.75 percent. This loss is lower than in the first simulation with just the CO_2 trading schemes because the adoption subsidy corrects for positive technology externalities related to the CCS technology (see Table 6.2). Technology externalities lead to underinvestment in the CCS technology according to what is optimal from a social welfare perspective. Knowledge gained during the development phase of the CCS technology, for example, might spill over to other firms in the electricity- or energy sector and indirectly increase their productivity. By subsidizing the use of the CCS technology, we 'pull' this technology out of its development phase and consequently bring its investment levels closer to the socially optimal level.

Figure 6.2 Effects of the cost-effective combination of differentiated CO_2-trading schemes and an adoption subsidy on electricity generation per technology (bln. €)

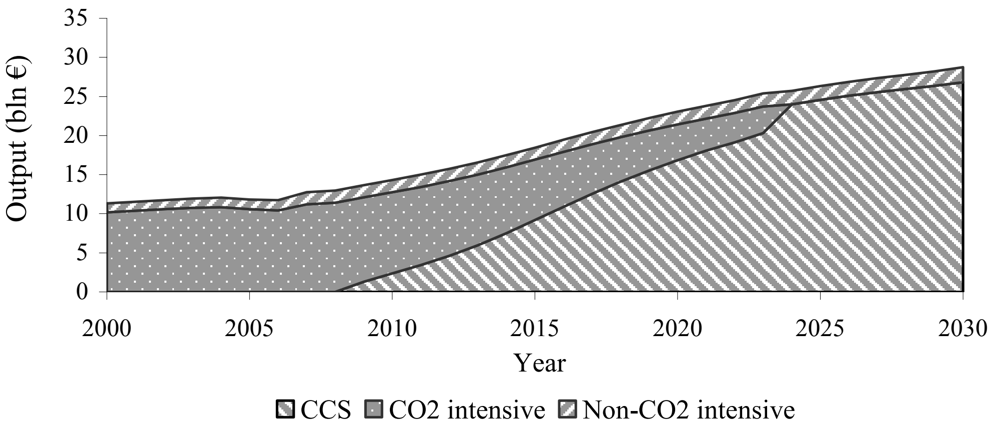


Simulation 3: Combination of differentiated CO_2-trading schemes and a directed R&D subsidy

Figure 6.3 shows that the cost-effective combination of differentiated CO_2-trading schemes with an R&D subsidy directed to the gas CCS technology also induces its adoption, albeit later in time and at a slower rate than with the adoption subsidy. Whereas the adoption subsidy directly improves competitiveness of the CCS technology by lowering its output price, the directed R&D subsidy only indirectly improves competitiveness by lowering one of the various input prices. It is only when sufficient knowledge capital has been accumulated that the input costs of knowledge capital services decreases to the extent that the CCS technology becomes competitive and gains market share. Similar to the first simulation with only the trading schemes, CO_2 efficiency of conventional electricity generation technologies improves in the meantime, making it more difficult for the CCS technology to gain market share.

The cost-effective combination of instruments now comprises shadow prices of €10.50 and €1.05 per ton CO_2 in the CO_2 intensive- and non-CO_2 intensive sectors and a directed R&D subsidy of 59 percent and entails a discounted welfare loss of 1.19 percent. This loss is lower than in the first simulation with only the trading schemes, but higher than in the second simulation with the additional adoption subsidy (see Table 6.2). Although the directed R&D subsidy also corrects for technology externalities associated with the CCS technology, it takes more time to receive the returns on the investments than with the adoption subsidy.

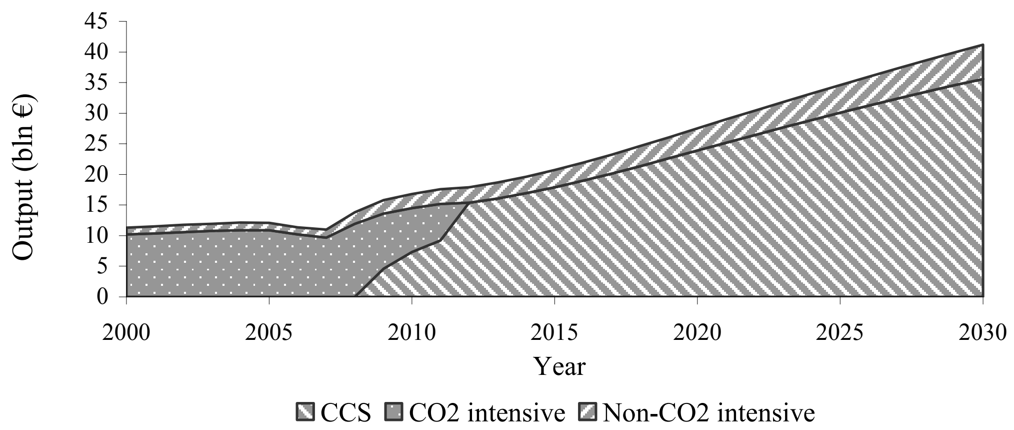
Figure 6.3 Effects of the cost-effective combination of differentiated CO_2-trading schemes and a directed R&D subsidy on electricity generation per technology (bln. €)



Simulation 4: Combination of differentiated CO_2-trading schemes and differentiated R&D subsidies

Figure 6.4 shows that the cost-effective combination of differentiated CO_2-trading schemes with differentiated R&D subsidies throughout the economy leads to more and faster adoption of the gas CCS technology than in the previous simulation with the R&D subsidy directed only to the CCS technology. More specifically, the cost-effective combination of instruments now comprises shadow prices of €19.60 and €10.10 per ton CO_2 in the CO_2 intensive- and non-CO_2 intensive sectors as well as R&D subsidies of 60 percent and 51 percent in the respective sectors. In contrast to the R&D subsidy directed only to CCS technology, the optimal set of differentiated R&D subsidies enhances economic growth in the whole economy and further increases the shadow prices of CO_2. Both these effects improve the competitiveness of CCS technology. Compared to the second simulation with the adoption subsidy, however, adoption occurs later in time and remains slower. Whereas R&D subsidies are first-best instruments to internalize technology externalities, they are not necessarily the most effective instruments to induce adoption of new technology because they only indirectly improve competitiveness of new technology as discussed above. Nevertheless, discounted welfare increases by 13.84 percent relative to the reference case and this policy combination is therefore superior from a welfare perspective as technology externalities are internalized throughout the whole economy.

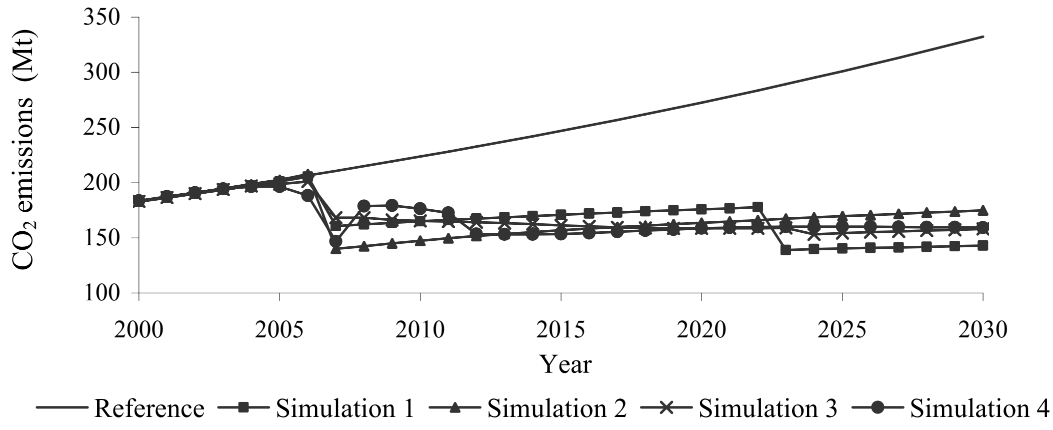
Figure 6.4 Effects of the cost-effective combination of differentiated CO_2-trading schemes and differentiated R&D subsidies on electricity generation per technology (bln. €)



Effects on CO_2 emissions

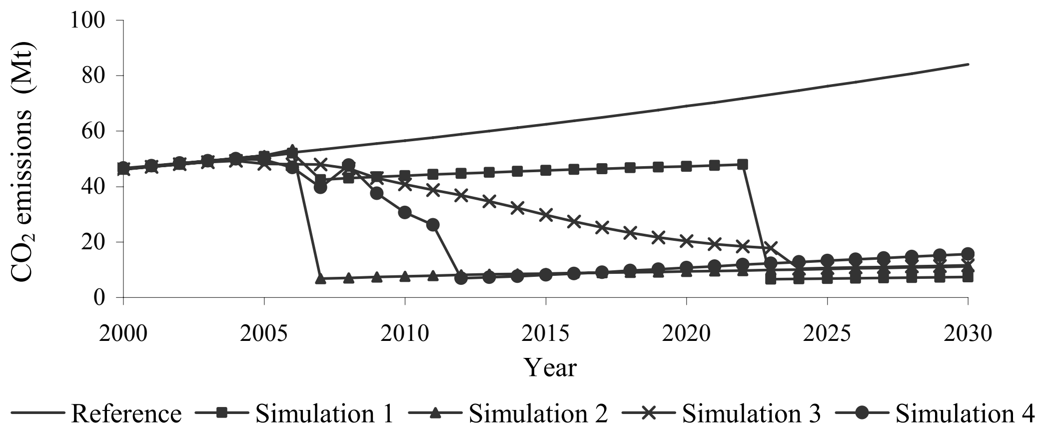
Figure 6.5 shows effects of the cost-effective policies identified in the four simulations above on CO_2 emissions in the Dutch economy. Aggregate CO_2 emissions are abated by 40 percent relative to the reference case, which corresponds to stabilization of emissions around 160 Mt CO_2 per year. The typical abatement pattern consists of relatively less abatement in early years and more abatement in later years. In the fourth simulation with both the trading schemes and the optimally differentiated R&D subsidies, for example, emissions are abated by a mere 15-20

Figure 6.5 Effects of the policy combinations on aggregate CO_2 emissions (Mt CO_2)



percent relative to the reference case in the first couple of years after the policies have been introduced, whereas emissions are abated by about 50 percent toward the end of the time horizon. Both the technology externalities and the adoption of CCS technology in later years reduce abatement costs in the future and hence reduce shadow prices of CO_2 emissions today (Goulder and Mathai, 2000). In the second simulation with the adoption subsidy, however, abatement is spread more evenly over time as the CCS technology is adopted immediately after we introduce the policies.

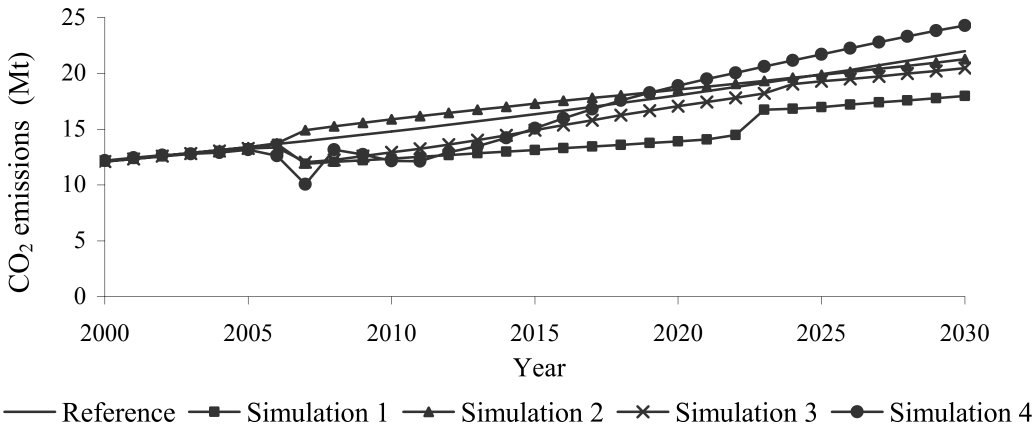
Figure 6.6 Effects of the policy combinations on CO_2 emissions in the electricity sectors (Mt CO_2)



Sectoral emission patterns also exhibit variation across the simulations. CO_2 intensities, differentiation of the policy instruments and adoption of the CCS technology all determine which sectors abate more and which sectors abate less. Figures 6.6 and 6.7 show effects of the cost-effective policies identified in the simulations above on CO_2 emissions in the two sectors most affected by possible adoption of CCS technology: the CO_2-intensive electricity sector and the energy sector.

Regarding the CO_2-intensive electricity sector, CO_2 emission levels correspond to the amount of electricity generated with the various generation technologies as shown in Figures 6.1 trough 6.4. The CCS technology is adopted to varying extents in the four simulations and the abatement burden of the CO_2-intensive electricity sector consequently increases to these extents.

Figure 6.7 Effects of the policy combinations on CO_2 emissions in the energy sector (Mt CO_2)



Regarding the energy sector, abatement of its CO_2 emissions correspond *inversely* to abatement of emissions in the CO_2-intensive electricity sector. The more the CCS technology is adopted in the CO_2-intensive electricity sector, the more market share electricity gains as an energy carrier and the more natural gas is demanded by the electricity sector ultimately leading to more CO_2 emissions in the energy sector. This effect is especially visible in the last three simulations with the additional technology policies and highlights that technology policy does not necessarily provide incentives to reduce energy use.

Fiscal implications

The cost-effective policies identified above have different fiscal implications (see Table 6.3). In the first simulation with only the CO_2 trading schemes, revenues from these schemes amount to 96 billion euros or 2.8 percent of gross domestic output over the entire 24-year period the trading schemes are in place.

These revenues are sufficient to finance technology policy that is limited in scope. Indeed, expenditures on the adoption subsidy amount to 32 billion euros or 0.9 percent of gross domestic output while revenues from the trading schemes are 83 billion euros or 2.4 percent of gross domestic output in the second simulation. Compared to the first simulation with only the trading schemes, however, revenues from these trading schemes now fall by 13 billion euros as the immediate adoption of the CCS technology makes it cost effective to shift some of the abatement burden away from the CO_2-intensive sectors. Similar fiscal implications can be observed in the third simulation with the R&D subsidy for CCS instead of the adoption subsidy. As it is cost effective to let the CCS technology gain market share only gradually in this simulation, both the R&D subsidy for CCS and its fiscal implications are smaller in size.

Finally, the fourth simulation with the optimally differentiated R&D subsidies shows clearly that there is a limit to the extent that revenues from the trading schemes can be used to finance technology policy. The expenditures on the R&D subsidies are now a factor 10 larger than the revenues from the trading schemes. Yet, this simulation also shows clearly that technology policy is self financing in the sense that gross domestic output increases more than the expenditures on the R&D subsidies. The latter now amounts to 1,536 billion euros over the entire 24-year period the policies are in place whereas the former increases from 3,425 to 5,493 billion euros.

Table 6.3 Fiscal implications of the policies

	Simulation			
	1	2	3	4
Gross domestic output in billion euros	3,425	3,482	3,446	5,493
Revenues from the CO_2 trading schemes				
In billion euros	96	83	91	158
As share of gross domestic output (%)	2.8	2.4	2.7	2.9
Expenditures on the subsidies				
In billion euros		32	12	1,536
As share of gross domestic output (%)		0.9	0.4	28.0

Notes: Numbers are aggregated from the time the policies are introduced (2007) till the end of the time period under study (2030) and are expressed as present values. Simulation 1 refers to differentiated CO_2-trading schemes; simulation 2 to the combination of differentiated CO_2-trading schemes and an adoption subsidy; simulation 3 to the combination of differentiated CO_2-trading schemes and a directed R&D subsidy; and simulation 4 to the combination of differentiated CO_2-trading schemes and differentiated R&D subsidies. Policies reported for these simulations are the cost effective policies to achieve the emission reduction and are not necessarily the minimum policies required to induce adoption of the gas CCS technology.

Sensitivity analysis

Table 6.4 reports the sensitivity of our results to key parameter values. We use central parameter values in all sensitivity simulations (see Tables 5A.5 and 5A.6) except for the parameter subject to analysis. We limit ourselves to CCS-related parameters given our focus on technology adoption.

Table 6.4 Piecemeal sensitivity analysis

Discounted welfare (% change)	Simulation			
	1	2	3	4
Regular simulation	0.00	0.00	0.00	0.00
25% higher externalities for CCS	0.00	0.02	0.05	0.01
Storage costs halved	0.07	0.05	0.09	0.03
Storage costs doubled	-0.16	-0.10	-0.23	-0.07
CCS for coal-fired plants	0.00	0.00	0.00	0.00
Cumulative output-share of CCS for gas-fired plants (%)	Simulation			
	1	2	3	4
Regular simulation	38.4	100	72.6	91.9
25% higher externalities for CCS	38.4	100	74.2	92.4
Storage costs halved	43.0	100	75.6	93.7
Storage costs doubled	24.3	100	67.8	87.6
CCS for coal-fired plants	38.4	100	72.6	91.9

Notes: Cumulative output shares of CCS for gas-fired plants are expressed in terms of total output of the CO_2-intensive electricity sector. Simulation 1 refers to differentiated CO_2-trading schemes; simulation 2 to the combination of differentiated CO_2-trading schemes and an adoption subsidy; simulation 3 to the combination of differentiated CO_2-trading schemes and a directed R&D subsidy; and simulation 4 to the combination of differentiated CO_2-trading schemes and differentiated R&D subsidies. Neither the CCS for pulverized-coal fired plants nor the CCS for integrated coal gasification combined cycles are adopted and hence their market shares are not reported.

We find that our results are robust to the range of parameter values considered. Combining differentiated CO_2-trading schemes with the adoption subsidy remains the most effective set of policy instruments to induce CCS technology whereas combining the CO_2-trading schemes with the optimal set of differentiated R&D subsidies remains the cost-effective set of policy instruments to induce CCS technology and ultimately to achieve the abatement target.

Turning to the specific parameters subject to analysis, increasing the coefficient value of technology externalities associated with innovation of the CCS technology by 25% has a positive effect on discounted welfare and adoption of the CCS technology as its productivity improves faster. This is especially visible in simulations 3 and 4, in which adoption occurs not immediately after the introduction of the policy combination. Further, halving the storage costs of the CCS technology to €2.50 per ton CO_2 has a positive effect on discounted welfare and adoption of the CCS technology as well because the lower storage costs reduce the markup over the cost of conventional electricity. The opposite applies if we double the storage costs to €10 per ton CO_2. Finally, specifying CCS also for PC and IGCC does not lead to any adoption of these technologies because of their high markup relative to the gas CCS technology. Consequently, discounted welfare and adoption of the gas CCS technology are not affected.

6.4 Conclusions

Environmental policy, such as a trading scheme to constrain CO_2 emissions, can induce technical change. Indeed, several pollution abatement technologies have been developed as a result of environmental policy. These technologies are not necessarily adopted immediately, however, because of prohibitive costs or market failures associated with technical change or both. Technology policy aimed at these market failures can induce adoption of CO_2 abatement technology and in turn reduce CO_2 emissions as well. As a caveat, we did not study institutional aspects of technology policy or the precise form such policy should take in practice. Instead, we addressed more general questions first: Is technology policy necessary in the first place to induce adoption of the discrete CO_2 abatement technology under study? Regarding CO_2 emission reduction, is it more cost effective to use technology adoption subsidies or R&D subsidies?

To answer these questions, we used the DOTIS model as specified and calibrated in Chapter 5 and included CCS as a discrete CO_2 abatement technology for gas-fired power plants in the CO_2-intensive electricity sector. Simulations revealed which policy combination is cost effective with respect to adoption of the CCS technology and ultimately with respect to abatement of CO_2 emissions.

Although it takes time, CO_2-trading schemes alone are sufficient to induce adoption of the CCS technology under current abatement targets. Combining the CO_2-trading schemes with R&D subsidies that are optimally differentiated across CO_2-intensive- and non-CO_2 intensive sectors leads to faster adoption of the CCS technology and is cost effective in achieving the abatement target. In fact, the economy improves relative to the reference case because of the correction for technology externalities throughout the whole economy. Although R&D subsidies are the first-best instrument to internalize technology externalities, they are not necessarily the most effective instrument to induce adoption of new technology. For that purpose, an adoption subsidy is preferred. Such a subsidy directly improves the competitiveness of the CCS technology by compensating for its markup over the cost of conventional electricity. Consequently, the CCS technology immediately substitutes for the conventional technologies used in the CO_2-intensive electricity sector.

Thus, is technology policy necessary in the first place? At first sight the answer must be no. After all, technology policy does not even provide incentives to reduce energy use and concomitant CO_2 emissions. The adoption subsidy, for example, increases demand for natural gas, which offsets some of the CO_2 abatement in the electricity sector by shifting CO_2 emissions to the energy sector. After taking a closer look, however, we find that technology policy speeds up the adoption of the CO_2 abatement technology and improves cost effectiveness of the emission reduction. So technology policy is not necessary in the strict sense of the word, but it might be necessary in a political sense as technology policy takes the sharp edges of the emission reduction.

Chapter 7 Conclusions

7.1 Introduction

My aim in this thesis was to study how policy instruments can direct technical change to those technologies with the greatest potential for cost-effective pollution abatement. To do this, I used an economic modeling approach. Specific attention was paid to the potential role that technology externalities play in the process of technical change. In the light of the climate change problem, I focused on the reduction of carbon dioxide (CO_2) emissions associated with energy use as a case study. The specific application was a model of the Dutch economy with attention to detail of its energy sector.

This chapter is organized as follows. Section 7.2 presents the answers to the research questions posed in Chapter 1. In Section 7.3, I derive my conclusions regarding the methodology used, the topic of directed technical change as well as policy prescription. Section 7.4 puts the policy discussion in perspective by bringing some reality to the discussion. Finally, Section 7.5 suggests topics for future research.

7.2 Answers to the research questions

In this section, I answer the questions posed in Chapter 1.

Q1 What are the determinants of the direction of technical change? (Chapter 3)

The degree to which economic forces induce technical change has been a subject of much debate and analysis. I focus on the degree to which economic forces direct technical change toward particular sectors or technologies by changing relative commodity prices. In terms of energy research, the oil price shocks of the 1970's provide a useful natural experiment on the impacts of prices on technical change. In some ways these price shocks are analogous to an environmental policy shock designed to change relative prices of CO_2-intensive goods. Both shocks change relative commodity prices and as such give rise to various effects throughout the economy that together determine the exact direction of technical change. On the supply side of the economy, a shock gives rise to a price effect and provides an incentive to develop knowledge capital that can be used in the production of the now relatively scarce and more expensive CO_2-intensive goods. At the same time, there is a market-size effect as the shock also provides an incentive to develop knowledge capital that can be used in the production of the now relatively abundant and cheaper non-CO_2 intensive goods, for which there ultimately is a bigger market (Acemoglu, 2002). On the demand side of the economy, the elasticity of substitution in consumption regulates the relative strength of the price-and market size effects. The more substitutable goods are, the less scarcity can command higher prices and the more powerful the market-size effect is relative to the price effect and vice versa. Finally, technology externalities reinforce the direction of technical change if they are present.

My model analyses in Chapter 3 show, however, that the extent to which changes in energy prices affect the direction of technical change is relatively small. The oil price shock, for example, increases production of knowledge capital goods in the energy sector by a mere 10 percent relative to the rest of the economy and only during the shock. Similarly, my model analyses in Chapter 5 show that environmental policy does not direct technical change to a great extent either. Changes in knowledge capital investments differ between CO_2 intensive and non-CO_2 intensive sectors by at most 20 percent if CO_2 trading schemes are used to reduce emissions. In contrast, technology policy aimed directly at possible technology externalities has far larger effects on the direction of technical change.

Q2 Do technology externalities play a role in technical change? (Chapters 2 and 4)

Technology externalities do play a role in technical change and cause the social returns to technical change to diverge from the private returns. Examples of positive technology externalities include knowledge spillovers and network externalities whereas the rent-stealing effect is an example of a negative technology externality. Although it is difficult to determine the magnitude of the various externalities separately, empirical evidence by Griliches (1992) suggests that overall, technology externalities are positive and large. As technology externalities are by definition not included in firms' decision making processes, they cause the market mechanism to yield less technical change than what is socially optimal. Estimates of the private returns to technical change lie in the range of 5-30 percent whereas the social returns have been estimated around 50 percent (Baumol, 2002).

My work focused on estimating these social returns as well as their time profile, recognizing that benefits of technical change are likely to accrue gradually over time. Similar to the previous literature, I found that social returns to technical change are sizable. In addition, however, I found evidence that the benefits extended over time, with the delayed response continuing up to eight years (Chapter 4). Such a delayed feedback occurs when previous technical change has an effect on today's technical change (Arthur, 1990). My finding shows that the feedback effect is strong: I find, for example, that a one percent increase in productivity ascribed to technical change six years ago still results in almost a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*. To a certain extent, this feedback is not anticipated by individual firms and as such it is an aggregate estimate of the technology externalities.

Q3 Which policy instruments can direct technical change such that CO_2-emission reduction becomes more cost effective? (Chapter 5)

I considered CO_2 trading schemes, R&D subsidies and a combination of both as possible climate policies. Using as the starting point a CO_2 trading scheme yielding a uniform shadow price of CO_2 emissions, I find that R&D subsidies that are optimally differentiated to achieve a 10 percent reduction in CO_2 emissions improve welfare by about 11 percent over a 27-year time span relative to the reference case without any policy intervention. This policy is considerably more cost effective than using CO_2-trading schemes and takes us to a double-dividend world where CO_2 emissions are reduced while improving welfare. My results suggest, however, that the differential policy to achieve the emission reduction needs to be very strong. Essentially, it means creating disincentives for R&D in CO_2-intensive sectors causing them to wither away, and creating large subsidies for non-CO_2 intensive sectors, accelerating their growth.

Instead of using R&D subsidies as the sole climate policy, I find that it is preferable from a welfare perspective to combine the R&D subsidies, aimed at internalizing the technology externalities, with the CO_2 trading schemes, aimed at internalizing the climate externality. This combination allows both instruments to be used for their first-best purpose and as a result achieves the 10 percent emission reduction while improving welfare by about 27 percent over a 27-year time span and avoiding any output contractions in the CO_2-intensive sectors.

Regardless of the particular policy instruments chosen, I find that technology externalities call for differentiation of instruments between non-CO_2 intensive- and CO_2-intensive sectors, such that the latter bear relatively more of the abatement burden. Regarding the CO_2-trading schemes, this implies that there are two schemes yielding two CO_2 shadow prices. Essentially the differentiation compensates for the CO_2 implications of the technology externalities. The welfare gain for differentiated CO_2-trading schemes is relatively small compared with uniform schemes. The gain is large for the differentiation of R&D subsidies. When R&D subsidies are used as the sole climate policy, for example, their differentiation leads to a 13 percent welfare improvement relative to uniform R&D subsidies. In fact, uniform R&D subsidies are negative in all sectors, essentially slowing economic growth to achieve the emission reduction.

Q4 Which policy instruments induce adoption of a specific CO_2-abatement technology such that CO_2-emission reduction becomes more cost effective? (Chapter 6)

To answer this question, I use CO_2 capture and storage (CCS) technology in the Dutch electricity sector as a case study of a specific CO_2-abatement technology. Components of the CCS technology are currently in various stages of development (IPCC, 2005). I assume that the

CCS technology is available from 2007 onward but not yet competitive at current electricity prices to reflect the costs of further development. Using as a starting point the differentiated CO_2 trading schemes, I find that combining the trading schemes with adoption- or various R&D subsidies leads to faster adoption of the CCS technology under study in the Dutch electricity sector and makes the emission reduction, as currently agreed upon in the Kyoto protocol, more cost effective.

Specifically, I find that the CO_2-trading schemes alone are sufficient to induce adoption of the CCS technology, albeit not until 2023. It is only when the CO_2 shadow price has increased enough in real price terms that the CCS technology becomes competitive.

Yet, combining the CO_2-trading schemes with an R&D subsidy earmarked for the CCS technology speeds up its adoption and improves cost effectiveness of the emission reduction. The CO_2 shadow price now works in tandem with the R&D subsidy to improve competitiveness of the CCS technology, which starts gaining market share already in 2009. Cost effectiveness improves slightly because of the internalization of technology externalities associated with the development of the CCS technology.

Combining the CO_2-trading schemes with an adoption subsidy for the CCS technology leads to its immediate adoption in 2007 in my model and further improves cost effectiveness of the emission reduction. Adoption is immediate as the adoption subsidy directly compensates for the mark up over the cost of conventional electricity. Because of the immediate and full adoption, the adoption subsidy internalizes more technology externalities than the directed R&D subsidy and cost effectiveness therefore improves further.

Finally, combining the CO_2-trading schemes with optimally differentiated R&D subsidies yields fast adoption of the CCS technology as well and is considerably more cost effective in achieving the emission reduction because of the internalization of technology externalities throughout the economy. In fact, the welfare improves by about 14 percent over a 32-year time span.

7.3 Conclusions

I derive the following conclusions from answering the questions posed in this thesis, categorized according to methodology, directed technical change, and policy.

Methodology

In this thesis, I have used computational experiments as a research method, which involves the three steps of (i) building a model of an economy, (ii) calibrating and testing of the model, and (ii) conducting model experiments designed to answer specific questions. Regarding the first step, I have developed the Dynamics of Technology Interactions for Sustainability (DOTIS) model. Specifically, DOTIS is an intertemporally dynamic computable general equilibrium (CGE) model that builds on Acemoglu's (2002) model of directed technical change. I conclude that Acemoglu's model allows for a detailed study of directed technical change, but the increasing returns associated with the technology externalities lead to a few complications. Specifically, the increasing returns may impose theoretical and practical limits on the predictability of the model. Moreover, the increasing returns forces one to allow for the possibility that multiple local optimums are general equilibria of the model. Global optimality of the computed general equilibrium can therefore not be guaranteed. In the absence of an 'all-solutions' algorithm, a heuristic search for multiple equilibria has been performed in Chapter 3 by making use of random starting values for the model variables that have been drawn from uniform distributions with varying ranges. Fortunately for empirical purposes, narrowing the ranges to realistic values sharply reduces the number of equilibria or even yields a solution that appears to be a unique equilibrium.

Regarding the second step, DOTIS has been calibrated to reflect characteristics of the Dutch economy as closely as possible along key dimensions, which relate to energy and technology in this thesis. Given the sensitivity of policy design and model results with respect to the technology externalities and given a relative lack of previous literature indicating their duration, I pursued a frontier approach for empirical analysis of feedback in technical change (Chapter 4). This approach is based on the literature of productive efficiency analysis, in particular the Malmquist productivity index, and has the virtue of overcoming some problems in the alternative patent-citation approaches. Specifically, the frontier approach estimates the impact of technical change on productivity, and therefore captures the quality and effectiveness of R&D activities as well as spontaneously arising technical change through, for example, knowledge spillovers. Other advantages of this approach include its applicability at any level of aggregation from firm level studies to cross-country comparisons and its capacity to handle multiple-input multiple-output technologies. The frontier approach is not a panacea, however: Various data adjustments as well as econometric problems such as endogeneity of regressors complicate estimation of the feedback effect. I conclude that the frontier approach offers a promising alternative to patent-citation approaches, but that the former should be seen as a complement rather than a substitute to the latter.

Finally, specific attention has been paid in Chapter 5 to the accounting of knowledge capital as technical change is modeled with the help of knowledge capital stocks. Such accounting in CGE models is relatively new and, when undertaken, is typically done in a rudimentary fashion because of absence of detailed information. Availability of Dutch investment data for knowledge capital that is consistent with the national accounting framework allows for an explicit representation of knowledge capital in the benchmark data of the DOTIS model. More steps undoubtly will follow, especially since statistical offices are preparing themselves for an expected revision of national accounting rules with respect to knowledge capital. I therefore conclude that the increasing availability of detailed data regarding knowledge capital clears the way for a wider use of knowledge-based models in policy analysis.

Directed technical change

What determines the direction of technical change is typically not made clear in economic model studies of climate policy. Based on the model analyses in this thesis, I conclude that the consumption side of the economy is important for directed technical change. In particular, the extent to which consumers can substitute one good for another determines the direction. Specifically, I find that a negative shock to the economy, be it an oil shock or the introduction of CO_2-trading schemes, directs technical change toward the now relatively scarce goods (intensive in CO_2 emissions or in their use of the energy resource or both) if substitution possibilities between goods are limited. The scarcity now has the leverage to increase incentives to develop new technologies that can be used in the production of the scarce goods. In Chapter 3, for example, substitution possibilities between energy and the rest of the economy are limited and the oil shock directs technical change toward the energy sector. If substitution possibilities between goods increase, however, scarcity has less leverage and there are now more incentives to develop technologies that can be used in the production of the relatively abundant goods (not intensive in CO_2 emissions or in their use of the energy resource or both) for which there ultimately is a bigger market. Consequently, technical change is directed toward the relatively abundant goods.[1] In Chapter 3, for example, there are ample substitution possibilities within the energy sector and the oil shock now directs technical change away from oil toward non-oil energy industries. Further, a positive shock to the economy in the form of R&D subsidies simply raises incentives to develop those technologies to which the R&D subsidies are directed. Finally, the technology externalities reinforce the existing direction of technical change.

Policy

Based on the model analysis in Chapter 5, I conclude that technology externalities call for differentiation of climate policy according to the CO_2 intensity of sectors, such that CO_2-intensive sectors face a higher marginal cost of abatement; *i.e.* a higher CO_2 price generated by a tighter trading scheme. This result is considerably different than the conventional environmental economic conclusion that equal marginal abatement costs across the economy lead to a cost-effective emission reduction. The intuition of this result is that climate policy instruments tend to direct technical change toward non-CO_2 intensive sectors leading to higher technology externalities and hence higher opportunity costs of abatement in these sectors. This

[1] The precise substitution elasticities at which technical change changes direction varies slightly between the three versions of the DOTIS model presented in Chapters 3, 5 and 6, depending on exact model specifications as well as data used in the calibration.

result is robust to CO_2 trading schemes, R&D subsidies, or a combination of both being chosen as climate policy as well as to alternative values of technology-related parameters. The welfare gain for differentiated CO_2-trading schemes is relatively small compared with uniform schemes. The gain is large for the differentiation of R&D subsidies; in fact, uniform R&D subsidies are negative in all sectors, essentially slowing economic growth to achieve the emission reduction with highly negative welfare effects relative to the reference case or the cases involving CO_2-trading schemes.

Further, it has been argued in the economic literature that cost effectiveness of climate policy improves when technology policy complements traditional environmental policy (see *e.g.* Goulder and Schneider, 1999). Indeed, the combination of CO_2 trading schemes and R&D subsidies is the most cost-effective climate policy in the model analysis of Chapter 5. In Chapter 6, I analyze cost effectiveness of similar combinations of CO_2 trading schemes and various technology policies but include, in addition, CCS as a specific CO_2 abatement technology. Based on this analysis, I conclude that introducing technology policy in combination with a CO_2 trading schemes increases effectiveness of inducing adoption of the CCS technology and improves cost effectiveness of achieving a given emission reduction. Welfare improves as technology policy corrects for technology externalities that underlie non adoption of the CCS technology. This result is robust to the use of adoption- or R&D subsidies as technology policy.

7.4 Policy perspective

At this point, it is useful to bring some policy reality to the discussion because the difficulty is how to design climate policy in reality. Regarding the choice of policy instruments, welfare can improve substantially if climate policy comprises both technology- and environmental policy. This is a double-dividend world where welfare improves while CO_2 emissions are reduced. It has proven difficult, however, to correct for technology externalities even without regard to emission reduction. The unrealized welfare gain from the technology externalities is evidence of that. Our best past efforts, patent protection and government funded R&D, leave us with significant underinvestment. To implement the cost-effective climate policy identified above requires that we overcome the known limits of government funding and intellectual property rights protection. Moreover, if we can overcome these limits we might as well compare our situation to a reference case in which technology externalities are already internalized without regard to emission reduction. Compared to that reference case, climate policy entails welfare losses rather than gains. So, the potential of technology policy as a climate policy depends in part on perspective and in large part on the confidence one has in the ability of the public sector to fine tune technology.

Regarding the differentiation of climate policy, lobbying and other rent seeking activities are expected barriers on the way. Differentiation of the CO_2 trading schemes is especially prone to rent seeking as the costs are focused while benefits are dispersed (Jaffe *et al.*, 2005). Although the differentiation makes the emission reduction more cost effective, setting up differentiated trading schemes opens more doors for lobbying firms to seek preferential treatment and avoid abatement costs. Differentiation of R&D subsidies is also prone to rent seeking but now because firms see direct benefit of potential government support for technologies they have under development. Further, directing technology policy to certain technologies or industries reduces available resources for the development of new technologies elsewhere in the economy, potentially locking out such technologies from the market. By picking today's winner, a directed technology policy might prevent tomorrow's challengers from even competing. Such a technology policy requires significant confidence in the ability of the public sector to pick and support winners.

To avoid both extremes of letting technology externalities impede the development of cleaner technologies altogether and potentially locking out tomorrow's winner, technology policy should have the right scope. But what is the right scope? In Chapter 6, I narrowed my focus mostly on CCS technology in the electricity sector but that is just one particular example of scope. The scope could have been narrower still, focusing only on CCS technology for gas-fired power plants. Alternatively, the scope could have been broader by focusing on cleaner technologies in the electricity sector in general. And, this focus on electricity did not pay attention to specific technologies in the transport sector such as fuel cells. Each particular scope differs regarding welfare effects and the risk of hindering the development of even better technology options, among others. Although I cannot say what the precise scope should be, I believe it is desirable for technology policy to have a broad enough scope to equally support all technologies that have the potential to achieve a given CO_2 abatement target without focusing on a specific technology per se. After having created such a level playing field, one can leave the decision of which technology is the winner up to competitive forces. As Arthur (1990) already said: *"Not a heavy hand, not an invisible hand but a nudging hand"*.

7.5 Suggestions for future research

I believe that the model analysis presented in this thesis offers a useful framework for thinking about directed technical change as a means to combat environmental problems in a more cost effective manner as well as a bridge to more applied work on this topic. Inevitably, the thesis has several limitations and below I identify those limitations that in my view are topics for fruitful future research.

Methodology

As the exact direction of technical change depends to a large extent on elasticities of substitution in consumption and technology externalities, special care should be taken to obtain more precise and disaggregated estimates of these parameter values before making specific policy recommendations. Regarding the substitution elasticities, it matters what the estimated substitution possibilities are between energy types on the one hand and between energy and other consumption goods on the other hand. Regarding the technology externalities, it is important to know what their precise distribution is across industries. Some industries may have more difficulty appropriating returns to investments in knowledge capital than others. Highly concentrated industries, for example, allow individual firms with large market shares to appropriate more returns to R&D, *ceteris paribus*, than industries with many small firms. Some industries are more interlinked than others, also affecting the cost-effective differentiation of policy instruments. The chemical industry, for example, is a source of relatively many knowledge spillovers to industries closely related to chemistry, such as pharmaceutics, rubber, and plastics, but not to other industries such as machines or metals. Current attempts to map the distribution of intersectoral spillovers should therefore be continued to increase coverage with respect to industries and countries.

I believe that the use of a frontier approach in empirical testing of technology externalities is promising. Although care should be taken in the nonparametric stage of the frontier approach to ensure that the technical change component of the Malmquist index is an undistorted measure of technical change, an estimator can be used in the subsequent parametric stage that allows intercepts and coefficients on the lagged endogenous variables to be specific to the cross section units (Weinhold, 1999). This allows for heterogeneity across the cross section in a panel data model. Further, an enhanced decomposition of the Malmquist index can be used. It can be shown that the technical change index is the product of a magnitude index and a bias index which, in turn, is the product of an output bias index and an input bias index (Färe *et al.*, 1997). Besides estimating path dependency at the factor level, one could empirically test hypotheses regarding productivity growth and energy biased technical change.

Directed technical change

To get a more complete understanding of directed technical change as a means to reduce CO_2 emissions in a cost effective manner, the modeling framework presented in this thesis can be applied at the industry- or technology level. In Chapter 6, for example, the DOTIS model has been specified to include CCS as a specific CO_2 abatement technology in the electricity sector, allowing for a detailed analysis of the direction of technical change in this sector. This example of including a specific abatement technology can readily be copied to other industries of interest, such as the energy sector at large or the transport sector. Further, this thesis does not elaborate on the exact institutional structure of technical change and it would be of interest to study the various roles that public technical change can play in directing technical change toward CO_2 emission reductions. Especially when sizable market barriers are present, it might be wise for a government to intervene by undertaking public R&D. One can think about the ITER nuclear fusion test plant that will never be realized if left to private agents in the market because of the huge risks involved.

Implications of the small open economy setting of the modeling framework are another issue that deserves further attention. In this thesis, I assume that the main trading partners of the Netherlands introduce similar policies in line with the Kyoto protocol, limiting the effects of international trade. Nevertheless, it might be optimal for a small open economy to adopt new technology from abroad rather than develop it on its own or vice versa. Which industries will find it profitable to import technology and which industries to export? Related is the concept of international knowledge spillovers (Coe and Helpman, 1995). Appropriability problems are not restricted to national borders and it is of great interest to study how this affects the domestic direction of technical change.

Policy

The climate policy instruments under study in this thesis have been differentiated between CO_2-intensive and non-CO_2 intensive sectors. Yet, within each of these broad sector groups, I assumed a uniform climate policy. Further differentiation of climate policy, especially among the CO_2-intensive sectors, would likely further improve cost effectiveness of policy and it is of interest to study to what extent further differentiation is feasible and desirable. Should CO_2-intensive industries such as paper or metals, for example, be treated more favorably than electric utilities because of the lower CO_2 intensities of the former?

Finally, my model analyses show an important role for technology policy as part of climate policy, but more detailed analyses are needed regarding its design. How can technology policy be designed such that the limits of government funding are overcome, for example? To what extent can we recycle revenues from environmental policy as well as from other tax bases? To what extent can international cooperation foster R&D and how can this be embedded in a post Kyoto agreement? Although the present thesis does not offer ready answers to these questions, it does indicate (i) the need to focus future agreements on both traditional environmental policy instruments and on policy directed toward technical change, and (ii) that a uniform CO_2 price across all sectors may not be as cost-effective as one that is differentiated to direct technical change and economic growth toward cleaner technologies.

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Curriculum Vitae

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