University of Strathclyde
Department of Economics

Technological Change and Sustainable Energy Policies
Modelling Exercises for Scotland and the UK

by

Marie Tamba

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Abstract

Amid growing environmental concerns, the UK energy sector faces considerable challenges in order to comply with national and regional commitments to decarbonisation. In light of these challenges, the government has implemented a number of policies aimed at ensuring sustainability in the UK energy sector (both in terms of environmental impact and security of supply), while ensuring that the reforms and changes to the sector are achieved at the lowest costs to consumers. Innovation in energy technologies are expected to play a large role in reaching this sustainability objective. The focus of this thesis is to explore the economic and environmental impacts of two UK sustainable energy policies, while considering the role that technological innovation might play in delivering on these objectives. The thesis is divided in two parts; each focusing on the system-wide economic impact of a specific energy policy instrument, in presence of technological change.

Part A focuses on the supply side of the electricity sector. It explores the impact of introducing targeted subsidies in a renewable energy sector in Scotland, in presence of endogenous learning-by-doing effects. The literature review highlights the growing awareness in the role of technological change in energy policy. Correspondingly, system-wide energy-economy-environment models used to analyse these policies have increasingly introduced endogenous technological change as a major design feature, whether it is induced through R&D spending or learning effects. Because the latter is the most commonly adopted, it is the focus of the modelling exercise in Part A. A number of alternative specifications of learning-by-doing are identified in the literature and are explored first through micro-simulations.

Then, in a CGE model for Scotland, learning-by-doing is introduced in the presence of a production subsidy in the marine energy sector.

As the subsidy stimulates the marine electricity generation sector through costs reductions in production, electricity generation from other sources is displaced and the Scottish economy experiences a small expansion. The presence of learning effects is found to accentuate the stimulus from the subsidy. Indeed the costs of marine generation are further reduced as the sector expands. The choice of assumptions to represent endogenous learning-by-doing is found to matter greatly for the speed and paths of adjustments. In particular, the use of an "economic" functional form (inspired by endogenous growth theory and originating in the top-down modelling literature) to represent learning is favoured in the model, but only when negative returns-to-knowledge are imposed.

Part B focuses on the demand side of the energy system and more specifically on households. It examines the economy-wide rebound effects from efficiency gains as a side effect of a one-off energy innovation at UK level: the roll-out of smart electricity meters. First, the household and total rebounds in electricity use in the UK are calculated using an Input-Output model, where reductions in household electricity expenditures are redistributed to other consumption goods. Results show that total rebound is generally smaller than household rebound, reflecting a negative indirect rebound from reductions in the industrial use of electricity. This is due to the relative electricity intensity of electricity compared to other sectors. A disaggregation of the electricity sector into network and generation activities reduces the indirect rebound, and thus the gap in household and total rebound and confirms the strong backwards linkages in electricity activities.

The analysis is extended to a CGE model incorporating endogenous prices and incomes. The same efficiency gain is simulated and its system-wide economic and environmental impacts (CO2 emissions) are established. Using findings from the econometric literature on household energy demand, several simulations are conducted to explore rebound effects with alternative consumption structures, where households have different substitution possibilities between electricity and gas. Increased substitution between fuels increases the household electricity rebound (as households substitute more efficient electricity for gas) and in turn total rebound; leading to the extreme case of backfire, but accompanied by the largest CO2 emissions reductions. CGE results persistently show a smaller total rebound than household rebound, (similarly to the IO results) suggesting that the reduction in total UK electricity use could be larger than the reduction in household consumption estimated by the policy-makers, by considering economy-wide effects.

Overall, the results of the modelling exercises of this thesis confirm the crucial role of technological change in achieving the goals of sustainability in energy policies, while providing insights on the assumptions for the analysis and modelling of these policies in an economy-wide framework.

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Chapter 1: Introduction

In line with the European Union targets, the UK is committed to reducing its greenhouse gas emissions by 42% (compared to 1990 levels) by 2020, as part of a longer-term objective of 80% emission reductions by 2050. Since the energy sector represents more than one third of total UK greenhouse gas emissions (DECC, 2013a), it has been a major sector of interest for policies targeting emission reductions. A number of policies have been implemented to achieve the decarbonisation of the energy sector while respecting the other two objectives of UK energy policy: affordability and security of supply. The focus of this thesis is to explore the economic and environmental impacts of two energy policies aimed at sustainability in the UK, while considering the role that technological innovation might play in delivering on these objectives.

1. Policies for a Sustainable Energy Future

Most of the targeted emission reductions in the energy sector are expected to be obtained from the decarbonisation of energy supply. As set out in the European Renewable Energy Directive (EU, 2009), the UK is committed to a target of 15% of its gross energy consumption coming from renewable resources by 2020. In this objective, a number of policy instruments have been introduced, focused on incentivising the increased use of renewable resources and technologies in energy supply for both heating and electricity generation. While a number of instruments have been put in place to incentivise the use of renewable heat (i.e. the Renewable

Heat Incentives[1], Renewable Heat Premium Payment Plan[2]), the decarbonisation of electricity generation has been the major focus of the government.

Policy-makers have relied on two major instruments to promote the increased penetration of renewables in the electricity mix. The first is the Feed-In-Tariffs (FiTs) scheme which encourages small-scale renewable electricity generation (less than five megawatts capacity) through fixed guaranteed payments for every unit generated, as well as additional payment for every unit exported to the grid. The second and major policy instrument for electricity decarbonisation has been the establishment of a traded renewable certificate scheme. Since 2002, the Renewable Obligations (RO) system has particularly aided the deployment of large-scale renewable energy generation by setting minimum requirements for suppliers to source a share of their electricity from renewable sources (the "obligations"), and by ensuring a price premium to renewable electricity generators (through the sale of certificates).

Since 2009, the new "banded" RO system has introduced differentiated policy support to renewable technologies based on their cost competitiveness compared with traditional generation. In effect, banded Renewable Obligation Certificates act as a targeted subsidy to renewable electricity generators, depending on the maturity level of the technology they use. Under this policy framework of ROs and FiTs, the share of renewable electricity has increased from less than 3% in 2002 to 11.3% of the total UK electricity generation in 2012. The pending Electricity Market Reform

[1] The RHI offers payments to the non-domestic sector for installing and generating heat from renewable technologies, through a fixed 20 year tariff designed to cover the cost of the installation.

[2] The RHI scheme is extended to the domestic sector in the spring of 2014, to replace the Renewable Heat Premium Payment (RHPP) Plan, under which households could claim grants to finance renewable heat installations (such as solar thermal water heater).

(EMR) is designed to maintain this policy focus in a fully-integrated system. While the FiTs system will remain in place for small-scale renewable installations, investments in larger scale generation are expected to be incentivised in a similar manner (DECC, 2013b), but differentiated by technology, with new Contracts for Difference (CfDs). Contracts for difference will ensure renewable generators receive a fixed payment, generally guaranteed for 15 years, through set of differentiated strike prices by technology[3]. *These differentiated "subsidies" for renewable energy technologies are the supply-side policy instrument explored in part A of this thesis.*

In addition to policies aimed at decarbonising energy supply, the possibilities for managing energy demand are increasingly put forward on the policy agenda for a sustainable energy system. The term demand-side management is often used to refer to any actions that can help reducing or shifting energy demand from peak to off-peak consumption periods. The Green Deal is the UK government's main policy incentive for energy demand-side management, which encourages efficiency improvements in UK homes[4]. In parallel, there are a number of measures targeted at managing energy demand from the non-domestic sector such as the Enhanced Capital Allowances[5] or the CRC energy efficiency scheme[6]. In addition to these, the UK government has announced the mass roll-out of smart meters to equip all homes and small businesses by the end of 2020 (DECC, 2013c). This new technology is expected to reduce energy consumption by improving the visibility of energy usage

[3]The level of strike prices for future CfDs will evolve over time as technology costs are expected to fall (DECC, 2013b).

[4] The Green Deal enables home-owners to make investments in energy efficiency, through loans that are repaid over time on their energy bills, while ensuring that repayments will not exceed energy savings from the improvements.

[5] The ECA scheme gives businesses financial incentives for investments in new energy-saving technologies

[6] The CRC scheme requires reporting and monitoring of energy use, and corresponding emissions for large organisations which must then purchase allowances

to consumers. It is also expected to play a role in the implementation and monitoring of *demand-side response* measures, as planned in the Electricity Market Reform (DECC, 2013b). Demand-side response refers to changing electricity-users' behaviour through the use of incentives, in order to smooth domestic electricity demand and reduce peaks. Described as a major component of the planned capacity market (created through the EMR to ensure security of supply in the UK market), demand-side response measures may include automated or user-controlled measures and will require a number of new technologies to be installed in UK homes to facilitate electricity consumption monitoring (POST, 2014). *The smart meter roll-out is the demand-side policy focus of part B of this thesis.*

Overall, this thesis examines the economic impact of two UK sustainable energy policies described above. These two policies will be studied in the specific context of technological change.

2. The Importance of Technological Change

Underlying all policy measures targeted at reducing carbon emissions from the energy sector is the essential requirement for innovation and technological improvements, both on the demand and supply sides. On the one hand, innovations will be crucial to deliver a low-carbon energy supply. While policies are targeted at investments in renewable technologies, technological improvements are expected to reduce the costs of these technologies and further incentivise their deployment: Indeed this is essential if renewables are ultimately to become competitive with conventional technologies. Likewise, innovations in carbon capture and storage technologies, as well as new electricity storage solutions will be crucial to make them commercially-accessible and further contribute to carbon emission reductions. On the other hand, innovations in products and processes are also central to demand-side management. The large scale deployment of smart meters and the gradual efficiency improvements in household appliances are two examples of how new (or improved) technologies contribute to the wider UK energy policy goals.

Technological change is widely accepted and cited in policy documents as a crucial component of energy policy. Policies directly targeted at innovations contributing to decarbonising the energy sector are already in place. In the UK, such policies include direct public funding of research and development activities in low carbon energy technologies, as well as the creation of a "Low-carbon Innovation Co-ordination Group" to assess and prioritise the need for public sector support for specific technologies (LCICG, 2014).

However, technological change is a complex process. Innovations in products and processes are dependent on a wide range of factors, both internal and external to the innovation or the innovator. Understanding the process of innovation, and its interactions with policy interventions in the energy sector is of primary importance. The design, testing, demonstration and wide-adoption of a technology are likely to be strongly affected by policies incentivising investments in low-carbon technologies. Also, some new technologies might change the costs and potential impacts of energy policies, and in turn alter the trade-off faced by policy-makers.

Due to the complex interactions between energy policy and technological innovations, it is crucial to study them jointly, in a framework that allows for the representation of both. Accordingly, in this thesis, I have chosen to use economy-

wide modelling methods to analyse the impacts of various energy policies, represented in conjunction with technological change.

3. Economic Modelling of Sustainable Energy Policies

System-wide models are widely-used tools for the system-wide analysis of policy impacts. Although a wide variety of macroeconomic model types and objectives exists, this thesis adopts a multi-sectoral general equilibrium approach to economic modelling. First, General Equilibrium models are commonly used tools to determine the impact of policy shocks on the wider economy. Second, as my objective is to represent the interactions of the energy system, the economy and the environment into one framework, the use of a multi-sectoral model is essential. First, such model is able to represent the sectoral interactions between the energy system and the rest of the economy, exposing the system-wide impacts of a policy targeted at the energy system. Second, the multi-sectoral framework (depending on its level of aggregation) allows for a specific representation of technological change by sector. Finally, it also enables the attribution of environmental impact to specific economic activities, and this is essential as energy and emission intensities vary significantly across sectors.

Whereas the simulation of a policy intervention in a multi-sectoral equilibrium model is often relatively straightforward, the representation of technological change or innovation seldom is. Depending on the component of technological change under consideration, different representations might be appropriate in different cases.

This thesis focuses on modelling policies in coordination with two major types of innovation. First, in addition to simulating policy support to the marine renewable energy sector, Part A of the thesis focuses on representing technological change as a *gradual process, using the concept of learning-by-doing. Then, in Part B, the impact of a one-off product innovation will be explored, through the modelling of the roll-out of smart meters to UK households, and its impact on electricity efficiency and the wider economic system.*

4. Thesis Structure

Part A: Learning-by-doing and Subsidies for Marine Energy Generation in Scotland

In Part A of the thesis, I model the impact of policy support to marine electricity generation in Scotland in the presence of learning effects, which reduce the production cost of this sector. A major challenge is to determine the appropriate representation of learning effects in a Computable General Equilibrium model. Chapter 2 presents a literature review relating to the economics of technological change in the context of energy and environmental policy. This literature review takes a general approach to technological change in environmental economics, in order to inform the understanding of modelling exercises that have related technological change and environmental and energy policies. First, in a microeconomic context, a number of market failures are identified relating to innovation and investments in environmentally-friendly energy technologies. The existence of these market failures, namely environmental externalities, knowledge externalities and uncertainty or diffusion externalities (Clarke and Weyant, 2002; Jaffe et al., 2005; Popp et al., 2010) is presented as a rationale for policy intervention. In response to these market failures, two approaches to innovation policy are then identified and discussed, specifically supply-push and demand-pull

(Nemet, 2009) policies. Supply-push policies refer to measures that promote investments in R&D activities. Based either on public spending, or incentivising of private spending, they usually aim at reducing the private costs of R&D and countering the knowledge externalities. In contrast, demand-pull policies focus on promoting the diffusion of new technologies to benefit from incremental process and product improvements. Both approaches to innovation policies are shown to be important because they target different parts of the technological change process. The review also indicates that each policy approach affects different technologies in different ways. Finally, the literature review addresses the need to study the complex interactions of energy policy, technological change, the economy and the environment in a comprehensive framework, namely Energy-Economy-Environment (EEE) models. Typically designed for the analysis of environmental or energy policies, EEE models have accounted for the importance of technological change. After initial modelling attempts focused on exogenous improvements in technology, endogenous technological change has been introduced in various ways, depending on the type and purpose of each model. The literature review identifies two major types of technological change in EEE models. Traditionally, R&D-driven technological change has been the focus of economic "top-down" models influenced by growth theory, while learning-by-doing is mostly included in "bottom-up" engineering models focusing on the energy system. Learning-by-doing is however increasingly used in recent modelling exercises of energy policies.

Chapter 3 follows up on the literature review by focusing on the learning-by-doing process and its variety of representation in EEE models. After defining the concept of learning-by-doing in more detail, it presents a review of the wide range of econometric work on learning rates for energy technologies, and proposes a number of explanations for the variation in estimates, including the use of one or two-factor learning curves, choice of variables, endogeneity issues). Next, in a detailed review of the EEE modelling literature, I identify three major distinctions in the representation of learning-by-doing in models with endogenous technological change. These three distinctions relate to the choice of equation form to represent the learning curve, the choice of variable to embody experience accumulation, and assumptions about returns to knowledge. Comparative micro-simulations are conducted to represent these alternative definitions of learning-by-doing in a simplified economic model with a Cobb-Douglas production function. The analysis highlights the dramatic differences in modelling results when using different learning-by-doing specifications.

Using the findings from Chapter 3, Chapter 4 proposes the first introduction of endogenous learning-by-doing in a CGE model for Scotland. Chapter 4 introduces learning-by-doing in an emerging renewable energy sector with high development potential in Scotland: the marine electricity generation sector. In a multi-sectoral Computable General Equilibrium (CGE) model for Scotland, marine electricity is stimulated through the implementation of a production subsidy in combination with learning-by-doing for the sector. Learning effects are introduced as an endogenous Hicks-neutral technological progress in the value-added production function. In an electricity-disaggregated version of AMOS (A Micro-Macro Model of Scotland, Harrigan et al., 1991), the alternative specifications of learning-by-doing identified in Chapter 3 are implemented successively. The modelling results confirm the expansionary effects of the subsidy on the targeted sector and the economy as a whole, while revealing some displacement of electricity use from traditional towards renewable sources. The introduction of endogenous learning-by-doing reinforces the positive impact of the subsidy by leading to efficiency gains in production. The comparison of alternative specifications confirms that modelling results are highly sensitive to technological change assumptions. Major findings show that the use of the so-called “economic” equation form (based on endogenous growth theory) is qualitatively closest to the empirical definition of learning-by-doing when using decreasing-returns to knowledge (i.e. the case referred to as “fishing-out”). The choice of variable embodying experience also affects modelling results. The results show that the use of cumulative production is the only specification leading to an s-shape diffusion curve of marine electricity production. Part A of this thesis represents the first attempt to introduce endogenous technological change in a CGE model for Scotland. By implementing alternative specifications in a comparative analysis, this study identifies the advantages and drawbacks of alternative representations of learning-by-doing in renewable energy sectors in a system-wide context.

Part B: Modelling the impact of the adoption of smart meters in the UK in an electricity rebound context

Whereas Part A is concerned with the modelling of endogenous and incremental technological change in the supply-side of the energy sector, Part B addresses the issue of a one-off product innovation introduced on the demand-side of the energy system. The objective is to analyse the impact of the mass adoption of smart meters by UK households. After a brief introduction presenting the policy background to the mass roll-out of smart meters, Chapter 5 introduces the concept of feedback in energy consumption. A review of major studies indicates that by improving the information households receive about their energy consumption (i.e. improving "feedback"), they can better manage and control their consumption, ultimately leading demand reductions through energy efficiency gains. Although the level of energy savings and their persistence in time is still debated in the literature, there is a general consensus that by improving feedback, particularly through the deployment of smart meters technologies with in-home displays, demand reductions can be achieved in the domestic sector. This is found to be the case for electricity demand only; there is limited evidence that gas savings will occur. It is generally recognised in the literature that improvements in energy efficiency can lead to rebound effects, whereby energy savings from efficiency improvements are mitigated (or fully offset in the case of backfire) by the implicit reduction in the price of energy services (in efficiency units). Although the focus of the energy rebound literature is generally on the production-side, a few studies have highlighted the potential for rebound effects from efficiency gains in energy consumption. Consequently, Part B models the system-wide economic and environmental impacts of efficiency gains in household electricity consumption in the UK, framed in the context of electricity rebound.

Chapter 5 focuses on modelling these impacts in an Input-Output framework. Calibrating our shock to the expected three percent reduction in household electricity consumption from the adoption of smart meters in the UK, the saved expenditures are redistributed to other consumption goods. The direct, indirect and induced impacts of the shock on sectors and the overall economy are identified. Two rebounds are calculated: the rebound in household electricity consumption and the rebound in total UK electricity use. Despite the general expectation that total rebound might be larger than household rebound, the analysis shows that this is not the case here: rebound in total electricity use in the UK is smaller than the rebound in household consumption, because the electricity sector is characterized by strong internal backwards linkages.

Rebound results are compared for two IO tables with an increasing level of disaggregation in the electricity sector. The disaggregation of electricity generation and distribution activities leads to a reduction in indirect rebound, suggesting that the aggregation of the electricity sector might lead to over-estimation of total rebound effects. Overall, total rebound is still smaller than the household rebound, suggesting that the reduction in total UK electricity use could be larger than the estimated three percent reductions in household consumption, due to economy-wide effects. Another contribution is the consideration of alternative substitution possibilities between gas and electricity in household consumption, informed by econometric estimates from the literature. In the case of increased substitution, gas consumption falls as a consequence of the fall in electricity price in efficiency units. Total rebound is then reduced, leading to further reductions in total UK electricity use. In contrast, if gas and electricity are complementary goods in household consumption (as suggested by econometric estimates for the UK in Baker et al., 1989), total rebound actually increases and is larger than direct rebound, mitigating the electricity savings in consumption suggested in the literature.

The analysis of system-wide rebound effects is expanded in Chapter 6, through the use of a Computable General Equilibrium model for the UK. Based on the same AMOS framework as used in Chapter 4, the version used in Part B is a national model, called UKENVI, which disaggregates the energy sector and endogenises sectoral CO2 emissions by fuel use. The analysis of the total rebound in the CGE framework enables us to relax the static assumptions of the IO analysis (no supply constraints, Leontief production structure, no changes in price). The same efficiency shock in household electricity consumption is simulated in the CGE model, in order to identify the impact of endogenizing prices and income on the rebound. In the dynamic CGE model, the existence of supply constraints lead to an excess in capacity in electricity sectors in the short-run, which drives the electricity price down in relative terms. This changes the rebound results.

Four scenarios are identified to emulate the simulations conducted in the Input-Output analysis. First, one scenario recreates the base IO simulations closely and confirms that total rebound is usually smaller than household rebound following an efficiency shock in household electricity consumption. However, household and total rebounds are smaller in the CGE than in the IO, suggesting that short and medium-term disinvestment effects in electricity sectors have driven the electricity price up in the long-run. In the three other scenarios, the household consumption structure is modified so that households can substitute between electricity and gas in a distinctive manner. This allows for identification of the impact of changing the elasticity of substitution between gas and electricity on the rebound results.

The findings show that the smaller elasticity of substitution, the smaller the household and total rebounds are. Decreasing the elasticity of substitution makes it harder for households to substitute in favour of the more efficient commodity (electricity). Therefore, when gas and electricity are complements, household electricity consumption, and total electricity use are reduced further. The case of increased substitution confirms that when the elasticity of substitution between electricity and gas is higher than one, backfire may occur, and households actually increase their electricity consumption, leading in turn to backfire in total electricity consumption. However, the environmental results show that in this case, CO_2 emissions reductions are the largest, as household gas consumption and the output of the gas sector are drastically reduced.

In conclusion, Chapter 7 offers an overview of the major contributions both from Part A and Part B of this thesis. A number of areas for future research are identified, in the context of modelling technological change and energy policy, as well as in the more general context of economic research in energy policy.

Part A: Modelling: Learning-by-Doing and Subsidies in the Marine Electricity Sector in Scotland

The increased penetration of renewable energy technologies (wind, solar, marine, photovoltaic, hydro, etc.) presents a number of advantages, which contribute to the goals of decarbonisation and security of supply in energy policy. These technologies rely on renewable resources, improving sustainability of supply. They do not emit greenhouse gases during operations, reducing the climate change impact of the energy system. Additionally, their deployment reduces the system dependency on fossil-fuel resources, in a context of increasing global demand and high price fluctuations, contributing to security of supply. Scotland has recognised the importance of these new technologies in delivering a low-carbon energy system, and has affirmed its commitment to their deployment by setting a leading target: renewable technologies must provide the equivalent of 100% of gross annual electricity consumption by 2020.

Despite the clear benefits from renewables, the technologies used to extract the resource are still largely uncompetitive with traditional generation. In terms of levelised costs, often used to compare energy technologies[7], renewable technologies remain far from competitive compared to gas, coal and nuclear generation. In the latest estimates from the Department of Energy and Climate Change (DECC, 2013), the levelised costs of onshore wind are estimated at £100/MWh, while offshore wind would lie between 148 and £179/MWh. Marine technologies are estimated to become commercialized in the next few years at levelised costs of £261/MWh for

[7] Levelised costs embody the economic costs of a generation technology over its lifetime.

wave electricity generation, and between 157 and £225/MWh for tidal generation. In comparison, the levelised costs of standard Combined Cycle Gas Turbine generation (CCGT) are estimated at £71/MWh, while those of nuclear may reach £89/MWh[8].

Therefore, to achieve its ambitious renewables target, Scotland relies on policy support to incentivise investment in these less competitive technologies. The Scottish Renewable Obligation system has been modified, like the wider UK policy, to introduce “bands” for different technologies, according to their level of development. For example, wave electricity is still considered in the early demonstration stages and thus receive particularly strong support (with 5 ROCs per megawatt hour produced) while offshore wind and tidal, with lower levelised costs receive 2 certificates, and onshore wind, 1. Acting as differentiated subsidies to renewable technologies, the banded Renewable Obligation system essentially attempts to internalise the positive externalities from renewable energy in private investment decisions, while targeting technologies in light of their technological development (embodied in their cost level). Ultimately, the objective of this policy support is to encourage investments in newer technologies, in order to reduce the costs of these technologies. The underlying assumption to this policy strategy is that through diffusion of the technology, technological improvements will reduce costs.

Part A of this thesis focuses on these issues and formally models the relationships between the deployment of renewable energy technologies (in particular, marine electricity generation), cost reductions (through learning effects), the rest of the energy sector and the overall economy. Chapter 2 presents a review of the literature

[8] The estimated costs of coal generation are higher (£111-126/MWh), due to the new requirement of equipping them with carbon capture and storage technology.

on the issues of technological change and energy policy, and its representation in models linking the economy, the environment and the energy system. Chapter 3 focuses on the modelling of learning-by-doing as a phenomenon of costs reductions through technology adoption. Chapter 4 presents the modelling of the impact of learning-by-doing in marine electricity generation in presence of subsidies targeted to the sector on the Scottish economy.

Chapter 2: Technological Change and the Modelling of Energy and Environmental Policy

1. Introduction

The relationships between the energy system, the environment and the economy are particularly complex. While a reliable and adaptive energy system is required to fuel economic growth, our energy systems, in their current state, are largely reliant on polluting technologies, resulting in damages to the environment. In parallel, future prospects of economic growth are subject to the potential environmental impacts of today's decisions in terms of energy policy. Amid growing climate change concerns, the coordination of environmental, energy and economic policies becomes necessary. Within this energy-economy-environment (EEE) system, technological innovations play a crucial role in harmonizing often contradictory objectives. Innovations in environmental and energy technologies are expected to make significant contributions to reduce the environmental impact of economic activities. These innovations are a necessary component in the objective of sustainable development and green growth. Therefore, technological change should be, and increasingly is, regarded as a policy objective in itself.

Section 2 presents the underlying rationale for support to innovation and technological change in energy and environment technologies. In a microeconomic argument, the so-called innovation market failures are identified, and rationale for countering these market failures through policy intervention is provided. Section 3 reviews the literature evaluating the different policy mechanisms (supply-push vs. demand-pull) that have been designed to have an impact on the technological change process of energy and environment technologies in particular. In order to understand the complex interactions between the energy, economy and environment (EEE) system, sophisticated tools for policy analysis have emerged, referred to as EEE models. These modelling tools are crucial to further our understanding of the short, medium and long-term impacts of policies on the EEE system. Since a modelling methodology is used throughout this thesis, the second half of this literature review chapter is centred on the economic concept of technological change in the context of environmental and energy policy modelling. Section 4 reviews the major contributions to the EEE modelling literature. Due to the scope of this thesis, the focus is centred on models that have introduced technological change.

2. Innovation Market Failures and Policy Intervention

The underlying concerns about climate change and its impact on our economies has triggered a renewed interest in the application of technological change theories to the environment and the energy sector. The development of environmentally-friendly and clean energy technologies has the potential to bring a “double dividend” to policy-makers. These technologies can both reduce our emissions of GHGs and other pollutants, but could also offer colossal cuts in the costs of these emission reductions, by providing cheaper and more efficient methods to produce or consume. Consequently, the development of such technologies is a crucial element of climate policy.

A better understanding of the technological change process is necessary to the implementation of policies designed to influence it. Research on technological change in environmental economics has grown into a field of its own, unifying theories from the economic, social, environmental and climate sciences. In light of standard economic theory, environmental economists have identified a number of market failures associated with technologies contributing to reduce the impact of our economies on the environment. Environmental and energy economics research has placed a strong emphasis on the obstacles to such technological developments, originating in the existence of these market failures. This provides a strong rationale in favour of policy intervention. This section identifies the most prominent market failures generally associated with innovation in environmental and energy technologies.

2.1. Environmental externality

Environmental economics is concerned with the analysis of policies targeted at correcting a market failure known as environmental externality. An externality is defined as a potential cost (or benefit) occurring as a side-effect of an economic activity, which does not enter the decision-making process of individual agents. An externality (which can be positive or negative) is defined as "an economically significant effect of an activity, the consequences of which are borne (at least in part) by a party or parties other than the party that controls the externality-producing activity" (Jaffe et al., 2005). Associated with a wide range of producing and consuming activities, environmental pollution is the most famed example of a negative externality. For an example of a negative production externality, take a firm that owns a coal-fired power plant. As it combusts coal to produce electricity, the power plant emits polluting gases such as carbon dioxide (CO_2) or sulphur dioxide (SO_2). These pollutants are responsible for major environmental damages, i.e., global warming and acid rains respectively. Contrarily to the costs of fuel or labour involved in generating the electricity output, the costs associated with these environmental damages (the negative externality) are not borne by the firm, and thus are not taken into consideration when choosing to operate the coal-fired power plant. In such situations, the role of environmental policy is to correct for this market-failure by providing incentives for reducing the polluting activities. Policies typically achieve this goal either by imposing monetary penalties that internalise the costs of pollution in the private decision function or by implementing a limit on the levels of pollution. To determine the optimal level of regulation for pollution, policies must compare the social costs of pollution to the social costs of abatement.

This trade-off becomes more complex when considering the existence of technological change. First, the development of new technologies might enable to keep producing output while reducing the externality associated with it. In the case of pollution, such technologies can be cleaner production processes, substituting for cleaner inputs or installing pollution-controlling equipment (Popp et al., 2010). Thus, technological change can potentially reduce the costs of pollution abatement and alter the costs trade-off considered by policy-makers in regulating activities: the existence of technological change can influence environmental and energy policy. Further, environmental policies themselves are also likely to influence technological change through a “price-induced” process. By internalizing the costs of pollution in the private agent’s decision function, policies might guide the direction of technological improvements towards cleaner processes (Popp et al., 2010). In the example developed above, the firm that owns the coal-fired power plant can decide to invest in developing an alternative way of producing electricity if the cost of polluting outweighs the cost of abating. For example, this firm might invest in carbon-capture technologies or simply switch its production towards renewable energy sources.

While technological change can lower the costs of compliance to environmental regulation, policies can lead to technological change directed at cleaner technologies. This two-way interaction has to be considered when estimating the social costs and benefits of policies, particularly in a dynamic framework. If long-term time horizons are considered, this interaction becomes crucial for the timing of policies. The early estimates of policy costs can be excessive and lead to weak environmental regulation, while stronger regulation could have in fact reduced the overall costs of policy in the medium and long run.

2.2. Knowledge externality

Another important market failure identified in the economics of technological change literature is the public good nature of knowledge. In his seminal work on technological change, Arrow (1962a) explores the properties of “inventions as the production of knowledge”. Assimilating knowledge to information, he investigates the incentives to innovate for both a monopolistic firm and a firm acting on a perfectly competitive market. He finds that in any situation, firms under-invest in innovative activity. A firm’s inability to appropriate the gains from innovative activities would decrease the incentives to innovate (Arrow, 1962a). This research highlights the non-excludable and non-rival properties of knowledge as a public good. If a firm invest in innovating activities, it incurs all the costs of innovation. This knowledge being non-rival and non-excludable, other firms can use it and get the benefits associated with it. This creates a positive externality, known as knowledge spillovers. Endogenous growth models such as Romer (1990) consider such spillovers a positive externality, and as the driver of economic growth.

However, from a micro-economic point of view, these spillovers distort the firm's decision process. A firm is reluctant to invest innovation and is tempted to free-ride on other firms' innovations. Under-provision of investments in R&D becomes an issue, as these innovations would have been beneficial in a social context. Overall social benefits from technological change (such as costs reductions of environmental policies) are not reflected in economic agents' private decisions.

The existence of knowledge market failures accentuates the need for policy intervention. If the existence of spillovers is not considered in the design of environmental and energy policies, the impacts of these policies could be weakened by the under-response from private agents (Clarke and Weyant, 2002). As knowledge spillovers lead to underinvestment in innovative activities such as R&D, policies can focus on several options (that are not mutually exclusive). First, they can correct the positive externality through restoring the appropriability of knowledge, using legal actions (e.g. intellectual property and patents law). Jaffe et al. (2005) argue that such instruments are inherently imperfect and innovators will always receive only a fraction of the benefits from investments in innovative activities. Other policies could also attempt to incentivise investments in new technologies to bridge the gap between private and public returns to knowledge.

2.3. Uncertainty

Popp et al. (2010) note that, although all investments can be regarded as risky; it is particularly true for investments in innovative activities. Rosenberg (1996) identifies several sources such as uncertainty about potential uses, the need for complementary technologies, potential for applications to other industries, etc. This uncertainty of returns to investments in technological change is associated with a different sort of market failure: incomplete information (Jaffe et al. 2005). As investors face large variances in expected returns to innovation (Scherer et al., 2000), incomplete information translates into a risk, which investors need to be compensated for.

This uncertainty poses a challenge to policy. On the one hand, the need for consistency and continuity in policies, as well as government and institution credibility is highlighted in the literature as a major determinant of uncertainty for investments in environmental technologies, and particularly so for investment in renewable energy. Kohler et al. (2006) point out that wind technology for instance needs guarantees of continued policy support to sustain competition with traditional technologies using cheaper fuels such as coal.

On the other hand, the costs of compliance to climate change regulations are highly dependent on these innovations, leading to uncertainty in policy making. Policies must address these uncertainties by correcting investors' exposure to risks and ensure the good implementation of regulations. Policies providing compensation for these risks and long-term engagements from governments have the potential to minimize uncertainty and at least partly counteract this market failure. Environmental and energy economics research focuses on the effectiveness of such policies and will be reviewed in Section 3.2.

2.4. Market failures influencing technology diffusion

Additional market failures associated with technological change for environmental and energy technologies have to do with the process of technology diffusion. Stoneman and Battisti (2010) define technological diffusion as "the process by which the market for a new technology changes over time". Broadly defined, technology diffusion refers to the dynamic process of market penetration where economic agents progressively adopt a new technology. As technologies develop over time, the process of adoption is not linear, and generally follows an S-shaped curve where market diffusion is plotted against time (Rogers, 1962). At early stages of technological development, the rate of adoption is relatively slow as agents face high costs and large uncertainties about the future. Adoption speeds-up as the technology enters a commercially-viable phase, to then plateaus once the market reaches a saturation phase.

During this diffusion process, new environmental and clean energy technologies are often highly dependent on policy support. Because the environmental and knowledge externalities are not fully reflected in the costs of these technologies, and because of uncertainty, they experience a basic dependence on regulation. Popp et al. (2010) reports that while general technological change research focuses on the spread of information and strategic behaviour of firms to explain technology diffusion, most studies of environmental technologies shows that their diffusion is mostly dependent on policy mechanisms.

A market failure directly associated with the diffusion process is the existence of increasing returns to adoption. Jaffe et al. (2003) provide a review of the literature on the causes of increasing returns to adoption. Because of the existence of learning effects[9] and network externalities[10], technologies becomes more attractive to investors, as the technology is increasingly used. This in turn leads to further adoption and diffusion of the technology, bringing more costs reductions. This virtuous circle (Jaffe et al, 2003) can be viewed as a positive externality which may cause delays in adoption, and suggests that early investments in a new technology could be sub-optimal.

The existence of increasing returns to adoption has also been linked to the problem of technological lock-ins. Technological lock-in corresponds to a situation where a technology becomes dominant with widespread diffusion through increasing returns effects (Kohler et al., 2006). This process might create additional barriers to entry for new technologies, when the costs associated with changing the system outweigh the benefits. Therefore increasing returns to adoption create a technological bias eliminating the conditions for competition amongst technologies and also produce the need for policy intervention.

3. Renewable Energy Policy and Technological Change

The previous section of the literature review identified market failures associated with environmental and energy technologies that might hinder the technological change process. These market failures all rationalise the need for policy intervention

[9] Learning effects refer to the observation of costs reduction as the technology is increasingly used (learning-by-doing or learning-by-using). Learning-by-doing is explained in details in Section 4, and is the focus of Chapter 3 and 4 of this thesis.
[10] Network externalities encompass learning effects but can be defined more broadly. They refer to any benefits to an individual agent that arise from a wider adoption of a technology. In an example relating to energy technology, a wider adoption of wind turbines leads to costs reduction in the production of the technology through learning effects, but also provides positive network externality through the larger geographic dispersion counteracting the variability of the wind resource.

to support environmentally-focused energy technologies. Although this need is well established in the literature, the choice of policy instruments is much discussed. Because of the focus of the next chapters on renewable energy generation, this section examines the policy options that are available to generate technological change for renewable energy technologies. First, the traditional dichotomy between supply-push and demand-pull technology policy approaches is presented. Secondly, the evaluation of these approaches in the literature is presented in the context of renewable energy policy.

3.1. Supply push Vs. Demand-pull policies

The major debate in the literature compares and contrasts “demand-pull” and “supply-push” policy approaches to technological change. On the one hand, demand-pull instruments originate in the price-induced theory of technological change (Hicks, 1932, Schmookler, 1966). If technological change can be induced by changes in prices from shifts in market forces, then policy instruments that influence market-demand for cleaner technologies can direct technological change towards them. On the other hand, supply-push instruments are justified primarily by the existence of uncertainty. Originating in the work of Rosenberg (1982) who described technological change as a dynamic process and a sequence of event, the justification of supply-push instruments lies in the uncertainty of investments in innovation which would hinder the expected effects of market forces.

Nemet (2009) distinguishes between these two approaches to policy in terms of the way they influence technological change: Where supply-push policies aim at decreasing the private costs and risks associated with investment in innovative activities, demand-pull policies increase the private pay-offs to innovation. This section of the literature review reports empirical and theoretical evidence in support of or challenging each of these two approaches, in the context of renewable energy policy.

3.1.1. Supply-Push instruments

Supply-push theory originates in the establishment of a strong correlation between R&D expenditures and innovation. Focusing on the innovation phase of technological change rather than the diffusion phase, supply-push policies are aimed at decreasing the private costs of R&D activities. As technological change is associated with the knowledge externality, measures are needed to correct for the suboptimal provision of investment in R&D. The objective of supply-push policies is to stimulate investments in early stages of technological development, where the knowledge externalities (spillovers) and uncertainty are the most prominent[11].

Supply-push policies include direct government spending in innovative activities. Examples of such spending include direct public R&D expenditures, in the form of research grants and programs, direct public support to education and training, public-funded and public-run research such as research in universities and national laboratories, direct funding of installations and demonstration projects (Nemet, 2009). Supply-push policies can also provide incentives for private investments in technological change. Examples include tax credits for firms investing in R&D activities or in knowledge exchange activities. The objective of supply-push policies

[11] Clarke and Weyant (2002) argue that early basic research has the most potential for wide application across technologies and therefore is less appropriable. This suggests that knowledge spillovers are largest in early basic research stages.

is to obtain ex-ante technological change which would reduce the subsequent costs for deployment of the technology.

Such policies can be designed for stimulating innovation in the economy as a whole, in the objective of fuelling economic growth, and are in that case often referred to as general "technology" policies. Recently, the need for supply-push policies targeted directly at renewable energies has been emphasised in order to offset for the additional market failures they face. An example of this is the European Union Strategic Energy Technology Plan (SET-Plan) adopted in 2008 which focuses on the development of new technologies in the energy sector (European Commission, 2007).

3.1.2. Demand-pull instruments

Aside from direct support to renewable energy technologies, another type of available policies to promote innovation is "demand-pull". Based on the idea that market demand is a large determinant in the diffusion of new technologies, demand-pull mechanisms correct for the uncertainty and diffusion market failures. Demand-pull policies are justified by the importance of "post-introduction" technological change, such as learning effects. Demand-pull mechanisms can attempt to reduce the risks associated with future returns on investments in new technologies. Moreover, demand-pull mechanisms can also attempt to offset the network externalities associated with diffusion, by encouraging early adoption. The objective of demand-pull policies is to create a market for new technologies which will support investment in these technologies and in turn reduce their costs. Examples of such policies include intellectual property regulation, subsidies to adoption, regulatory standards or taxes and subsidies on competing technologies (Nemet, 2009).

Several demand-pull mechanisms are available to policy-makers focusing on the energy technology system. Environmental economists often differentiate between price and quantity mechanisms. This distinction is also referred to as “market-based” vs. “command and control” instruments and the effectiveness and efficiency of each method is highly debated in the literature (Popp et al., 2010). Quantity mechanisms impose quotas or standards to economic agents. Such policies allow little flexibility in the way firms and consumers can achieve the quantity objectives and are traditionally used for pollution control policies. Examples include standards relating to car emissions or energy-efficiency of appliances. In contrast, price mechanisms induce investments in new technology through the manipulation of prices as market-signals. Allowing for more flexibility than “command and control”, price mechanisms are widely used in energy policy. Subsidies to renewable energy, taxes on fossil-fuels and guaranteed prices are examples of price mechanisms.

The two major policy instruments often debated for the development of renewable energy technologies are Feed-in Tariffs (FITs) and Green Certificates (GC). FIT schemes ensure a guaranteed price for electricity generated from renewable energy sources for a delimited time period (often more than 10 years). Generally, FIT programs provide an obligation on the electric utility company to buy generated electricity from renewables at a tariff decided by the regulator. This acts as a subsidy to the electricity generator to compensate for the competitive disadvantage of renewable technologies to traditional electricity generation. While FITs are a price-based instrument, green certificates can be considered a hybrid price-quantity measure. Traditionally in such schemes, electricity suppliers must ensure that a fixed portion of their electricity supplied to consumers comes from renewable energy sources. The quota can also be applied to electricity producers or consumers. The number of green certificates is determined centrally as a target of electricity to be supplied from renewables. The GC can then be acquired by the suppliers along with the renewable electricity; and in the case of tradable GC, they can be exchanged independently. Suppliers must provide a certain number of certificates at the end of a given period or pay a penalty. This flexible quantity-based instrument allows a specific target to be reached while minimizing the cost of compliance, as suppliers marginal costs are equalised throughout the market via trade of the certificates.

3.2. Assessing the impact of energy policies on innovation

The supply-push and demand-pull policy mechanisms discussed above are designed in the same policy objective: delivering a larger penetration of renewable technologies in the energy system at the lowest costs possible by enabling technological change and innovation. The effectiveness of different policy instruments in increasing the penetration of renewable is addressed in the literature. With particular attention to wind and PV renewable technologies, studies have compared the ability of different instruments (such as FITs and Green Certificates) to increase the capacity of renewable technologies. Menanteau et al. (2003) point out that although quantity and price-based mechanisms should theoretically bring equivalent outcomes, price mechanisms such as FITs prove superior to quotas in achieving renewable energy targets. Mitchell et al. (2006) attributes the success of FITs (in Germany) compared to the UK system of certificates to its stronger ability to reduce investors’ risks. In a cross-country analysis of policies in 12 countries, Lewis and Wiser (2007) point out the superiority of market-based approach to renewable energy policy (like FITs) and mention the existence of a home market as a pre-requisite to wind energy penetration.

However, the focus of this section is another important aspect of policy assessment: the effectiveness of supply-push and demand-pull mechanisms to induce technological change in energy technologies and reduce the overall costs of policy intervention.

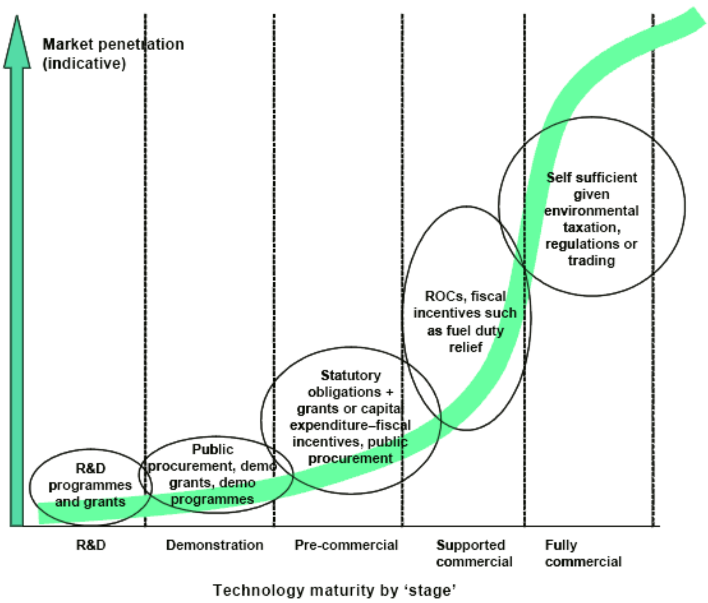
Few empirical studies have looked at the impact of energy policy measures on innovation for renewable energy technologies. In the environmental economics literature, early studies confirmed the link between environmental policy (such as pollution control) and innovation towards cleaner technologies. For good reviews of this literature, see Jaffe et al. (2002) and Popp et al. (2010). With the relatively recent availability of data indicators of innovation (such as patent or R&D expenditures), studies have attempted to estimate the relationship between policy instruments and innovation in environmentally-friendly technologies. Lanjouw and Mody (1996) in a study of the US and 16 other countries, and Brunnermeier and Cohen (2003) focusing on the U.S. both conclude that pollution abatement expenditures (considered as a proxy for environmental regulation stringency) increases the number of patents in environment-friendly technologies. Jaffe and Palmer (1997) and Hamamoto (2006) find a significant correlation between abatement expenditures and the level of R&D expenditures in the U.S. and in Japan respectively. Fewer studies have directly looked at the choice of environmental policy instruments and environmental innovation. Newell et al. (1999) relate changes in energy prices and energy efficiency standards to the evolution of appliances models characteristics. They find that the price effects lead to both the adoption of new models and the decline of old ones, while standards just eliminate the old inefficient appliances. Popp (2003) investigates the number of patents under the implementation of SO2 tradable permits and finds evidence of improvements in technologies, while Popp (2006) provides cross-country comparisons of SO2 policies and patents.

A very limited number of studies focus on the impact of renewable energy policy and the choice of instruments on technological change. Johnstone et al. (2010) conduct a cross-country analysis of renewable energy policies and renewable energy patent data. This panel data study of 25 countries (high-income) for 26 years (1978-2005) includes a database of policy instruments constructed at the IEA and patent applications counts for renewables energy disaggregated between 5 technologies (Wind, Solar, Geothermal, Ocean and Biomass). When possible, each policy instrument is transformed into a continuous variable in order to represent regulation stringency. This is the case for R&D expenditures, FITs, certificates. For policies that differ too drastically amongst countries (e.g. tax credits), the authors used dummy variables to represent the effect of implementation itself.

The authors find that environmental and energy regulations (such as the Kyoto Protocol) have a strong impact on patenting activities in renewable energy technologies. In terms of supply-push policies, they confirm the significant influence of public R&D expenditures on overall renewable technology patenting. Disaggregating the data by technology, technology-specific R&D expenditures are a significant determinant of patenting for Wind, Solar and Geothermal technologies only. For demand-pull policies, differences also appear between technologies. Renewable certificates only affect patenting activities in wind and geothermal technologies while FITs affect solar technology more strongly than wind. The authors explain the differences in effectiveness of policy instruments with the differences in technology costs. As wind and geothermal power seem to be the cheapest, the use of a flexible instrument such as certificates enables firms to invest in the lowest-cost technologies. In contrast, FITs are often differentiated by technology and can be beneficial to more expensive technologies such as solar. These findings suggest that different policy instruments might be required to trigger innovations and costs reductions for technologies depending on their costs (reflecting different stages of technology maturity).

In an analysis of the UK innovation systems for renewable energy technologies, Foxon et al. (2005) confirms this intuition and argues that an effective renewable energy policy should enable a technology to smoothly move along the s-shaped technology development curve.

Figure 2.1: Energy technology maturity and policy measures



Source: Foxon et al. (2005) : S-curve of technological development and policy instruments

They further point out the necessary diversity of an effective renewable energy policy which must vary alongside the development of the technology. They provide an idealised picture of the required policy for each stage of development (Figure 2.1)

An analysis of these findings can be traced back to the supply-push vs. demand-pull debate. At early stages of technology maturity, namely R&D and Demonstration and Pre-commercial, the adequate policies cited are examples of supply or technology-push policies. As the technology moves towards the supported-commercial phase, the adequate policies change to demand-pull measures in order to create a demand on the market. In simple terms, the link between policy and innovation relates to the theory explained above, supply-push policies are appropriate for inducing early stages, non-incremental (radical) innovation while demand-pull policies focus on creating incentives for diffusion incremental technological change.

Foxon et al. (2005) highlight the difficulties associated with the transition periods between technology development phases and the need for suitable transitions in policies as well. Nemet (2009) reports that a consensus has been reached in the literature that a combination of both types of policies is needed but raises the question of the allocation of public resources to each type of policy. In a case study of wind energy, the paper credits a lack in valuable patents to the difficulties from demand-pull policies to bring out non-incremental innovation and the early convergence towards a dominant design. In a recent paper, Laleman and Albrecht (2012) advocate for a mix of demand-pull and supply-push measures for wind and PV technologies in Europe, but recommends that the ratio of pull-to-push measures be increased through raising R&D expenditures while decreasing subsidies. Similarly, in a case study for PV technology, Nemet and Baker (2009) argue that

R&D are more critical to long-term technology costs reductions than subsidies, but also point out that subsidies can provide a hedge against the risk of R&D only-policies offering uncertain R&D outcomes.

In light of this literature review, policy intervention in favour of renewable energy developments appears justified. In addition, the technological change process for these technologies is of primary importance to determine the type of policy support that should be put in place, as different policy affect the technological process in different ways. Finally, innovations in renewable energy are also likely to change the costs of climate change mitigation and environmental policy.

To capture these complex interactions when estimating the impact of renewable energy policies, it is necessary to represent them in a system-wide context to determine their environmental and economic impact, while considering technological progress. Energy-Economy-Environment (EEE) models have been developed in recent years to systematically address these complex interactions. They are particularly useful tools to assess the impact of renewable energy policies. But they must be augmented to include endogenous technological change, in order to accurately represent the interactions. The next section of this literature review focuses on the introduction of technological change in EEE models

4. Technological Change in Energy-Economy-Environment models

Global efforts have been directed towards designing a range of climate and energy policy instruments, in response to the growing challenge of climate change. The need for adaptive tools to evaluate the impacts of these policy instruments has led to the rapid development of models encompassing one or several aspects of the energy-environment-economy system interactions. These models are very diverse in their design, theoretical underpinnings, objectives and geographical focus but are widely referred to as energy-economy-environment (EEE) models. Most of the recent EEE models provide a dynamic analysis of policy enabling to determine both short-run and long-run policy impacts. In these dynamic frameworks, the importance of technological change is widely recognised as a key feature of EEE models (Loschel, 2002). Therefore, models have generally incorporated some form of technological change in their framework.

This section aims to review the major recent contributions to the EEE modelling literature, with a particular focus on the treatment of technological change. Section 4.1 introduces the well-known distinction between two energy-economy-environment modelling approaches reported in the literature, namely bottom-up and top-down, but highlights the recent emergence of hybrid models attempting to combine strengths from both approaches. Section 4.2 identifies the different methods by which leading EEE models (of all types) have introduced technological change, looking at the origins of these methods in the theoretical economics literature.

4.1. Modelling approaches: Bottom-Up vs. Top Down

Different types of models have been developed over the years to assess the long-term impact of energy and environment policies. Before proceeding to the detailed review of these models incorporating technological change, an important observation from the literature is the distinction between two broad modelling approaches: namely bottom-up and top-down (IPCC, 1996). Bottom-up and top-down models differ mainly by the level of details in their representation of the economy and energy systems (Bohringer, 1998, Loschel, 2002). Bottom-up models are centred on a highly detailed disaggregation of the energy system and the technologies it includes. On the other hand, top-down models put the emphasis on a comprehensive representation of the economy. Models in each category generally feature different degrees of detailing of the energy and economy systems. This section develops in turn the main features of top-down and bottom-up models and identifies their strengths and weaknesses. It concludes with the emergence in the literature of hybrid models and the difficulties associated with integration techniques.

4.1.1. Top-down

Top-down refers to models that focus on economy-wide impacts of environmental and energy policies. Traditionally, top-down models are based upon economic theory foundations. They concentrate on representing economic agents (such as households or industries) and their interactions on markets (such as goods or factor markets) through well-established macroeconomic functions. They generally make use econometric estimation techniques for calibration from historical economic data. Top-down EEE models are often described as general macroeconomic models which represent the economy and the energy systems in highly aggregated terms (Sjim, 2004).

This top-down approach to modelling encompasses different types of models, identified in the Innovation Modelling Comparison Project report (Edenhofer et al., 2006):

- General equilibrium models balance demand and supplies between economic agents on all markets. Each agent uses relative-price signals to optimise their decisions. Computable General Equilibrium models are most commonly used. They offer a multi-sectoral representation of the economy and are solved for multiple time periods. They generally calculate a static equilibrium for each time period where all markets clear, creating dynamic adjustments over time. Examples of such models and their treatment of technological change are considered in more details in section 4.3.
- Optimal Growth models aim for the inter-temporal optimisation of social welfare. Such models are based on neoclassical (early models) or endogenous growth theories (introducing drivers of endogenous technological change). Based on the idea that economic growth drives emissions, this approach models growth dynamics over long-term horizons and is a preferred method for global climate change impact assessment models. The examples of optimal growth models include Goulder and Mathai (2000), DEMETER (Van der Zwaan et al., 2002), RICE (Nordhaus, 1994, 2002, and Castelnuovo et al., 2005) and MIND (Edenhofer et al., 2006).
- Econometric models are a less-common method for EEE modelling and use time-series data to estimate a system of differential equations for simulations.

Top-down models are found particularly suitable for analysis of macro-economic impacts of environmental and energy policies due to their ability to model sectoral and geographical interactions and feedback effects (Sjim, 2004). Their focus on macroeconomic theory is at the expense of a disaggregation of the energy system (Böhringer, 2008). They often (but not always) consider the energy system as a single economic sector represented through a smooth production function (usually Cobb-Douglas or Constant Elasticity of Substitution functions). They are seen as sacrificing important technological details specific to each energy technology for economic theory consistency.

4.1.2. Bottom-up

In contrast, bottom-up models refer to partial models of the energy system and are based on engineering principles. Also commonly called “energy-system” models, bottom-up models provide a great degree of disaggregation of the energy system: they offer a detailed representation of current individual energy technologies and processes as well as projections on their technological improvement potential. Bottom-up models are a more unified approach to modelling and are mostly based on similar objectives and assumptions. They usually make use of linear programming techniques to optimise energy supply systems (through cost-minimization). They generally incorporate exogenously determined energy-demand projections which represent their only link to the wider economic framework.

Examples of bottom-up models are MESSAGE (Messner, 1997, Grübler and Messner 1998), GENIE (Mattson, 1998, Mattson and Wene, 1997), and MARKAL (Seebregts et al., 2000) and are discussed further later in subsequent sections. Bottom-up models have the advantage of a more accurate representation of the energy systems and the future possibilities for changes in the system, since they are based on engineering data and assessments. Their weak link to the rest of the economy and inability to model feedback effects with energy demand limits their applications to economy-wide impact assessment exercises, and questions their abilities for long-tern projections.

4.1.3. Hybrid

Since strengths and weaknesses of these two model approaches have been identified, great effort has been put into combining both methods to take advantage simultaneously of the level of technological details in the energy sector from bottom-up models and the disaggregated representation of the economy in top-down model. The Third Assessment Report of the IPCC (2001) provides an overview of the distinctions between bottom-up and top-down models but recognises that it has become increasingly ambiguous, as more efforts are made to integrate bottom-up structures of the energy sector into macro-economic top-down models. However, combining these models can pose problems, such as inconsistencies in structure and philosophy, a lack of data convergence, a loss in flexibility and transparency. The most straightforward approach to combine them is to focus on one type of models and include a reduced- form of the other.[12] The examples of hybrid models presented in Section 4.3 are MERGE (Manne et al., 2006) and MESSAGE-MACRO (Rao et al., 2006).

Despite their underlying differences, bottom-up and top-down modelling literatures have both accepted the importance of endogenizing technological change in the energy sector to analyse the impacts of energy and environmental policies. The next section reviews several top-down, bottom-up and hybrid EEE models that have introduced technological change.

[12] However, Bȍhringer (1998) identifies the origins of the difficulties to integrate both approaches in the way energy technologies are represented. While in top-down models such as CGE models use restrictive CES production functions, bottom-up models often capture many technological options represented through discrete Leontief functions. Bȍhringer (2008) proposes the introduction of a mixed-complementarity problem (MCP) with weak inequalities in the Arrow-Debreu equilibrium framework. For a detailed mathematical description of the MCP see Bȍhringer (2008).

4.2. Introducing Technological Change in EEE models

Most recent EEE models have recognised the importance of introducing technological change in order to accurately represent short-run and long-run impacts of policies. Due to the large number of models introducing technological change, this section will focus on a few selected EEE models of the top-down, bottom-up and hybrid literature which have all introduced a new element of technological change. A few reviews of technological change in EEE models already exist in the literature. Loschel (2002) first surveyed models of environmental policies introducing technological change. Edenhofer et al. (2006), Gillingham et al. (2008), Kahouli-Brahmi (2008) and Popp et al. (2010), among others, offer more recent reviews of this modelling literature. The objective of this section is not to present a new exhaustive survey of this literature. It is rather to focus on representative examples of the major techniques used to introduce technological change in EEE models.

Identifying these techniques by model type is of particular interest to this thesis since the next chapters focus on introducing technological change in a Computable General Equilibrium for Scotland. Section 4.2.1 describes early attempts to introduce technological change as an exogenous feature of EEE models (where technological change is only a function of time). Section 4.2.2 details how more recent models have introduce endogenous technological change in different ways, through R&D accumulation, learning-by-doing effects or both.

4.2.1. Exogenous TC

Most EEE models assume some exogenous rate of overall Hicks-neutral productivity growth (Loschel, 2002). However, this form of exogenous technological change pertains to the overall economy and is not specific to energy or environmental technologies. Early EEE models introduce an additional element of technological change through exogenous improvements to environmental or energy-related activities. The most common approach to introducing this kind of technological change is to include an Autonomous Energy Efficiency Improvement (AEEI) parameter to increase energy-efficiency overtime (Nordhaus, 1994). The AEEI parameter can exogenously improve the energy-efficiency of total output in the economy in each modelling period or be sector-specific (Popp et al., 2010). It is introduced as an exogenous parameter in the production or cost function, as a factor productivity-improving or factor price-reducing parameter (Loschel, 2002). For example, Hanley et al. (2009) introduce an AEEI parameter in the CGE model for Scotland in the context of rebound and back-fire effects of energy-efficiency improvements.

Another common method of exogenous technological change in EEE models is the introduction of backstop technologies. These technologies usually represent low-carbon or carbon-free energy sources that are not yet commercialised (e.g. nuclear fusion). They are assumed to be available in unlimited supply and to have high and constant marginal costs compared to traditional technologies, reflecting the need for large R&D investments to make them competitive (Loschel, 2002). The switch to the backstop technology occurs when the price of traditional energy sources (inclusive of carbon policy) rises above the costs of the backstop technology (Popp et al., 2010). This switch occurs suddenly, and generally leads to full adoption of the backstop technology thereafter. Although the use of AEEI parameter and backstop technologies is relatively simple and transparent, our literature review has pointed out that technological change depends on more complex drivers than only the passage of time. Particularly in the analysis of environmental and energy policies, feedback effects between technological change and policy can only be represented endogenously.

4.2.2. Endogenous TC

Much like technological change has the potential to reduce the costs of energy and environmental policy, the policies themselves (whether demand-pull or supply-push) can induce technological change through promoting innovation and diffusion. This feedback effects between policy and technological change have been recognised by EEE modellers, moving away from exogenous representation of technological change. This section describes a few selected models that have introduced endogenous technological change. The methods and techniques to do so vary between models but are mostly consistent amongst models of the same type (top-down or bottom-up).

4.2.2.1. R&D Technological Change

The first common approach to endogenous technological change in EEE models is to introduce R&D-induced technological change. Almost exclusively used in top-down models, this method has strong theoretical foundations in endogenous growth theory (Romer, 1990, Lucas, 1988, Grossman and Helpman, 1994 and Aghion and Howitt, 1998).

Theoretical Underpinnings

First introducing the concept of technological change in a growth model, Solow (1957) included an exogenous technology parameter in the production function to account for changes in attainable output for a given level of inputs. Solow described technological change as "any kind of shift in the production function" (Solow, 1957, p.312). It is important to note that this economic definition of technological change as a "change in the production function" is narrower than one used in other fields (such as engineering). Solow (1957) finds that the long-run rate of economic growth is exogenously determined by the rate of technological progress, which proved unsatisfactory in explaining the origins of technological progress, as a source of growth. In reaction, a new class or models emerged to introduce endogenous technological change, in the so-called "endogenous growth theory". Major contributions to this theory include Romer (1990, 1996), Grossman and Helpman (1991), Aghion and Howitt (1992) and Jones (1995). Instead of being exogenously determined (as a function of time only), technological change can now be determined in the economic system itself.

Romer (1990) was the first to propose a growth model which would encompass an endogenous technological progress driven by R&D activities. Extending the neoclassical growth model, endogenous growth models introduce a new R&D-producing sector, which determine technological change. Similarly to the neoclassical model, Romer (1990)'s model is based on an economy-wide Cobb-Douglas production function based on two factor-inputs, namely capital and labour.

$$Y(t) = [(a_K)K(t)]^{\alpha}[A(t)(a_L)L(t)]^{1-\alpha} \tag{2.1}$$

Where $Y(t)$ represents production, $K(t)$ and $L(t)$are the capital and labour stock respectively. a_K and a_L represent respectively the shares of capital and labour that are used in the production of output. $A(t)$ can be considered as a stock of knowledge which embodies technology as a determinant of the productivity of inputs. An important observation is that in endogenous growth models, technological change often applies to the labour inputs only, reflecting the so-called Harrod-neutral technological change (Harrod, 1942).

Hicks (1932) first introduced the classification of technological change between labour-augmenting, capital augmenting and neutral technological change. He defines neutral technological change as leaving the ratio of marginal product of capital to marginal product of labour unchanged. In a general functional form, Hicks-neutral technological change assumes that an increase in technological change improves the productivity of capital inputs and labour inputs simultaneously. In contrast, Harrod (1942) and Solow (1970)-neutral technological change refers to improvements in the productivity of labour and capital respectively.

The knowledge stock $A(t)$ is made endogenous to the model through the introduction of a new sector. This sector represents the production or accumulation of new knowledge $\dot{A}(t)$, which contributes towards the knowledge stock $A(t)$. It takes the following Cobb-Douglas form:

$$\dot{A}(t) = B[(1 - a_K)K(t)]^{\beta}[(1 - a_L)L(t)]^{\gamma}A(t)^{\phi} \tag{2.2}$$

Where B is a shift parameter, $B \geq 0$, $\beta \geq 0$ and $\gamma \geq 0$.

Labour and capital stocks are shared between the good producing sector and the R&D accumulating sector. $1 - a_K$ and $1 - a_L$ represent respectively the shares of capital and labour that are used in the production of R&D. Knowledge is non-rival; this is reflected in the full use of the knowledge stock A(t) in both production functions. This introduces an important observation from endogenous growth models, namely the influence of the stock of knowledge on the R&D production sector. The parameter ϕ embodies this influence and can be referred to as a "returns-to-knowledge" parameter. Depending on the value of ϕ, the influence of past-knowledge on the accumulation of new knowledge changes drastically. Several options are considered in the literature.

- $\phi < 0$ corresponds to the case where increases in the level of knowledge decrease with the current knowledge stock. This is referred to as "fishing-out".
- $\phi = 0$ corresponds to constant return to scale where the accumulation of knowledge is independent from the current stock of knowledge
- $\phi > 0$ assumes that the current stock of knowledge has a positive impact on knowledge accumulation, the so-called "standing on shoulders" case.
- $\phi = 1$ is the initial assumption in the Romer model, and corresponds to one specific case of standing-on-shoulders.

Based on these theoretical foundations from the neoclassical economics literature, a number of EEE models have introduced and R&D driven endogenous technological change process.

EEE Models with R&D technological change

EEE models introducing R&D-driven innovation usually represent technological change through a knowledge stock which increases with investments in R&D expenditures. Endogenous technological change is entirely driven by R&D activities. Early examples of these models focus on climate change mitigation and CO2 emission abatements. Some of these models consider R&D activities as reducing carbon emissions. The RICE model (Regional Integrated model of Climate and the

Economy, Nordhaus and Yang, 1996) was the first integrated assessment model of climate change to be modified to introduce this type of technological change in a neoclassical growth framework. In its early versions, the RICE model considers the rate of emissions as a function of the flow of carbon-saving R&D expenditures. Nordhaus (2002) develops the R&DICE version of the model where carbon-intensity (carbon emission per unit of GDP) is determined by an innovation production frontier as a function of R&D spending in the carbon-energy sector. Buonanno et al. (2003) extend the RICE model to include a knowledge production function (called “innovation”) increasing with R&D investment. They configure it to the situation of “standing-on-shoulders”, where new innovations build on past knowledge. The knowledge stock in turn improves energy-intensity. In another top-down example, Goulder and Mathai (2000), R&D technological change decreases the costs of abatement activities[13].

In multi-sectoral top-down models with R&D technological change, the treatment of R&D expenditures is different. They are interested in a more general specification of technical change, in contrast with climate models focusing on carbon emission abatement). In such models, R&D spending influences sectoral productivity, so as to reduce the costs of more energy-efficient technologies. In a General equilibrium framework, Goulder and Schneider (1999) introduce an R&D-producing sector (based on endogenous growth theory) which provides R&D services to other sectors. The other sectors invest in R&D in the same way as they invest in capital stocks. The knowledge stock then reduces production costs or improves factor efficiency.

[13] Goulder and Mathai (2000) also introduce learning-by-doing technological change. This will be discussed in the next subsection.

As pointed out in Gillingham et al. (2008) the advantage of using R&D-driven technological change in CGE models is that it provides additional information on inter-sector interactions, such as spillovers or crowding-out. Spillovers and crowding-out from R&D have opposite influences. While R&D spillovers between industries diffuses costs-reductions or productivity improvements, crowding-out can counterbalance this positive effects if R&D is in limited supply, and R&D in energy-saving activities reduces the potential for R&D activities in the rest of the economy[14]. This non-exhaustive review of models with R&D technological change presents a first approach to endogenous technological change. The next section focuses on learning-by-doing effects.

4.2.2.2. Learning-by-doing Technological change (LBD TC)

The second most common approach to endogenous technological change in EEE models uses the empirically strong phenomenon of learning-by-doing. Learning-by-doing describes the process of cost reductions resulting from gains in cumulative experience (Arrow, 1962a).

Origins in the literature

The first article to acknowledge the existence of learning effects in manufacturing was published by Wright (1936). From observations in the airframe manufacturing sector, he found that unit labour costs tend to decrease with accumulated workers experience. More precisely, he named the “progress curve” the fact that costs showed a constant percentage decrease with each doubling of cumulative output. A decade later, Wright’s finding was developed and applied to war material by the RAND

[14] Wing (2003) and Popp (2004) address this crowding-out effects in more details.

Corporation, a think-tank created by the U.S. government to develop a “Science of warfare” during the Cold War, and the concept was named “Learning-By-Doing” (Yeh et al., 2007). Extended in 1968 by the Boston Consulting Group (BCG, 1968), Learning-by-Doing theory was applied to the relationship between output price and cumulative industry output; it was redefined through the “experience curve” as the learning phenomenon at the industry level. Subsequent studies of learning have revealed the existence of LBD in a large number of industries (Argote and Epple, 1990).

In its original form, learning-by- doing (LBD) is expressed as an exponential function of cumulative experience as below:

$$C(t) = C_0 \, . \, G(t)^{-\alpha} \tag{2.3}$$

Where $C(t)$ is the unit cost of production at time t, $G(t)$ is cumulative experience, C_0 is the cost of the first unit produced, and α is the learning elasticity. The learning rate is then defined as the percentage decrease in unit cost for every doubling of experience, as in equation (2.4):

$$LR = 1 - 2^{-\alpha} \tag{2.4}$$

The economic implications of learning-by-doing (LBD) have been expressed by Arrow (1962b). In a simplified economic model, he chooses to use cumulative gross investment as an index of experience. Sheshinski (1967) generalises the Arrow model of learning. Consider the following production function where output is produced using labour and capital:

$$Y_t = A(G, t). F(K, L) \tag{2.5}$$

A is the factor productivity parameter, and is defined here as a function of cumulative experience G and time[15]. The learning hypothesis formulated by Arrow (1962b) is an attempt to explain the growth of output through accumulation of experience. Two alternative assumptions can be used to account for cumulative experience. Arrow (1962b) proposes to depart from previous models where experience was only represented by output and to use a new proxy: cumulative gross investment. He justifies this choice through the idea that technological change is embodied in new capital goods; therefore investments in capital are the main drivers of learning effects. This will be discussed further in the next chapter.

Models with Learning-By-Doing

Due to its strong empirical roots in manufacturing industries, learning-by-doing (LBD) is the preferred method for bottom-up models to endogenise technological change in energy sectors[16]. The first energy-economy model to introduce LBD was developed by Messner (1997) and Grübler and Messner (1998) in the MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact). In this dynamic linear model of the energy system, the objective function minimises the sum of discounted overall costs of the energy system. Technological change is represented through a LBD function where costs of the technology are a decreasing exponential function of cumulative experience embodied in cumulative installed capacity. Following this advancement in the MESSAGE model, many other bottom-up models have adopted this specification of LBD to introduce endogenous technological change. In the GENIE model (Global

[15] This accounts for technological progress that is not explained by experience gains.
[16] Although recent top-down models have also recognised its importance and increasingly include a LBD component.

ENergy system with Internalized Experience curves), Mattson and Wene (1997) use LBD technological change in a model where the total costs of the global energy systems are minimised. In turn, Kypreos and Barreto (1998) and Seebregts et al. (1998, 2000) introduce LBD for energy technologies in the well-know MARKAL model for optimizing a simple global electricity system and for Western Europe respectively.

Moreover, some hybrid bottom-up/top-down models have also adopted this learning curve specification. This choice is motivated by the method used to construct them, as they typically incorporate the technological details of the energy system from bottom-up models into top-down macro-economic frameworks. Manne and Wene (1992) present the first formal link between the MARKAL model and the top-down economic growth model MACRO, using an iterative process where MARKAL informs MACRO in terms of energy costs, while MACRO informs MARKAL in terms of energy demands.

Another example of such hybrid top-down/bottom-up model is MESSAGE-MACRO (Messner and Schrattenholzer, 2000) and incorporates technological change. It combines a version of the energy system MESSAGE model described above with LDB, and the top-down MACRO model framework as well. Rao et al. (2006) extend this hybrid model through a link with climate model (MAGICC), to impose a GHG concentration target in the running of the MESSAGE model. Manne and Richels (2004) develop MERGE (Model for Estimating the Regional and Global Effects of greenhouse gas reductions) which links nine regions of the globe each represented by an individual bottom-up energy system model through a macro-economic growth model. In all these hybrid models, endogenous technological change is represented through the use of learning curve in energy technologies detailed in the bottom-up part.

Furthermore, a few top-down models have introduced LBD to respond to the growing bottom-up literature confirming the importance of learning effects. Influenced by the endogenous growth literature, Goulder and Mathai (2000) is the first example in the literature of a top-down model combining R&D and LBD technological change. In a partial equilibrium model of knowledge accumulation with a central planner, this model examines two specifications for endogenous technological change where increases in the stock of knowledge reduce the costs of emission abatement activities sector. In the first specification, the stock of knowledge is an increasing function of investments in R&D. In the LBD case, the stock of knowledge is an increasing function of the abatement activities themselves (reflecting this idea of costs reduction associated with experience). In an effort for consistency in the analysis, they introduce both R&D TC and LBD in the same knowledge accumulation function where "fishing-out" occurs.[17]

In the spirit of Goulder and Mathai (2000), other models have introduced LBD as a stock-updating production function. Rasmussen (2001) presents a multi-sector general equilibrium model for Denmark to examine the influence of learning-by-doing in renewable energy technologies. The model differentiates between the renewable energy generation sector and the renewable energy capital sector, which provides capital inputs to the first one. In this model, LBD increases the stock of knowledge in the production function of renewable energy capital sector,

[17] The importance of this specification for the endogenous technological change modelling literature will be discussed in greater details in Chapter 3.

representing improvements in the productivity of inputs. The renewable energy capital sector becomes more efficient, embodying improvements in the technologies, and lowering the costs of the renewable generation sector.

However, other top-down models have been more greatly influenced by the bottom-up approach to energy modelling and have introduced LBD using the traditional learning curve specifications. Van der Zwaan et al. (2002) develop the DEMETER model (Decarbonisation Model with Endogenous Technologies for Emission Reductions) introduces LBD. DEMETER is a macroeconomic model of climate change with two energy producing sectors (fossil and non-fossil) used as inputs in production. Cumulative capacity for both energy sectors generate costs reductions in both investments in new capital and operation and maintenance activities[18]. Another example is the MIND model (Model of INvestment and Technological Development, Edenhofer et al., 2005) where learning is a side effect of extraction activities in the fossil-fuel sector and as a function of cumulative capacity in the renewable energy sector. All these models, their introduction of learning-by-doing and their findings are explored in more details in the next chapter.

5. Conclusion

Learning-by-doing appears to currently be the most popular method to incorporate endogenous technological change in EEE models. It originates in bottom-up models, but is more and more widely used in hybrid and top-down models as well. This superiority can be attributed to both the strong empirical validation of the LBD phenomenon and the relative simplicity of application in models. Based on a single

[18] Although they assume costs reduction potential to be much more limited for fossil-fuel energy technologies compared to non-fossil-fuel.

equation relating costs and cumulative experience, the ease of application of the LBD technological change approach has also been identified as a weakness. Nordhaus (2009) warns against the risk that using this method places too much emphasis on the LBD mechanisms of technological change, while undermining the importance of R&D mechanisms.

Nevertheless, the learning-by-doing process appears to be an ideal first-step in the introduction of endogenous technological change in an EEE model. Part A of this thesis represents the first attempt to introduce endogenous technological change in the AMOS model framework. A learning curve is introduced in the marine energy sector, in order to represent technological improvements in this emerging renewable sector in Scotland. However, the learning-by-doing process and its representation in an EEE model are complex. The next chapter of this thesis will focus uniquely on learning-by-doing for energy technologies. It will identify the different specifications of LBD in EEE models in more details than this chapter. After presenting some results of previous modelling attempts, a number of learning-by-doing specifications are identified to be implemented in the model. They are individually tested in a micro-simulation context first, before being introduced in the AMOS model in Chapter 4.

Chapter 3: Learning-by-doing in Energy-Economy-Environment models

1. Introduction

The methods employed to represent technological change in EEE models have evolved over the past two decades, moving away from exogenous towards endogenous representations. Technological change has been recognized as a process that does not simply occur on its own over time. The literature review of Chapter 2 discussed the introduction of both R&D and LBD-induced technological change in different types of EEE models. The latter (LBD) seems to be a common method used in most models focusing on energy issues.

This chapter focuses on the implementation of learning-by-doing, hereafter referred to as LBD, into EEE models, and particularly LBD applied to the energy system. Section 2 reviews the recent econometric literature focused on the estimation of learning rates for energy technologies. Section 3 develops the literature review of EEE models begun in Chapter 2, with a special emphasis on models incorporating LBD. This review brings to light a variety of representations of LBD in EEE models including differences in equation forms, experience proxies and parameter values. These differences in specifications and their implications for the modelling exercise are then explored in Section 4 through the use of micro-simulations. Finally, Section 5 concludes the chapter on LBD theory and practices and introduces Chapter 4, which implements LBD in marine renewable energy generation into a Computable General Equilibrium model for Scotland.

2. Estimation of Learning Rates for Energy Technologies: a Literature Review

2.1. Estimating the learning curve

Many EEE models put the emphasis on modelling technological change for the energy sector, due to its crucial role in determining carbon emissions (see for example Messner, 1997; Miketa & Schrattenholzer, 2004; Rasmussen, 2001). These models have mostly implemented endogenous technological change through LBD functions. In order to calibrate such functions, estimates of learning rates for energy technologies are required, reflected in the parallel increase in the number of econometric studies of learning rates for energy technologies.

These studies have focused on estimating the empirical learning curve, first identified by Wright (1936), which defines costs as a decreasing exponential function of cumulative experience. This learning curve function is repeated in this chapter in equation 3.1 below.

$$C_t = C_0.(G_t)^{-\alpha} \qquad (3.1.)$$

C_t is the costs of the technology at time t, C_0 is the costs of the first unit produced, G_t is the cumulative experience variable and α is the learning elasticity parameter.

From this equation, the learning rate (LR) is expressed as a function of the learning elasticity parameter, as follows:

$$LR = 1 - 2^{-\alpha} \qquad (3.2)$$

Accordingly, the learning rate represents the costs reductions (in percentage terms) that occur with every doubling of cumulative experience G_t. The learning elasticity α can be estimated econometrically by transforming equation 3.1 into a logarithmic form. A general specification for the learning curve estimation model is given in equation 3.3 below.

$$\ln(C_t) = \ln(\mathrm{C}_0) - \alpha \ \ln(G_t) + \varepsilon \tag{3.3}$$

where ε is the error term

Econometric studies have focused on estimating the learning rate for different energy technologies and have produced a wide-range of estimates, which have been surveyed in McDonald and Schrattenholzer (2001) and more recently in Kahouli-Brahmi (2008). McDonald and Schrattenholzer (2001) reports 42 learning rate estimates, which are either re-estimated from available datasets (for 26 estimates) or simply reported when the data was not available (for 16 estimates). These estimates cover a large number of technologies (oil extraction, gas turbines, nuclear power plants, coal and lignite power plants, GTCC power plants, wind turbines, PV modules, biomass and others) over different geographical locations (e.g. OECD, US, North Sea, Germany, Japan, Denmark) and different time periods. They find a median value for learning rate estimates of 16-17% which they conclude is comparable with another study of overall manufacturing learning rates (Dutton and Thomas, 1984). The major observation from the review is the wide variation in estimates, even for similar technologies. The 42 estimates range from -11% for global learning rate for GTCC power in the 1980s (Claeson, 1999)[19] to 34% for OECD learning rates for GTCC power between 1984 and 1994 (Kouvaritakis et al.,

[19] Claeson (1999) uses prices as a dependent variable. Price data can be considered inferior to costs as a performance measure in this estimation process; as prices are affected by other external factors than costs. One explanation provided for the negative learning rate in this study is short-term oligopolistic pricing behaviour (Claeson, 1999)

2000). This wide range illustrates the importance of underlying assumptions in the estimation model. Another important finding from McDonald and Schrattenholzer (2001) is that studies using more recent data generally report lower learning rates, suggesting that technologies at more mature development stages experience smaller learning effects[20]. In addition to issues with price data and possible depreciation of learning rates, the review points out five additional factors that might have generated variation in estimates, namely: differences in performance proxies (investment costs or production costs) and/or experience proxies (cumulative installed capacity or cumulative production), differences in variable definitions, differences in R&D intensity, differences in economies of scale, and some costs variability driven by labour and financial markets (i.e. land costs, wages or interest) across locations over time.

Kahouli-Brahmi (2008) provides a more recent review of econometric studies, including a larger number of estimates reflecting the growing research interest in LBD for energy technologies. This review provides 94 estimates, classified in the same manner as McDonald and Schrattenholzer (2001) including the energy technology studied, the geographical scope of the study, the time period covered, the choice of dependent variable (performance measure) and independent variable (experience measure). However, an important distinction is added to the Kahouli-Brahmi (2008) review. It differentiates between one-factor and two-factor learning curves. This distinction is highlighted in Section 2.2 below, while Section 2.3 addresses the issue of time-varying learning rates. Section 2.4 discusses the choice of performance and experience proxies in the estimation and finally Section 2.5

[20] This issue is addressed in more detail in section 2.4.

discusses other issues in the econometric estimation of learning rates, such as endogeneity and omitted variable bias.

2.2. One-factor or two-factor learning-curve

The distinction between one-factor and two-factor learning curves resides in the variable(s) which are assumed to influence costs. In the case of one-factor learning curves, costs reductions are obtained only with increases in cumulative experience. In contrast, two-factor learning curves have been developed recently to include the impact of R&D activities on costs, described as *learning-by-researching* (LBR). Thus, two-factor learning curves represent cost reductions from experience gains and R&D expenditures into one model.

$$C_t = C_0 . G_t^{-\alpha} . H_t^{-\beta} \tag{3.4}$$

Equation 3.1 in the previous section represents the one-factor learning curve, while equation 3.4 represents the two-factor learning curve[21]. The only difference between the two equations is the addition of the variable H_t, representing an R&D knowledge stock. To the same extent that α is the LBD elasticity, β is the elasticity of learning-by-researching. H_t is considered a function of the previous knowledge stock and R&D expenditures, as represented in equation 3.5[22].

$$H_t = H_{t-1}(1 - \delta_H) + R\&D_{t-x} \tag{3.5}$$

$R\&D_t$ represents research and development expenditures at time t, while x is a time lag between the expenditures and their contribution to the knowledge stock[23]. Another generalisation is the existence of depreciation δ_H of the knowledge stock

[21] Adapted from Kahouli-Brahmi (2008) for consistency with the notation used in this thesis.
[22] A general formulation is adopted here to match the notation in this thesis and to reflect the equation chosen in Kahouli-Brahmi (2008).
[23] The time lag is included here to keep the equation general.

which refers to the general treatment of the capital stock in economics. This two-factor learning curve leads to a new regression model in the same form as equation 3.3 but with an additional independent variable (equation 3.6).

$$\ln(C_t) = \ln(C_0) - \alpha \ln(G) - \beta \ln(H_t) + \varepsilon \tag{3.6}$$

Originating in Kouvaritakis et al. (2000), two-factor learning curve estimation models became popular in the mid-2000s with Klaassen (2005). Kahouli-Brahmi (2008) reports a large number of studies, using one and two-factor learning curves. Comparing both LBD and LBR rates, the review also finds a wide range of estimates. The 77 Learning-By-Doing rate estimates range from -17% for wind turbines between 1981 and 2000 in Europe (Neij et al., 2003) [24], to 41.5% for waste to electricity technology globally from 1990 to 1998 (Jamasb, 2007). Similarly, variability exists in the 17 Learning-by-Researching estimates. LBR rates range from 1.25% for global coal conventional technologies to 43.7% for waste to electricity technology (Jamasb, 2007). Although both specifications (one and two-factor learning curves) seem to provide a wide range of estimates, the choice of specifications is a factor generating variation in itself. Soderholm and Sundqvist (2007) address the issue of modelling specification as a major cause of variability in estimates. Using a single panel dataset of wind power in four European countries from 1986 to 2000, they allow the model specification to vary and find that the use of one or two factor learning curves changes the LBD estimates[25]. This observation is also made in Jamasb (2007). In a recent meta-analysis of learning rate estimates for wind power, Lindman and Soderholm (2012) also address this issue and confirm that

[24] Once again, some negative estimates are found in the review. Neij et al. (2003) also uses price data of wind turbines instead of costs, corresponding with the negative findings of Claeson (1999) found for GTCC power plants.
[25] Other model specifications explored in Soderholm and Sundqvist will be explored in section 2.4.

the use of single-factor learning curves tends to produce higher LBD estimates than two-factor learning-curves, as it incorrectly attributes some costs reductions from R&D to experience accumulation.

2.3. Different learning rates for different phases of technological maturity?

The time period covered in the data has also been identified as a major source of variations in estimates. McDonald and Schrattenholzer (2001) and Kahouli-Brahmi (2008) report different estimates for the same technologies over different time periods. For instance, MacGregor et al. (1991) find a decrease in learning rates for gas turbines between 1958 and 1990. They find a rapid learning rate of 22% between 1958 and 1963, and a 9.9% learning rate between 1963 and 1980. McDonald and Schrattenholzer (2001) attributes part of the variation in LBD rates between time periods to the possibility that experience depreciates over time. According to this argument, as technologies mature with time, lower gains from learning-by-doing are available. Jamasb (2007) furthers this argument taking into consideration both the LBD and LBR effects. Referring to the different stages of the technological change process from Schumpeter (1942), as well as the demand-pull vs. supply-push debate, the paper points out that LBD and LBR rates differ at different stages of technology maturity. Using a two-factor learning curve model, Jamasb (2007) differentiates between 12 technologies according to their “perceived” level of technological development. The technologies are broadly classified into 4 stages of development: Emerging (solar thermal and off-shore wind power), evolving (nuclear power, waste to electricity and onshore wind power), mature (supercritical coal, conventional coal, lignite, GTCC from 1990-1998 and large hydropower) and reviving technologies

(GTCC 1980-1989[26], CHP and small hydropower). Using this classification, he finds significantly different LBD and LBR rates for technologies at different stages of maturity. The estimations show that both emerging technologies and mature technologies exhibit low LBD and LBR rates, suggesting that technological change is more difficult at very early and very late stages of the technology development process. In contrast, evolving technologies display high LBD and LBR rates signifying that opportunities for future development promotes technological progress through both increases in experience and R&D expenditures. Finally, reviving technologies exhibit low LBD rates but high LBR rates. These findings are reported from Jamasb (2007) in Table 3.1.

Table 3.1: Technology maturity and learning rates

Development Stage, Learning Rate, Capital Intensity, and Market Opportunity for the Technology Categories

	Learning by Doing	Learning by Research
Mature technologies	Low	Low
Reviving technologies	Low	High
Evolving technologies	High	High
Emerging technologies	Low	Low

Source: Jamasb (2007) The Energy Journal

These findings have important implications for both the econometric and modelling literature. The current specification of the learning curve (whether it is one or two factor learning curves) does not allow for time-varying learning rates. This specification suggests that as long as experience increases, cost reductions are achievable, without bounds, which is likely impossible in industries. Jamasb (2007)

[26] The combined cycle gas turbines data was separated into two technologies due to the existence of a structural break in the data (Jamasb, 2007).

confirmed that once technologies have entered the evolving phase, the learning opportunities for these technologies might reduce in the future. These findings advocate in favour of an alternative functional form that would introduce more flexibility in the learning-by-doing behaviour.

2.4. The choice of performance and experience indicators

Another important observation on the econometric estimation of learning rates was identified in McDonald and Schrattenholzer (2001). They point out that variations in the estimates are likely to be caused by differences in the choice of performance and experience indicators. In the context of the learning curve, a performance indicator refers to the variable affected by technological change (e.g. technology costs or price) while an experience indicator refers to the variable embodying experience accumulation (e.g. cumulative production, cumulative capacity). In the econometric studies of learning rates, the performance indicator is the dependent variable while the experience indicator is the independent variable.

In terms of performance indicators, econometric studies cited in the reviews tend to use either cost measures or price measures. Cost measures include technology investment costs in $/kW of installed capacity (see for example Kouvaritakis et al., 2000; Klaassen et al., 2005; Jamasb, 2007; or Soderholm and Klaassen, 2007) or production costs in $/kWh of electricity production (see for example Wene, 2000; IEA, 2000; Ibenholt, 2002; and Neij et al., 2003). Price measures, such as the technology price in $/kW for investment in new capacity (see for example Claeson, 1999 and Neij, 2003) or the sale price of electricity generated in $/kWh (see for example Fisher, 1974 or IEA, 2000), are used as a proxy for technology costs and are less commonly used.

In terms of experience indicators, most econometric studies have used one of two main options. Some papers use cumulative installed capacity in MW, as it embodies investments in new capital goods, e.g. new wind turbine or a new gas power plant. Examples of such studies are numerous and include MacGregor et al. (1991); Kouvaritakis et al. (2000); Klaassen et al. (2005); Jamasb (2007); and Soderholm & Klaassen (2007). Other studies have used cumulative production in TWh, embodying the experience in producing electricity using one technology. Examples of these studies include Fisher (1974); IEA (2000); and Wene (2000). Fewer studies have also represented experience using cumulative sales of electricity (for example Solar PV estimates in IEA, 2000). In these studies, performance and experience indicators are closely linked. Studies using investment costs or price in new capacity usually chose cumulative capacity to embody experience, while studies using production costs or prices to represent performance generally use cumulative production to embody experience[27].

Recent papers (since 2005) and interestingly most studies considering two-factor learning curves, have used investment costs ($/kW) as a measure of technological progress and cumulative capacity as a measure of experience. McDonald and Schrattenholzer (2001) observe that using production costs and cumulative production leads to higher learning rate estimates than when using investment costs and cumulative capacity. For example, IEA (2000) estimates LBD rates for wind

[27] Studies using production price for a performance measure can sometimes use cumulative sales to represent experience (IEA, 2000).

power both with production costs and cumulative production (32% for the US and 18% for the EU) and investment costs and cumulative capacity (8% for Germany and 4% for Denmark). Production costs decrease faster with cumulative production than investment costs with cumulative capacity.

2.5. Other issues with econometric estimation

Other issues have been raised recently with regards to the econometric estimation of learning rates for energy technologies. These issues have been recognised to be factors in the variability of the learning rate estimates and are often cited as weaknesses of the learning curve estimation. Two major issues are explored in this section: omitted variable bias and the endogeneity problem.

Soderholm and Sundqvist (2007) suggest that omitted variable bias is a major problem in the estimation of the learning rates for wind power[28]. They suggest the existence of other explanatory variables such as input prices and scale effects. Isoard and Soria (2001) first explore the implications of differentiating between economies of scale and learning-by-doing for energy technologies. They refer to returns to scale as a short-term issue as they change with changes in output, whereas learning effects are long-term issues, since they shift the production possibility frontier. Both Isoard and Soria (2001) then Soderholm and Sundqvist (2007) derive a Cobb-Douglas cost function in which advances in technology are determined through a three-factor learning curve. This enables them to introduce scale effects in the regression model.

[28] In econometrics, if an independent variable with a non-zero coefficient is excluded from a regression model but is correlated with any of the other variable in the model, then the coefficients estimates are biased.

They obtain a logarithmic econometric specification of the Cobb-Douglas cost function as shown in equation 3.7:

$$\ln(C_t) = \ln(C_0) - \alpha \ln(G) - \beta \ln(H_t) + \mu Q_t + \varepsilon \tag{3.7}$$

Where α and β are the LBD and LBR elasticity parameters respectively, and γ is an unknown parameter representing $\mu = \frac{1-r}{r}$ where r is the return to scale parameter. Q_t is the level of output at time t. In the case of constant returns to scale $r = 1$, $\mu = 0$ and the model returns to a simple two-factor learning curve.

Soderholm and Sundqvist (2007) find a negative μ estimate implying increasing returns to scale. The introduction of the scale effect is found to be significant at the 1% level when added to the one-factor learning curve and the LBD rate decreases from 5% (without scale effects) to 1.8% (with scale effects). However, in the two-factor learning curve they find that the addition of scale effects is not significant. They also explore the impact of another omitted variable on the model, namely prices. In their study for wind technology, they add a variable to the regression model in equation 3.7, representing feed-in tariffs set by policy-makers[29]. They find this new variable to be statistically significant and the associated coefficient to be positive. This signifies that an increase in feed-in prices lead to increases in technology costs. This may be due to wind power generator receiving higher tariffs that gives them an incentive to choose less favourable sites or to the decrease in competition leading to less cost reduction efforts.

[29] Their analysis is restricted to wind energy technology in four countries, where the feed-in price (received by wind electricity generators) is determined either in a fixed tariffs system (Denmark, Germany, Spain) or a competitive bid system (UK).

Another issue raised by Soderholm and Sundqvist (2007) is the presence of endogeneity in the regression model. Cumulative capacity does not only reduce investment costs through LBD, it is also likely to be influenced by investment costs as well, so that its inclusion as an experience indicator creates a potential endogeneity problem. As investment costs decrease, more capacity will be installed, while more capacity leads to decreases in costs. Using Instrumental Variable (IV) estimation to counteract endogeneity, they find higher LBD rates and lower LBR rates than previously. In parallel to this research, Soderholm and Klaassen (2007) and Jamasb (2007) deal with the endogeneity problem by using a system of simultaneous equations; they introduce the concept of a diffusion equation which would be simultaneously solved with the learning curve. Soderholm and Klaassen (2007) introduce a diffusion equation where cumulative capacity is determined by the investment cost (per KW), the feed-in price for wind power, the price of coal as input for electricity production and finally a variable representing the "legal" or policy environment towards the technology[30]. Using the same two-factor learning curve model as Soderholm and Sundqvist (2007), they find a LBD rate of 3.1% and a LBR rate of 13.2% which are both smaller than previously reported estimates.

Jamasb (2007) uses a slightly different diffusion model where the capacity is determined by the investment costs (per kW) and a time trend only. This issue of the time trend, also raised by Papineau (2005) and Soderholm and Sundqvist (2007), relates to the importance of separating the effects of learning from the effects of time on technological change. The latter find that including a time trend significantly impacts on the LBR rates whereas it has little impact on LBD rates. However, in the

[30] This "environment" variable is hard to quantify and therefore the amount of government R&D spending on each technology is used as a proxy (Soderholm and Klaassen, 2007).

meta-analysis of learning rates for wind power estimations, Lindman and Soderholm (2012) find that the inclusion of the time trend does not significantly explain variations in estimates.

2.6. Summary

Energy technologies have been the object of many recent econometric studies attempting to estimate technological change through learning effects. The estimates produced by these studies vary across technologies according to their level of technological development, but they also vary across studies looking at the same technology. These variations have been explained through differences in estimation models, different time periods and geographical scope as well as differences in the variables and definitions used. Despite the large consensus that learning rates may vary across a technology's life-cycle, no dynamic estimation model has been proposed to address this issue. Similarly, the role of spillovers (both geographical and between technologies) has not yet been properly addressed[31].

Despite the econometric issues associated with estimating the learning rates, the Energy-Economy-Environment (EEE) modelling literature has implemented endogenous learning curves and used the estimates to calibrate models. The next section of this chapter reviews the EEE modelling literature that has implemented learning curves. It identifies several forms of learning curves which reflect some of the issues addressed in this section.

[31] Soderholm and Klaassen (2007) propose a first attempt at quantifying the impact of R&D spillovers on costs reductions. They report statistically insignificant results but a lack of data limits their analysis.

3. Learning-by-doing in Energy-Economy-Environment models

As noted in the literature review of Chapter 2, Energy-Economy-Environment (EEE) models have recently transitioned from modelling innovations exogenously to introducing endogenous specifications of technological change. Two methods have been the most commonly applied to represent technological change in models: R&D-driven knowledge accumulation and Learning-by-doing (LBD). As noted previously, the choice of preferred method mostly depends on the theoretical foundations of the model. Bottom-up models, which are developed in the engineering literature, tend to introduce LBD technological change due to its strong empirical foundations, while R&D-technological change is preferred by top-down models influenced by the macroeconomic endogenous growth literature.

However, LBD has increasingly been implemented in top-down models as well, in response to numerous studies showing its crucial role in technology development. LBD is currently the most popular method to represent technological change in EEE models, as can be explained by the simplicity of LBD in its original functional form. The implementation of LBD in EEE models is the focus of this chapter. Although most bottom-up models have introduced the simple learning curve specification described above, this specification can pose theoretical, methodological and computational problems for some models. In particular, some top-down models modify the traditional R&D technological change process to accommodate endogenous LBD, modifying the LBD function itself. This section reviews the modelling literature of all types, which have introduced LBD. In doing so, it identifies the major variations in LBD specifications and their origins in the modelling literature.

3.1. Traditional learning curves origins in engineering models

3.1.1. First Bottom-up models with LBD

Because of their high degree of technological detail on the energy system, bottom-up models have been the preferred tool for the analysis of energy policy instruments that target specific technologies. They have also been the first models to integrate learning-by-doing as an endogenous feature. The first bottom-up model to introduce LBD is the MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) developed by Messner (1997) and Grübler and Messner (1998). In this dynamic linear model of the energy system, the objective function minimises the sum of discounted overall costs of the energy system. Using the traditional learning curve, MESSAGE introduces endogenous technological change, as follows:

$$C_t = C_0.(CC_t)^{-\alpha} \tag{3.8}$$

Where C_t represent investment costs of the technology, C_0 represent the costs of the first unit, CC_t is the cumulative installed capacity and α is the learning elasticity. Investment costs are a decreasing exponential function of cumulative experience embodied here in cumulative installed capacity. This corresponds to the major one-factor learning curve model used in the econometric literature estimating learning rates for energy technologies, as shown in equation 3.1 previously.

Introducing this LBD specification for six energy technologies at stages of different technological development (Advanced Coal, Gas combined cycle, Nuclear, Wind, PV and Solar thermal), Messner (1997) shows that early investments in new energy technologies are needed in order to lower the overall costs of the energy system. Messner (1997) concludes that the traditional "backstop" technology modelling method, which assumes that a low-cost technology will become available at some point in time without requiring upfront investments, is misleading for policy analysis. Furthermore, early investments in new technologies are crucial to realise their technological improvement potential. Grübler and Messner (1998) subsequently use the MESSAGE model with endogenous learning in a climate policy context. Their simulations explore the emission adjustment paths to a few IPCC scenarios with CO2 concentration limits, and the results confirm that early investment in demonstration of new technologies is a requirement to meet long-term emission targets at lower costs.

Following this advancement in the MESSAGE model, other bottom-up models have adopted this specification of LBD. Mattsson and Wene (1997) introduce LBD technological change in another engineering model of the energy sector. In the GENIE model (Global ENergy system with Internalized Experience curves), the objective is the cost-minimization of the global energy system; and learning curves are applied to photovoltaic and fuel cells technologies. The best of the known solution is identified, where advanced coal and GTCC dominate electricity production. This results in the quadrupling of CO2 emissions from 1995 levels, illustrating the risk of technology lock-in, which could prevent emerging technologies from gaining experience through investments and significantly penetrating the energy mix. A CO2-constrained scenario is also presented, PV and fuel cells dominate electricity production, but with an increase in the overall costs of the energy system. However results show that in this scenario, the costs of fuel cells and PV are considerably reduced through earlier investments in capacity.

In parallel to the MESSAGE and GENIE models, applications of the MARKAL model (acronym for MARKet ALlocation) also introduced endogenous learning curves (Baretto and Kypreos, 1998 and Seebregts et al., 1998; 2000). Seebregts et al. (1998) present a European version of MARKAL with 15 European Union countries and 500 energy technologies and processes. In the majority of scenarios analysed, LBD is endogenized for only 3 key technologies[32] (on-shore wind, fuel cells and solar cells) to limit the impact of endogenous LBD on the model results. The same learning curve described above is used. Several scenarios with and without learning are run introducing a CO2 emission limit or a carbon tax. There are compared to a base case scenario, where growing environmental concerns only displace a comparatively limited amount of polluting and energy-intensive industries. In the base case scenario, two of the three key technologies do not penetrate the system significantly if LBD is not present (fuel and solar cells). Results also show that, in the presence of learning, technologies with high costs but with previously limited applications tend to get installed to their maximum capacity levels to optimally exploit the costs reduction potential, leading to cases of technology “lock-in” (e.g. PV). But if the investments do not start in the short term due to competitiveness issues, then this can lead to long-term technological “lock-out” (e.g. fuel cells).

[32] “Key technologies” are defined as technologies that are “clearly distinctive with respect to the energy conversion process” (Seebregts et al., 1998 p. 41). These key technologies can each have numerous applications, e.g. 20 different types of heat pumps, heat pump being a key technology.

3.1.2. Further advancements with hybrid models

Hybrid bottom-up/top-down models have also adopted this "traditional" learning curve specification. This choice is motivated by the method used to construct them: they typically incorporate the technological details of the energy system from bottom-up models into top-down macro-economic frameworks. In an example of such model, Kypreos and Bahn (2003) and Manne and Richels (2004) develop MERGE-ETL (Model for Estimating the Regional and Global Effects of greenhouse gas reductions with Endogenous Technology Learning). MERGE-ETL is specifically designed to clarify the role of LBD with respect to the choice of CO2 abatement policy. MERGE links nine regions of the world, each represented by an individual bottom-up energy system model, into a global macro-economic growth model. Endogenous technological change is represented by a traditional learning curve for 8 technologies in the bottom-up part of the model.

Bahn and Kypreos (2003) compare different CO2 limit scenarios, with and without learning, and find that LBD reduces energy production costs over time: the energy factor becomes cheaper compared to capital and labour, as the capacity of learning technologies builds up. In terms of the economic impact of CO2 policy, results show that LBD reduces the GDP losses from CO2 constraints, and the tougher the constraint, the larger the benefits from LBD.

Manne and Richels (2004) use a later version of MERGE where a traditional learning curve is implemented on a non-defined energy technology entering the system in later years (backstop). The model is used to compare CO2 abatement scenarios where constraints are imposed on the LBD technology, in terms of its potential for cost reductions and for expansion. Results show that with high cost reduction potential and no expansion constraints, the CO2 emission pathway is lower than otherwise. In terms of the costs of CO2 abatement, LBD is found to substantially reduce the overall costs of the transition to the CO2 constraint.

Another example of hybrid model is MESSAGE-MACRO (Rao et al., 2006), which combines a version of the MESSAGE model described above with LBD, with the MACRO top-down framework also used in MERGE (endogenous growth model). Their findings confirm that LBD can lead to overall long-term costs reduction of the energy system under a carbon constraint through short-and medium-term investments in technologies with learning potential.

3.1.3. Extensions with two-factor learning curves

Some bottom-up and hybrid models have recognised the importance of R&D effort, especially in the early stages of a technology development. These models have extended the traditional specification of LBD in order to represent two-factor learning-curves, including R&D-induced technological change, in addition to experience gains. An example of such bottom-up model is ERIS (Baretto and Kypreos, 2004 and Miketa and Schrattenholzer, 2004). ERIS (Energy Research and Investment Strategies) introduces a two-factor learning curve where costs are a decreasing function of cumulative installed capacity and knowledge stock, which grows with R&D investments and depreciates over time.

With a two-factor learning curve applied to wind and photovoltaic energy, Miketa and Schrattenholzer (2004) look at both the optimal R&D expenditures and capacity deployment for each technology in two scenarios: one in a world where there is no constraints on total R&D expenditures, and the other where the technologies are competing for R&D. They find that in the non R&D-constrained world, R&D expenditures increase late in the technology development phase, because R&D is better utilised when a market is already established for the technology. Interestingly, in the R&D-competition case, neither technological lock-in nor crowding-out (where one technology crowds-out the other by being attributed most of the finite R&D expenditure supply) occurs. R&D expenditures are found to lead to overall energy system costs reductions compared to the case without opportunity for R&D.

Most of the models (bottom-up and hybrid) described above focus on total system costs under climate change policy constraints and confirm that introducing learning curves for energy technologies can drastically change the costs of abatement policies and change the time paths of renewable technology diffusion.

3.1.4. Top-Down models with traditional learning curves

A few top-down economic models have been influenced by the engineering approach to energy modelling and have introduced LBD using the same traditional learning curve specification as bottom-up models. Van der Zwaan et al. (2002) develop the DEMETER model (DE-carbonisation Model with Endogenous Technologies for Emission Reductions). This study presents a global macroeconomic model of climate change, where fossil and non-fossil energy inputs enter a CES production function of consumer goods. Learning curves are implemented in both energy sectors, through which cumulative capacity leads to costs reductions in both investments in new capital and maintenance and operation efforts; although the costs reduction potential is assumed much more limited for fossil-fuel than non-fossil-fuel energy. Alternative scenarios are designed: with targets for global temperature increase, corresponding to CO2 concentration limits, with and without endogenous learning and with endogenous or exogenous energy demand. The results largely confirm the conclusions of bottom-up models, that the presence of LBD leads to earlier emission abatement to meet the imposed carbon constraints and also reduces the overall costs of compliance.

MIND (Model of INvestment and technological Development, Edenhofer et al., 2005, 2006) is another example of top-down model with endogenous learning in a renewable and non-renewable energy sectors. In MIND, learning occurs as a side effect of extraction activities in the fossil-fuel sector and as a function of cumulative capacity in the renewable energy sector. Findings show that the introduction of endogenous technological change reduces the costs of climate change mitigation; LBD reduces the losses in global welfare from carbon constraints.

All the models described in this section have used the empirically derived specification of the learning curve, where specific investment costs for technologies are a decreasing function of cumulative installed capacity; while a few have used a two-factor learning curve specification. These models confirm that introducing endogenous technological change leads to earlier investments in cleaner technologies and reduce the overall costs of the energy system.

However an alternative specification of LBD has been applied in EEE models, emerging from the top-down economic literature, influenced by the emergence of endogenous growth theory in macroeconomics. This is explored in details next.

3.2. The influence of Endogenous Growth theory on Learning-by-Doing

The link between economic theory and the treatment of endogenous technological change in top-down models is strong. This has led to the development of new specifications for learning-by-doing, based on the principles advocated in the endogenous growth literature.

3.2.1. Endogenous Growth Theory and R&D

Informed by the extensive economic theory literature of endogenous growth (Romer, 1990; Lucas, 1988; Aghion and Howitt, 1992; Grossman and Helpman, 1994; Jones, 1995), early top-down models with endogenous technological change focus on the effects of R&D spending on knowledge accumulation (Loschel, 2002). In contrast to the traditional neoclassical growth models with exogenous technological change and diminishing returns to capital, new endogenous growth theory treats innovation as an economic activity in and of itself, resulting from private profit-maximizing decisions. Generally, the stock of knowledge (representing the level of technology in the production function) accumulates over time through the use of a separate "knowledge" sector production function, as formally described in Chapter 2, and shown again in equation 3.9 below:

$$\dot{A}_t = B[(1-a_K)K_t]^{\beta}[(1-a_L)L_t]^{\gamma}A_t^{\phi} \tag{3.9}$$

Knowledge, or efficiency, A_t grows in every period through a production (accumulation) function, depending on the shares of labour and capital stocks devoted to research activities. Thus, technological change is dependent on the allocation of capital and labour between R&D and output. Another important concept is that of “returns to knowledge”. The value of the ϕ exponent determines the influence of the stock of knowledge on the accumulation of new knowledge and embodies returns to knowledge. In the simplifying case $\phi = 0$, the creation of new ideas is independent of the past stock of knowledge. If $\phi > 0$, there are positive external returns to knowledge, i.e., idea creation is made easier by previous accumulation of knowledge. This concept is commonly referred to as “standing-on-shoulders”. Finally if $\phi < 0$, there are negative external returns to knowledge; the so-called situation of “fishing-out”, where the pool of knowledge is considered finite, thus any past advancements renders future accumulation harder. Technology (knowledge) is voluntarily treated as non-rival in this theory, and it enters both the R&D and general production function entirely, creating the potential for infinite growth.

Influenced by the prevalence of such economic models in the 1990s, early models of climate change and policy have introduced endogenous technological change through an R&D production function. These models have different objectives than traditional engineering energy models, and focus on the environmental and economic impact of technological change. A number of these models were cited in Section 4.3 of Chapter 2. Because the focus of this chapter is learning-by-doing, these models are not listed here. However, their influence on top-down models with LBD is crucial, and this is discussed in the next section.

3.2.2. Introducing Learning-by-Doing in R&D models

Goulder and Mathai (2000) is the first example in the literature of EEE top-down models which combines the R&D approach with LBD. In a partial equilibrium model of knowledge accumulation with a central planner, this paper examines two specifications for endogenous technological change, where increases in the stock of knowledge in general, reduce the costs of emission abatement activities sector. In the first specification, the stock of knowledge is an increasing function of investments in R&D. In the LBD case, the stock of knowledge is an increasing function of the abatement activities themselves (reflecting this idea of costs reduction associated with experience). In an effort for consistency in the analysis, they introduce both R&D and LBD technological change in the same knowledge accumulation function where "standing on shoulders" occurs.

This treatment of LBD is different from the traditional learning curve as LBD is effectively treated as a knowledge production function increasing the knowledge stock in each period. Importantly, the production of new knowledge from learning effects is dependent on previous levels of learning-by-doing (here "standing-on-shoulders" occurs[33]). Goulder and Mathai (2000) explore analytically and numerically both specifications under two central planner objective functions: a cost-effectiveness criterion (obtaining and maintaining a given level of atmospheric CO2 concentration at the lowest cost) and a benefit-cost criterion (where the concentration target is set endogenously to optimise the trade-off between benefits from carbon abatement and costs of abatement). The paper finds that including R&D or LBD technological change reduces the overall costs of reaching a concentration target and reduces the optimal carbon tax. The results also point out that the presence of LBD and R&D technological change leads to larger abatement efforts (in the benefit-cost criterion) than otherwise. Finally, they find that despite an overall increase in

[33] They also conduct a sensitivity analysis on the case of "fishing-out" and find as expected that the effects of technological change on the results are diminished.

abatement efforts, the R&D technological change leads to delayed abatement due to the potential for costs reductions in the future.

3.2.3. A new approach to learning from Endogenous Growth Theory

In the spirit of Goulder and Mathai (2000), other models have introduced LBD as a stock-updating production function. Rasmussen (2001) presents a multi-sectoral general equilibrium model for Denmark to examine the influence of learning-by-doing in renewable energy technologies. Renewable energy is represented in two sectors: a renewable energy production sector and a renewable energy capital supply sector. Learning affects the production function of the renewable energy capital sector, through technological improvements in the productivity of inputs. In this way, technological change is only embodied in new vintages of capital. The stock of knowledge, embodying input productivity, is increased (updated) every period, as a function of the renewable capital sector production in that period. Like Goulder and Mathai (2000), knowledge is also affected by previous knowledge stock, but in Rasmussen (2001) it corresponds to the case of fishing-out, where past accumulation in the knowledge stock lead to less technological change potential in the future.

This paper compares a business-as-usual scenario, with a CO2 abatement scenario (where a cap and trade of emission is set up to be consistent with the Danish commitments to the Kyoto Protocol). Both scenarios are run with and without endogenous LBD. Including LBD for energy technology is found to significantly reduce the total welfare costs of CO2 abatement. Rasmussen (2001) also finds that including LBD leads to less short-term abatement efforts and less short-term investments in the renewable sector, which seems to contradict models with traditional learning curves but confirm Goulder and Mathai (2000) findings with

R&D technological change. This delayed abatement is explained by the tendency of forward-looking firms to postpone their investments since the costs of renewable energy will reduce in the future. Rasmussen (2001) also observes that because of the formulation chosen for LBD with strong diminishing returns, the long term impact of technological change on productivity growth is not very sensitive to abatement efforts.

Castelnuovo et al. (2005) propose a modification to the original RICE model (Nordhaus and Yang, 1996), in which learning occurs directly in the production function. Following the idea of Goulder and Mathai (2000), Castelnuovo et al. (2005) investigate technological change with two formulations: one with R&D expenditure augmenting a knowledge stock and the other one with LBD. Alternative formulations are included directly in the production function. In the case of R&D-driven technological change, the knowledge stock increases the productivity of both labour and capital factors. In contrast with LBD, increases in the capital stock raise productivity, by augmenting the output elasticity of capital by the learning elasticity in the Cobb-Douglas production function (generating increasing returns to scale). Additionally, the emissions to output ratio is also modified to be reduced with R&D or LBD knowledge. The model is divided into 6 regions (USA, Japan, Europe, Former Soviet Union, China, and the Rest-of-the-World) each with a central planner that can decide the level of abatement. A business-as-usual scenario is compared with two Kyoto abatement commitment scenarios: one where trade of CO2 permits between regions is allowed and one where is it not. Each scenario is optimised under R&D and under LBD technological change specifications. Findings show that both endogenous R&D and LBD technological change reduce the costs of compliance to the Kyoto Protocol. A flexible compliance mechanism with trade is confirmed less costly than the alternative scenario. Other findings show that LBD specification leads to larger welfare losses than R&D technological change, due to the addition of one control variable (investments in R&D) in the latter case, which better redistributes abatement efforts between agents.

A different version of this LBD specification is proposed by Bosetti et al. (2006) in another extended version of the RICE model (Nordhaus and Boyer, 1999) in which they incorporate endogenous technological change from both LBD and R&D sources. In the FEEM-RICE model (Fondazione Eni Enrico Mattei), Bosetti et al. (2006) create an Energy Technological Change Index (ETCI) to embody technological progress in the production function. ETCI is an exponential function of cumulative abatement efforts and the knowledge stock, which increase period-by-period with the abatement flow and R&D expenditures respectively[34]. Increases in the ETCI raise the productivity of energy inputs in the economy-wide production function, and also enters the carbon emission function, which is linked to energy inputs into production. In contrast with the RICE model where carbon-intensity of energy input decreases exogenously over time (Boyer and Nordhaus, 2000), in FEEM-RICE, carbon intensity is a decreasing function of ETCI. Bosetti et al. (2006) compares three different carbon stabilisation scenarios optimised by the central planner, in terms of their impact in inducing technological change and their impact on GDP losses from the carbon constraint. Findings suggest that including both R&D and LBD technological change reduces the costs of compliance with carbon policy.

[34] Representing learning-by-doing and R&D technological change respectively.

In comparison with the bottom-up literature which implements a traditional learning curve, for the energy sector specifically, top-down models have been focused more largely on the costs of compliance to CO2 emission reduction policies. These models have largely been influenced by endogenous growth theory and have adopted a variety of LBD specification deriving from the concept of production of a knowledge stock. Moreover, where bottom-up models seem to provide unified conclusion about the impact of endogenizing technological change, results from top-down models are less in agreement. Although most models predict that endogenous technological change reduces the overall costs of abatement, they differ in their conclusions concerning the impact of policy measures on induced technological change. Overall, the observations made in Sections 2 and 3 confirm that the specification of the learning-by-doing phenomenon is an important determinant of modelling results. The objective of the next section is to explore and compare the alternative specifications identified in this literature, through implementing them in micro-simulations of learning-by-doing, in a partial economic model of production.

4. Micro-simulations of alternative LBD specifications

Since the representation of learning-by-doing varies between Energy-Economy-Environment models, it is likely that the choice of specification will impact simulation results. In this section, this is explored by testing the several alternative specifications identified in the previously discussed literature[35]. The objective of this section is to explore these alternative specifications of LBD in a simple micro-simulation exercise, and draw preliminary conclusions about the choice of models

[35] The differences between these specifications originate either in the review of econometric estimations of learning curves in Section 2 or in the review of models used for policy analysis which endogenize LBD in Section 3

for our subsequent chapter. Section 4.1 develops the simple partial microeconomics model of production used for this exercise. Section 4.2 identifies the alternative specifications of LBD. Section 4.3 reports and compares the results of the micro-simulations.

4.1. Choice of model

4.1.1. The Production Function

In order to provide a clear picture on the impact of LBD specification on modelling results, a simple model is chosen to represent LBD in production. One production function is represented where LBD increases the productivity of inputs. A simple Cobb-Douglas production function is chosen for this analysis. The production function is described in equation 3.10:

$$Q_t = A_t . [K_t^{\gamma_K} . L_t^{\gamma_L}] \tag{3.10}$$

In this equation, Q_t is the output of production at time t, A_t is the total factor productivity parameter, K_t and L_t are the stock of capital and labour used in production at time t respectively. γ_K and γ_L are the positive output elasticities of capital and labour respectively. Constant returns to scale in this simple modelling exercise so that $\gamma_K = 1 - \gamma_L$.

The learning-by-doing phenomenon influences the production function through the total factor productivity parameter A_t. This is an important assumption, where costs reductions from learning-by-doing are embodied in improvements in the productivity of both factors. This assumption is explained in more details in section 4.1.2.

4.1.2. Should technological progress be embodied in costs reductions or in productivity gains?

As shown in Sections 2 and 3, the variable embodying technological progress varies between different studies. Studies looking at the econometric estimation of learning curves use both production and investment costs, but have recently preferred investment costs. In the modelling literature, bottom-up engineering models are concerned with energy system costs and embody technological progress in investment costs. In contrast, economic top-down models are based on production functions, where technological progress corresponds to a change in a knowledge parameter, which improve input productivity. It is important to differentiate between these alternatives because they all technically refer to different technological improvements.

Investment costs, as used in the bottom-up engineering models, encompass all the costs associated with the installation of new capacity (planning, construction, equipment, etc…). With LBD, these investments costs reduce with cumulative experience, generally a result of installing new capacity. In bottom-up models, this LBD relationship is directly described in the cost function. In contrast, representing LBD in top-down models is more complex, as noted in Section 3. Economic models with endogenous technological change are based on foundations from growth theory and generally use production functions, where technological change is embodied in a knowledge stock. Improvements in the knowledge stock improve the productivity of inputs. More precisely, the knowledge stock can improve the productivity of capital, labour or both equally, corresponding to the Solow, Harrod and Hicks-neutral definition of technological change respectively. With input price held constant, the productivity of inputs is inversely related to cost reductions. The major distinction between investment costs in engineering models and the economic cost function is that the latter costs are influenced not only by the level of technology, but also by the prices of inputs to production.

It can be noted that the issue of technological change that is labour, capital or even energy-saving is not raised with the use of the Cobb-Douglas function. In Cobb-Douglas, improvements in either capital or labour productivity always correspond to a change in total factor productivity. This will however be relevant with a Constant Elasticity of Substitution production function, and is discussed in Chapter 4.

In the simple model used in this chapter with a Cobb-Douglas production function and constant returns to scale, the parameter embodying technological change is total factor productivity A_t. As shown in equation 3.10, increases in A_t leads to Hicks-Neutral technological change, i.e. less capital and labour are necessary to produce the same level of output (or more output can be produced using the same amount of capital and labour). It can be shown that improvements in factor productivity translate into costs reduction if the Cobb-Douglas production function is expressed as a cost function. An example formulation of the Cobb-Douglas cost function is described in Isoard and Soria (2001) and Soderholm and Sundqvist (2007).

The cost function minimises the costs of production given a specific amount of output y and a set of input prices, r and w, which embody the unit cost of capital and labour respectively. The Cobb-Douglas cost function with constant returns to scale is derived from the production function in appendix A and the final result is shown in equation 3.11.

$$C_t = y * A_t^{-1} * \left(\frac{r}{\gamma_K}\right)^{\gamma_K} * \left(\frac{w}{1-\gamma_K}\right)^{1-\gamma_K} \tag{3.11}$$

From this function, we can see that total factor productivity (TFP) A_t in inversely related to production costs. With constant input prices, the costs of producing y decrease with improvements in TFP.

4.2. Alternative Learning-by-doing specifications

Using the model described in Section 1, several alternative specifications of the LBD are explored in this Chapter. Three criteria of the specifications are identified and discussed here.

4.2.1. Equation form

The first and most important criteria for specifying LBD identified in the literature is the choice of equation form. As noted in Section 3, top-down and bottom-up models do not typically represent learning-by-doing with the same functional form. Bottom-up engineering models (and a few hybrid and top-down models) have used the traditional learning curve specification which is described (now using TFP) in equation 3.12 below:

$$A_t^n = A_0(G_t)^\alpha \tag{3.12}$$

In this equation, A_t^n is the total productivity parameter at time t, calculated with the engineering specification, A_0 is the initial value of TFP, G_t is the cumulative experience up to time t and α is the learning elasticity. This specification is derived from equation 3.1 but modified to reflect improvements in productivity rather than reductions in cost. Thus, the exponent (the learning elasticity α) is positive in this relationship, as cumulative experience increases TFP. This specification is hereafter referred to as the "engineering" learning curve[36].

The second major LBD equation form is identified in the top-down economic literature and is influenced by endogenous growth theory. This specification is based on the concept that knowledge is created during each period (like output) in a production function. This specification is represented in equation 3.13:

$$A_t^c = A_{t-1}^c + g_t^{\alpha} \tag{3.13}$$

In this equation, g_t is the flow of experience, as opposed to cumulative experience G_t in equation 3.12. A_t^c is the Total Factor Productivity (TFP) in period t, calculated with the economic specification. TFP increases in each period through a stock-updating function, with the flow of experience. This specification is hereafter referred to as the "economic" learning curve.

There major difference between these two specifications is based on the use of cumulative or flow experience. In the economic learning curve specification, the stock of knowledge A_t is increased periodically with an exponential function of the new flow of experience. In contrast, the engineering learning curve is based on an exponential function of the cumulative experience recalculated in every period. This distinction leads to large differences in results when using the engineering or the economic learning curves. This is explored in section 4.3.1.

[36] The engineering learning curve is the only specification used in the econometric literature to estimate the learning rates. The estimated learning rates applied to alternative functional forms are taken from this literature, and could be inappropriate in these cases, but we are restricted by existing estimates.

4.2.2. Returns to knowledge

As discussed in the literature review, the concept of learning-by-doing has been adapted to top-down economic models through a new definition of the learning curve and a new equation form. So far, the economic learning curve was defined without returns to knowledge. In other words, the past stock of knowledge, embodied in the TFP level of the previous period did not impact the accumulation of new knowledge.

This specification can be tested in comparison to alternatives, by modifying equation 3.13 to introduce the influence of past knowledge on the accumulation of new knowledge. This can be seen in equation 3.14.

$$A_t^c = A_{t-1}^c + g_t^\alpha . \left(A_{t-1}^c\right)^\phi \tag{3.14}$$

In this equation adapted from the Top-Down EEE modelling literature from Section 3, the past stock of knowledge (or level of TFP) influences the accumulation of new knowledge, according to the parameter ϕ. This parameter represents the returns-to-knowledge parameter. Three possibilities are explored in this chapter:

- If $\phi = 0$, equation 3.14 can be simplified back to 3.13. The past level of technological change does not influence the accumulation of new knowledge. Therefore, the returns to knowledge are constant.

- If $\phi < 0$, the past level of technological change influences the accumulative of new knowledge negatively. This is referred to as “fishing-out”. This situation represents a case where there is a finite amount of TFP gains to be achieved, and the more learning is achieved in the past, the more difficult it becomes to improve TFP.

- If $\phi > 0$, the past level of productivity has a positive influence on the accumulation of learning effects. This is referred to as "standing-on-shoulders". This situation occurs when past experience gains improves the feasibility of future TFP gains. The more improvements in TFP which occurred in the past, the more TFP improves with experience. These three alternative specifications are compared in micro-simulations in section 4.3.2.

4.2.3. Experience proxy

As noted in Sections 2 and 3, early definitions of learning curves focus on the empirical relationship between unit costs of production and cumulative production. Following work by Arrow (1962) exploring the economic implications of LBD, investment in new capacity is a preferred measure of experience, as Arrow argues that technological progress is embodied in new capital stock.

The distinction between production and capital as a proxy for experience is crucial for some models. For multi-period Computable General Equilibrium (CGE) models for example, this distinction matters greatly. In such models with price substitution, production of one sector is driven by the demand for this sector's output. In the absence of a shock in the model, sectoral production continues at its current level in each period. This leads to a steady increase in cumulative production over time. In contrast, in the absence of a shock, investment in new capital stock only occurs to replace depreciated capital. Capital stock does not increase. Thus, whether cumulative experience is represented by cumulative production or by capital stock will matter for the model results.

Finally, an additional distinction can be made between capital stock and cumulative investments. Capital stock takes into consideration the depreciation of capital. Using capital stock as cumulative experience is equivalent to depreciating experience itself. Such depreciation would correspond in a certain level of forgetting (vs. learning) by doing. Depreciation of knowledge in energy sectors has been documented in the past. Nemet (2012) finds that knowledge acquired from experience in installing and operating wind farms loses its value overtime, suggesting the existence of knowledge depreciation in the context of learning-by-doing. Grübler and Nemet (2012) also review the literature for evidence of knowledge depreciation in industries, and particularly in energy industries such as nuclear power. They associate knowledge depreciation to two main phenomena: "innovation-driven technological obsolescence"[37] and the turnover of knowledge holders in organisations and sectors (human capital volatility)[38]. While the authors acknowledge that learning-by-doing knowledge can be subject to depreciation, this has seldom been tested in the context of learning-by-doing in energy sectors.

Three alternative definition of experience are explored and modelled in this section: experience as cumulative gross investment, cumulative production and capital stock. The results will be discussed in section 4.3.3.

4.3. Results

This section presents the results of the micro-simulations using the model listed in Section 4.1 and alternative specifications identified in Section 4.2. The simulations are run using excel for 20 periods. For each simulation, two sets of results are

[37] New investments are made to replace old capital, some knowledge previously accumulated is lost, as capital vintages become obsolete.
[38] Particularly important when a technology relies heavily on tacit knowledge from individuals

presented graphically, reporting the percentage change from the base value in total factor productivity A_t and the level of output Q_t. Because quantitative results are not the objective of this section, the use of percentage change from base value is justified. Rather, the micro-simulations are meant to provide qualitative comparisons between specifications.

In terms of parameters for the production function, we assume no increase in the labour force ($L_t = \bar{L}$), a depreciation rate of capital δ of 0.1 where the capital stock increases with gross investment $\bar{g}$. The base values of $A_{t,}$ K_t, L_t and Q_t are all set equal to 1 in period 0. The output elasticity of labour is equal to the output elasticity of capital and their sum is equal to 1 (corresponding to constant returns to scale, with $\gamma_K = \gamma_L = 0.5$). In all simulations, gross investments in each period are constant ($\bar{g} = 2$), thus cumulative gross investments grow at a constant rate. While A_t is endogenous, these parameters are kept constant, to compare specifications based only on the modifications of the LBD function identified in the previous section, which determine the behaviour of total factor productivity. Unless stated otherwise, the default learning elasticity parameter is 0.322. This corresponds to a learning rate LR=20%[39], which is a standard learning rate used in the literature[40].

The next three sections compare the LBD specifications according to the criteria described previously, i.e. the equation form (engineering or economic learning curve), the returns to knowledge (constant, increasing or decreasing) and finally the

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[39] The learning rate corresponds to the percentage costs reduction for every doubling of cumulative experience. It is calculated using the learning elasticity using equation 3.2.
[40] Although recent LR estimations using two-factor learning curves tend to produce estimates of LBD smaller than 20%.

choice of experience proxy (cumulative gross investment, capital stock or cumulative output).

4.3.1. Equation form

This section explores the differences between the two LBD equation forms, namely the engineering learning curve and the economic learning curve. The two functions in equation 3.12 and 3.13 are restated in Table 3.2 below for convenience.

Table 3.2: Engineering and Economic Learning Curves

	Engineering	**Economic**
A_t as a function of experience embodied in gross investment g	$A_t^n = A_0\left(\sum_{i=0}^{t} g_i\right)^{\alpha}$	$A_t^c = A_0 + \sum_{i=0}^{t}(g_i^{\alpha})$
With constant gross investment ($g_1 = g_2 = g_t = \bar{g}$)	$A_t^n = A_0(t.\overline{g})^{\alpha}$	$A_t^c = A_0 + t\,.(\overline{g}^{\,\alpha})$
Calibrating A_0 so that $A_0^n = 1$ and $A_0^c = 0$, we find	$A_1^n = (g_1)^{\alpha}$	$A_1^c = (g_1^{\alpha})$

The two specifications can be simplified to express A_t as a function of the constant gross investment. Comparing the two newly found expressions, several observations can be made. First, using the same value for the learning elasticity α leads to different learning rates in the two specifications. The use of learning elasticity estimates computed with the traditional engineering learning curve in the economic learning curve specification might lead to over or under-estimation of the learning rates[41]. The second observation is the difference in exponential form for these two models. The engineering learning curve is essentially a power function of the sum of gross investment, while the economic learning curve is a sum function of powered terms. This distinction leads to drastic differences in the behaviour of these two functions depending on the value of the exponent (namely, the learning elasticity).

Thus, in order to compare these equations, two sets of results are presented, using two values of the learning elasticity, either smaller or larger than 1. If $\alpha = 1$, both functions follow the same linear growth with the economic TFP value being always superior to the engineering TFP by the value of A_0. If $\alpha > 1$, the engineering learning curve leads to exponential increases in TFP (convex pattern), while the economic learning curve still leads to linear increases in TFP. When $\alpha < 1$, the increase in TFP with the engineering learning curve follows a concave pattern, while the economic learning curve still leads to a linear increase in TFP. The economic specification will always lead to lower level of TFP than the engineering learning curve when $\alpha > 1$, while it will always lead to larger value of TFP when $\alpha < 1$.

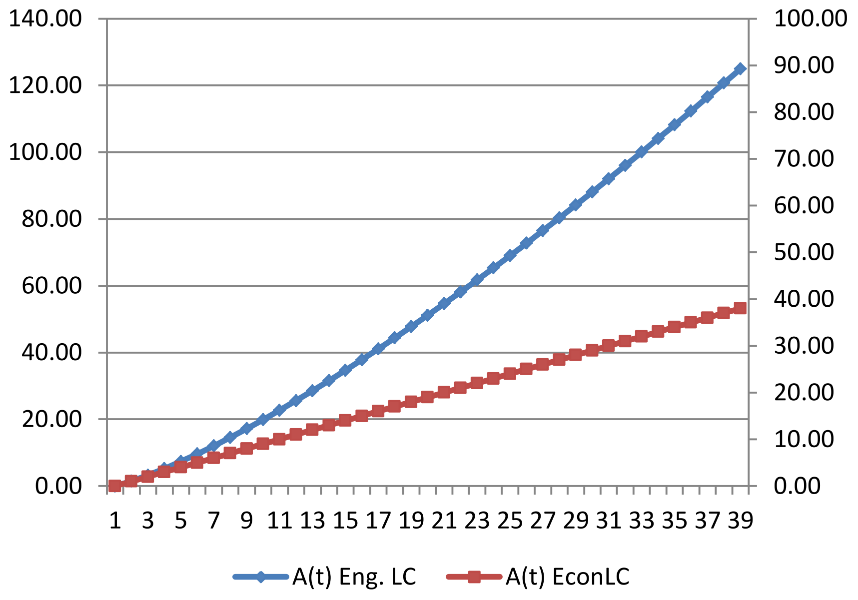
These analytical observations are better verified graphically using micro-simulations. Two values of alpha are chosen for the modelling: $\alpha = 0.32$ corresponds to a standard learning rate of 20%, while $\alpha = 1.32$ corresponds to a large learning rate of 60%.

Figures 3.1 and 3.2 represent the evolution of TFP in terms of percentage change from their base value, when $\alpha > 1$ and $\alpha < 1$, respectively. These graphs confirm that, given constant investment, the economic learning curve produces a linear increase in TFP regardless of the value of α. In contrast, the engineering specification of the

[41] However, since there are no estimates using the economic specifications in the literature, we are constrained to use the available ones.

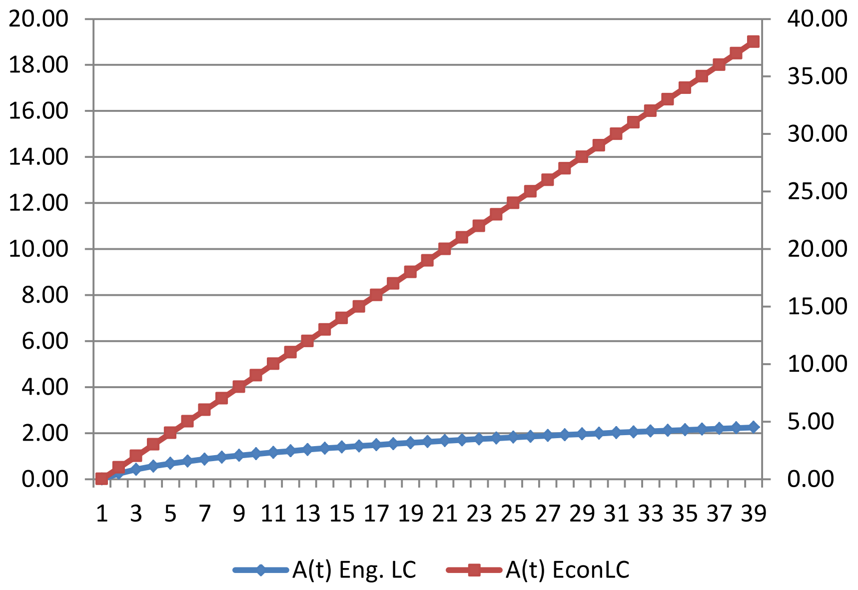
learning curve leads to either a convex increase in TFP when α > 1 in Figure 3.1 or a concave increase in TFP when α < 1 in Figure 3.2.

Figure 3.1: Percent Change in TFP with alpha =1.32.



Note: A_t^c is represented on the secondary axis

Figure 3.2: Percent change in TFP with alpha = 0.32



Note: A_t^c is represented on the secondary axis

The economic specification imposes a linear relationship with constant gross investment, while the engineering specification offers more flexibility, and linearity as a special case.

Another important finding is the influence of the TFP specification on the output results. The output functions are shown in Table 3.3 as a function of each of the two TFP specifications.

Table 3.3: Output

	Engineering	**Economic**
Output function Q_t as a function of TFP, K_t and L_t	$Q_t^n = (t.\bar{g})^{\alpha}.(L_t)^{\frac{1}{2}}.(K_t)^{\frac{1}{2}}$	$Q_t^c = (1 + t.(\bar{g})^{\alpha}).(L_t)^{\frac{1}{2}}.(K_t)^{\frac{1}{2}}$

Output is an increasing function in TFP, labour and capital. While in our case labour is fixed, the capital stock increases with constant gross investment $\bar{g}$, so output increases in both TFP and Capital Stock until K reaches a threshold, where gross investment is equal to the depreciation of the capital stock, expressed as: $K^* = \bar{g}/\delta$.

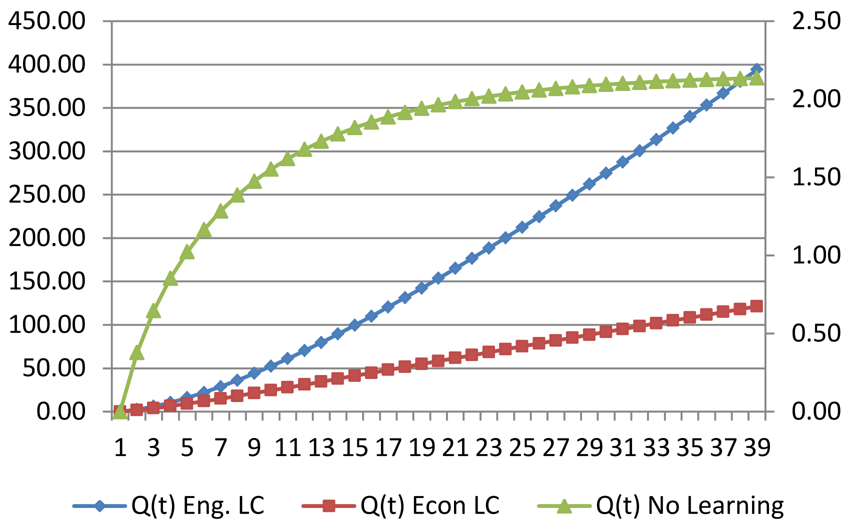
We can rewrite the equations from Table 3.3, by replacing the capital stock by its threshold value, eliminating L_t as it equals $L_0 = 1$. Table 3.4 below shows these modifications and the 1st and 2nd derivatives of the output functions at the threshold. In both specifications, output increases with both TFP and capital stock up until the capital stock reaches the threshold.

Table 3.4: Output derivatives at the threshold

	Engineering	Economic
Output Q_t as a function of TFP and K^*	$Q_t^n = (t.\bar{g})^{\alpha}\left(\frac{\bar{g}}{\delta}\right)^{1/2}$	$Q_t^c = (1 + t(\bar{g})^{\alpha})\left(\frac{\bar{g}}{\delta}\right)^{1/2}$
First derivative of output at the threshold	$\frac{\partial Q_t^n}{\partial t} = \alpha.\frac{\bar{g}^{\frac{1}{2}+\alpha}}{\delta^{\frac{1}{2}}}.t^{\alpha-1}$	$\frac{\partial Q_t^c}{\partial t} = \frac{g^{\alpha+\frac{1}{2}}}{\delta^{\frac{1}{2}}}$
Second derivative of output at the threshold	$\frac{\partial^2 Q_t^n}{\partial^2 t} = (\alpha - 1)\alpha.\frac{\bar{g}^{\frac{1}{2}+\alpha}}{\delta^{\frac{1}{2}}}.t^{\alpha-2}$	$\frac{\partial^2 Q_t^c}{\partial^2 t} = 0$

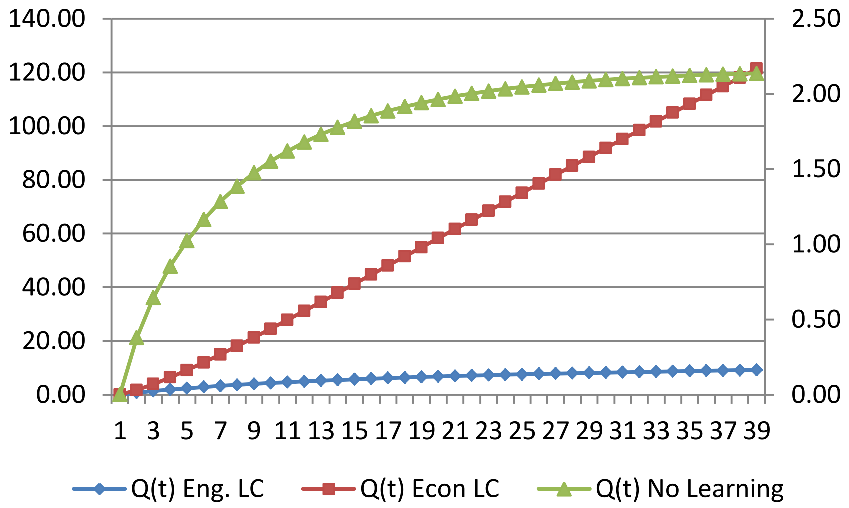
At $K^* = \frac{\bar{g}}{\delta}$, output increases only with TFP as the capital stock only renews itself through gross investment. At this point, the behaviours of the two output functions differ from each other. In the case of the engineering learning curve, output continues to increase in TFP (first derivative positive) but at a decreasing (or increasing) rate when $\alpha < 1$ (or ($\alpha > 1$) as shown by the second derivative. In contrast, regardless of the value of the learning elasticity, once the threshold is reached in the economic learning curve specification, output increases (positive first derivative) at a constant rate. Figures 3.3 and 3.4 below represent the evolution of output without learning and with the economic and engineering curve specifications, when the value of alpha is higher and lower than one respectively.

Figure 3.3: % change in Output from base year when alpha =1.32



Note: Q_t without learning is represented on the secondary axis

Figure 3.4: % change in output from base year when alpha = 0.32



First, with constant TFP, and constant gross investment, output converges towards a constant increase of around 2% in our simulations. The economic learning curve leads to a roughly linear increase in output towards the end of the simulation in both cases. The engineering learning curve shows a convex pattern in Figure 3.3 and a concave one in Figure 3.4.

The micro-simulation results confirm the analytical study. When the learning elasticity is larger than 1, the engineering specification is stronger than the economic, i.e. the TFP and the output grow larger in the engineering specification. Whereas when the learning elasticity is smaller than 1, the economic specification is stronger and leads to larger increases in TFP and in output. An important note must be drawn here regarding the value of the learning elasticity. A value of α equal to 1 is equivalent to a learning rate of 50%[42], which is larger than any of the empirical estimates from the econometric literature. A value of $\alpha < 1$ is therefore expected and confirms that the traditional engineering learning curve specification leads to diminishing returns. Indeed, as experience accumulates, it becomes harder and harder to double it, and thus to obtain the 20% costs reductions. In contrast, the economic learning curve specification leads to linear increases in both TFP and output, which are likely to be overestimated using the empirically estimated learning rates.

4.3.2. Returns to knowledge

In the previous section, the economic learning curve was defined with no returns to knowledge. In other words, the past stock of knowledge, embodied in the TFP level of the previous period, did not impact the accumulation of new knowledge.

In this section, the existence of positive or negative returns to knowledge in the economic specification is explored. These returns to knowledge represent the way past gains in TFP influence the accumulation of new TFP gains.

[42] This is calculated using the engineering curve specification, where $LR = 1\text{-}2^{\alpha}$.

Three cases are explored by running micro-simulations on the economic learning curve specification, namely positive, negative or zero returns to knowledge. For this, equation 3.14 is used and repeated below:

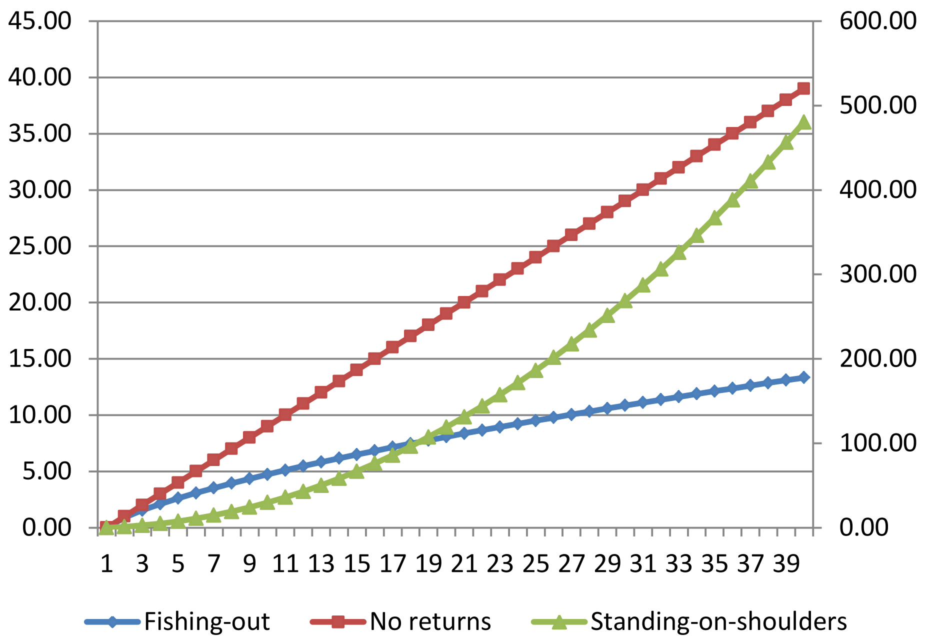
$$A_t = A_{t-1} + g_t^{\alpha} * A_{t-1}^{\phi} \tag{3.14}$$

Changing the returns to knowledge corresponds to changing the value of parameter ϕ. Three simulations are run for 3 different values of ϕ = 0, -0.5 and 0.5. Introducing positive or negative returns to knowledge changes the behaviour of the function[43]. It enables to bring in non-linearity to the economic learning curve specification. We expect a positive ϕ parameter to introduce increasing returns to TFP and thus increasing returns to production. In contrast, a negative ϕ parameter corresponds to decreasing returns to TFP and decreasing returns to production. These two cases correspond to “fishing-out” and “standing-on-shoulders” respectively. The results of the simulations for TFP are shown in Figure 3.5.

In the case of $\phi = 0$, the evolution of TFP is linear, as highlighted in the previous section. The results for this simulation are the same as the economic specification with $\alpha < 1$ above. In the case of fishing-out, the accumulation of past knowledge reduces the opportunity for future knowledge accumulation, representing a situation with a limited amount of knowledge. When ϕ is negative in fishing-out, TFP still increases with experience, but at a decreasing rate, revealing a TFP accumulation pattern similar to the common engineering learning curve specification (with $\alpha < 1$).

[43] When ϕ= 0, the specification is equivalent to the economic learning curve analysed in the previous section, with a learning rate of 20%.

Figure 3.5: TFP as % change from base year

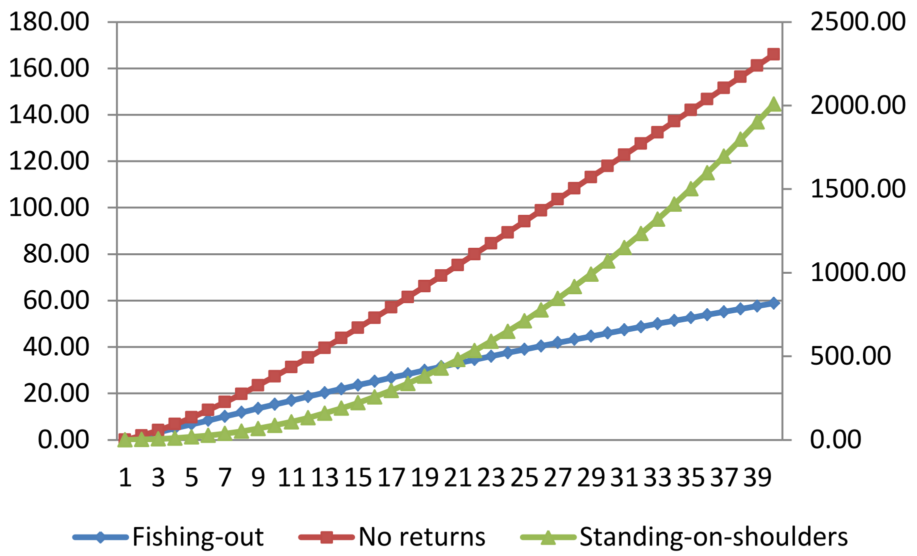


Note: Standing-on-shoulders case is represented on the secondary axis (right)

In contrast, the case of standing-on-shoulders, with a positive returns-to-knowledge parameter, leads to exponential growth in TFP. Often associated with knowledge from R&D activities, the situation of standing-on-shoulders suggests that past improvements in the stock of knowledge facilitate future accumulation of knowledge. In this case, TFP increases at an increasing rate, following a similar pattern to the engineering learning curve with a large learning rate ($\alpha > 1$).

Figure 3.6 represents the evolution of output with the economic learning curve specification in the cases of fishing-out, no returns, and standing-on-shoulders.

Figure 3.6: Output as % change from base year



Note: Standing-on-shoulders case is represented on the secondary axis (right)

Figure 3.6 reveals output paths that are similar to the evolution of total factor productivity. As pointed out previously, ignoring the influence of the past stock of knowledge on TFP improvements, the economic specification leads to constant growth in output after an initial threshold is reached. While fishing-out leads to a concave increase in output, standing-on-shoulder generates exponential growth in output.

In relations to the literature, the case of fishing-out in technological change is arguably more realistic than standing-on-shoulders in the context of learning-by-doing. Indeed, it has been shown that gains from LBD become harder to achieve over time (MacDonald and Schrattenholzer, 2001). As the technology progresses from early stages of development towards a wide commercialisation, less and less costs reductions are achievable in production. The engineering learning curve states that costs reduce at a constant percentage with every doubling of experience. The level of cost reduction does not stay constant but actually decreases with cumulative experience, as it becomes harder and harder to double cumulative experience as it increases. This case of fishing-out is the only version of the economic specification which exhibits a concave shape of efficiency gains, like the engineering learning curve. This could be considered a more realistic representation of the LBD process in economic models.

4.3.3. Experience Proxy

Three alternative definition of cumulative experience are explored and modelled in this section. Each alternative definition is embodied through a different variable and is only presented here in the engineering learning curve equation form, to allow for simpler comparison. Up to now, all simulations conducted in this chapter have used cumulative gross investment as the proxy for experience. The simulations presented here also use two other variables to proxy for experience, namely capital stock and cumulative production. The engineering learning curve functional form is represented in equation 3.12 and repeated in Table 3.5 for convenience. Table 3.5 also details each alternative learning-by-doing function where experience is embodied in three alternative variables.

As pointed out previously, the capital stock also represents the accumulation of investment over time but includes depreciation in each period. Therefore, changing the experience proxy from gross investment to capital stock is expected to produce qualitatively similar (although lower overall) results in the evolution path of TFP.

Table 3.5: Engineering Learning Curve with Alternative Experience Proxy

Learning curve with cumulative experience **G**	$A_t = A_0 (G_t)^{\alpha}$		
With the flow of experience **g**	$A_t = A_0 \left(\sum_{i=0}^{t} g_i \right)^{\alpha}$		
Alternative experience Proxy	Cumulative Gross Investment	Cumulative Production	Capital Stock
	$A_t = A_0 \left(\sum_{i=0}^{t} GI_i \right)^{\alpha}$	$A_t = A_0 \left(\sum_{i=0}^{t} Q_i \right)^{\alpha}$	$A_t = A_0 (K_t)^{\alpha}$

Note: GI_t is Gross Investment, Q_t is output and K_t is the capital stock.

However, when using cumulative production to embody experience, the results are expected to change significantly. While cumulative gross investment is assumed to grow at a constant rate in the simulations, cumulative output increases with both capital stock and TFP. Therefore, the use of cumulative output to embody the stock of experience is expected to lead to a larger and faster increase in TFP, and in turn larger increases in output.

The results for the evolution of TFP and output for the three alternative experience proxies are presented in Figures 3.7 and 3.8 below.

Figure 3.7: TFP as % change from base year

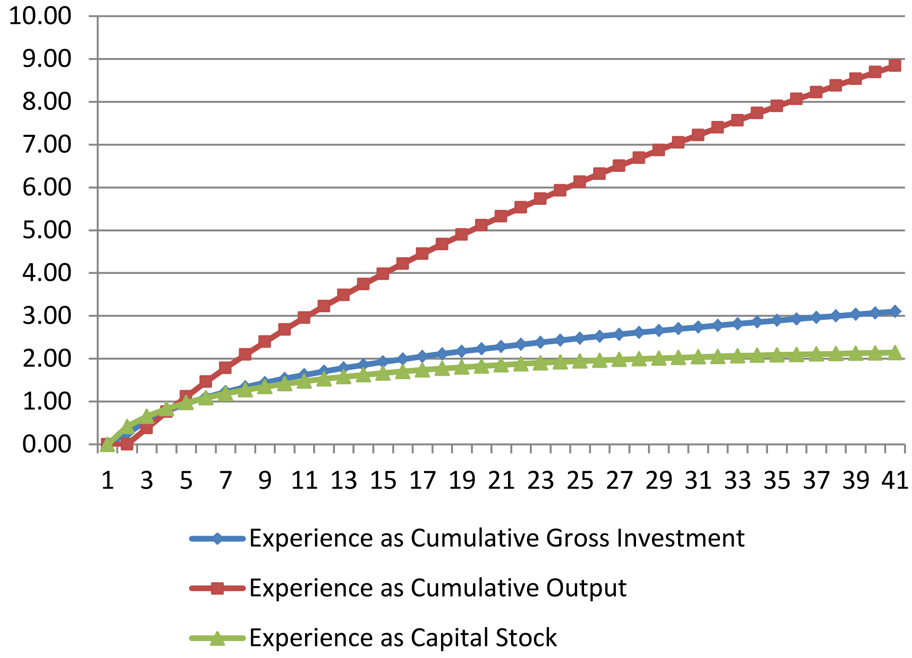
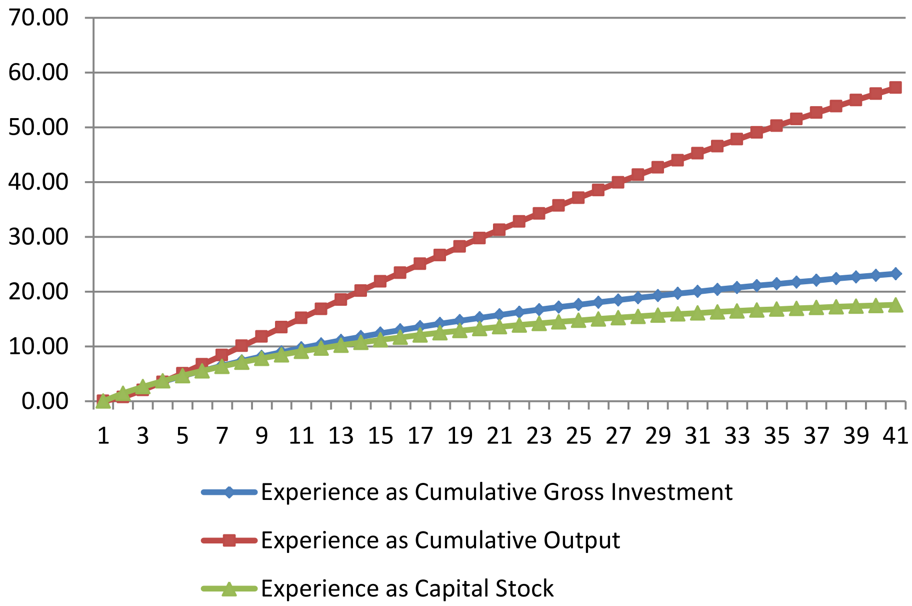


Figure 3.8: Output as % change from base year



As expected, when capital stock embodies experience, TFP increase in a similar pattern but at a slower rate than when using cumulative gross investment. This delay in knowledge accumulation corresponds to the depreciating of capital stock, which in this case, also translates to depreciation in experience and knowledge itself. The evolution of output follows a similar trend to that of TFP, as highlighted in the previous simulation. Output also increases less overall when using capital stock as a proxy for experience, as TFP is lower, when compared to cumulative investments.

In the third alternative, cumulative output is used to proxy for experience. In this case, TFP still increases at a decreasing rate (driven by the functional form of the engineering learning curve), but TFP increases at a much larger proportion than when using cumulative investment. This is explained by the fact that cumulative production itself increases faster than cumulative investment, which is assumed to grow at a constant rate.

While cumulative production as a proxy for experience originates in the early discovery of learning-by-doing, economists have argued that experience is better embodied through investments in new capital. The use of capital stock as a proxy for experience enables the modeller to account for depreciation of the knowledge stock. However, this corresponds to the limited assumption that knowledge depreciation corresponds to capital depreciation.

The exact consequences on modelling results of the choice of proxy to embody experience are likely to vary drastically between models, depending on their focus and their type. The implications of the choice of proxy should thus be discussed in the context of each EEE model representing learning-by-doing. This will be discussed in more details in the context of CGE models in the next chapter of the thesis.

5. Conclusions

The study of learning-by-doing for energy technologies has become the focus of a large area of research, driven by the potential economic and environmental benefits of technological innovation in such a central industry in climate change mitigation. Many econometric studies have estimated the learning rates for a range of energy technologies from conventional generation, such as fossil-fuel or nuclear, to new renewable options like wind and solar photovoltaic. These estimates have been constructed on a variety of datasets mostly in developed economies. The review of this literature reveals a wide range in learning rate estimates, which vary not only across technologies but also across datasets covering the same technology. These variations have been explained through differences in estimation models, time periods and geographical scope, as well as differences in the variables and definitions used.

The literature review has identified several factors of particular importance in explaining variations in estimates. First, the choice of model to estimate the learning rates matters. One-factor learning curves tend to produce larger LBD estimate than two-factor learning curves which consider also the impact of R&D on technology costs. Some studies have also pointed out additional issues with the econometric specifications of the models. Omitted variables such as economies of scale or feed-in prices may lead to overestimations of learning rates. The endogeneity of investment costs and installed capacity of technologies has also been pointed out, leading to the development of simultaneous equation estimation models introducing a diffusion equation in addition to the learning curve. Additionally, the variations in estimates can also be driven by differences in the choice of variables to represent experience and performance. Reviews found that studies using production-linked variables tend to generate larger learning rate estimates than studies using investment variables. Finally, recent contributions have suggested that variations in learning rate estimates could be due to the systematic variation in the learning rates, as the technology matures over time. In particular, learning-by-doing opportunities appear to be largest after an initial introduction phase, while they tend to decrease as the technology reaches maturity. This hypothesis has however never been formally tested in a model allowing for a flexible learning rate over time, highlighting an opportunity for future research in the evolution of learning-by-doing over a technology's life-cycle.

In parallel to these econometric studies, learning-by-doing has recently become a common feature of Energy-Economy-Environment (EEE) models, representing endogenous technological change. Traditionally, bottom-up models are developed in the engineering literature to represent the energy system and tend to introduce LBD technological change due to its strong empirical origins in manufacturing. As explained in Chapter 2, R&D-technological change is often preferred by top-down models influenced by the macroeconomic literature on endogenous growth. However, LBD has also been increasingly implemented in top-down models, inspired by numerous studies showing its crucial role in representing technological change.

While bottom-up models usually introduce learning-by-doing in its most traditional form, top-down models have introduced new definitions and specifications of the learning-by-doing phenomenon. Using general production functions, top-down economic models generally represent the effects of learning-by-doing as improvements in labour, capital or total factor productivity, where more experience reduces the quantity of inputs needed to produce the same output. In addition, influenced by advances in endogenous growth theory, top-down models have introduced the learning process through a different functional form than the traditional learning curve, where learning-by-doing is an accumulating stock of knowledge, increasing gradually with a flow of experience. Overall, the observations made in the literature review sections of this chapter confirm that the specification of the learning-by-doing phenomenon is an important determinant of modelling results.

Using a simple model of Cobb-Douglas production, the alternative specifications identified in the literature are tested with regards to three important criteria through a set of simple micro-simulations. First, the differences in equation forms of learning-by-doing between engineering and economic models are explored, where total factor productivity improves with experience. The results suggest that the economic specification, with a period-by-period building of a knowledge stock through learning-by-doing, leads to linear improvements in total factor productivity when investment (experience) is constant, regardless of the value of learning elasticity. In comparison, the engineering equation form of learning-by-doing, which calculates total factor productivity in each period using total experience accumulation, leads to either concave or convex shapes in the paths of TFP over time, when the learning elasticity is superior or inferior to one respectively. A learning elasticity value of less than one is expected from the literature since it corresponds to a learning rate smaller than 50%, and confirms that the traditional engineering learning curve specification leads to diminishing returns.

A closer look at the economic specification through the introduction of a non-zero returns-to-knowledge parameter reveals that the economic specification can become qualitatively similar to the engineering specification in the case of fishing-out. In this case, improvements in TFP are rendered more difficult by experience gains in previous periods, reflecting one property of the traditional learning curve, in that each doubling of experience becomes more difficult to obtain as experience increases. In contrast, the situation of standing-on-shoulders modelled in some instances in top-down studies appears far removed from the traditional learning curve. The results of standing-on-shoulders lead to exponential growth in TFP and output, compared to an increase at a decreasing rate in the case of engineering specification.

Finally, a set of simulations looking at alternative experience proxy reveal that the choice of variables does impact modelling results significantly. A comparison of gross investment and output as measures of experience reveals that the latter leads to much larger improvements in TFP and output as there is a feedback effect entering the output function. Finally, the use of gross investment or capital stock as the experience proxy leads to qualitatively similar results in the evolution of TFP and output; but capital stock always reduces the potential for technological improvements since it includes depreciation. While a few studies suggest that experience can depreciate as a knowledge stock in the same way as knowledge accumulated through R&D, this treatment could be seen as restrictive as it assimilates experience depreciation to that of the capital stock.

In conclusion, this chapter highlights the importance of model specification when introducing learning-by-doing in Energy-Economy-Environment models. Several distinctions can lead to drastically different results depending on functional form and key parameter values, and modellers should be aware that their assumptions about the technological change process have a dramatic impact on the modelling results, particularly in a policy recommendation context. The next chapter of this thesis develops the first attempt to introduce endogenous technological change in a Computable General Equilibrium model for Scotland. Chapter 4 makes use of the observations of this chapter to explore the economic and impact of learning-by-doing improvements in an emerging renewable energy sector in Scotland, namely marine electricity generation.

Chapter 4: Introducing Endogenous Learning-By-Doing in Marine Electricity Generation in a CGE Model for Scotland

1. Introduction

This chapter introduces endogenous technological change in a Computable General Equilibrium model for Scotland, through learning-by-doing effects in the marine electricity sector. As demonstrated in the previous chapters, technological change is a fundamental factor to consider in both the design and analysis of energy and environmental policies. The choice of assumptions about technological change is equally important when using modelling tools to inform policy-making. Considering these observations, the objective of the modelling research conducted in this chapter is twofold. First, this chapter aims to observe the economic impact of policy support for a renewable energy technology, in presence of endogenous technological change in the CGE model. The second objective is to inform the choice of assumptions for modelling endogenous technological change through learning-by-doing in the CGE model for Scotland. This chapter introduces endogenous learning-by-doing in the marine electricity generation sector. Through a number of simulations where the marine electricity sector receives a production subsidy, the analysis explores how this newly introduced technological change affects the general and sectoral economic impacts of policy support to the sector.

Marine electricity generation has become a primary objective in the Scottish renewable energy policy agenda. The Scottish government has set the very ambitious target to generate the equivalent of 100% of gross annual electricity consumption from renewable energy sources by 2020. As of the first quarter of 2013, onshore wind represents the largest share of renewable electricity capacity in Scotland with 4,109 MW installed capacity (DECC, 2013a), followed by hydropower (1,499MW) and offshore wind (190MW). In contrast, marine technologies are still in the early stages of technology development and represent 5 MW of installed capacity in Scotland and accounted for less than 0.5% of renewable electricity generated in 2012. However, the resource potential is huge, as Scottish waters are estimated to hold 25% of Europe's tidal power and 10% of its wave power (Scottish Government, 2014). Therefore, the development of marine electricity technologies is subject to growing interest in the Scottish renewable energy policy.

The choice of simulating a production subsidy is determined by the current type of policy support to renewable energy generation in Scotland: namely the Renewables Obligation system[44]. Renewables Obligation Certificates (ROCs) are tradable certificates which are issued to eligible electricity generators for each MWh generated from renewable resources. These ROCs are then sold electricity suppliers, which must meet a certain level of renewable obligation (i.e. a certain share of the electricity supplied must be from renewable sources,) and provide the regulator, Ofgem, with a certain number of certificates. The RO system effectively acts a quota system for renewable electricity generation and a production subsidy to renewable electricity generators. The banding of ROCs introduced differentiation between renewable energy technologies. Designed to incentivize investment in less-developed technologies, the different bands in ROCs represent the number of certificates attributed to a MW generated by a specific technology. While onshore wind support

[44] The Renewable Obligation System is planned to be replaced by a Feed-in-Tariffs system from 2015 onwards under the UK Government’s pending Electricity Market Reform (DECC, 2013b).

is limited to 1 ROC/MWh, offshore wind and marine technologies are favoured by the system, with 2 ROCs/MWh for wind and tidal and 5 ROCs/MWh of wave-generated electricity (Scottish Government, 2011). In this chapter, the introduction of a production subsidy in the marine electricity generation sector is designed to represent this targeted policy support to the sector.

The relatively early stage of development of the marine electricity sector makes it an optimal testing subject for the learning-by-doing hypothesis. The levelised costs of marine generation technologies (namely wave and tidal) are currently much larger than these of fossil-fuel technologies (Allan et al., 2011). DECC (2013d) projects the levelised costs of future wave installations commissioned by 2025 between £215 and £259 per MWh generated, and those of future tidal installation between £148 to £207 per MWh. In comparison, levelised costs of traditional generation technologies are rarely estimated to be higher than £80 per MWh. The potential costs reductions from learning-by-doing could considerably reduce the levelised-costs of wave and tidal technologies to make them competitive against traditional generation. This is precisely the rationale behind policy support attributed to marine technologies in Scotland which benefit from specific Renewable Obligation treatment. In light of these objectives, the simulations are run with a production subsidy to the marine electricity generation, which is also subject to costs reduction from endogenous learning-by-doing.

The remainder of the chapter is structured as follows. After a brief discussion of the theory underlying CGE modelling, Section 2 introduces the Computable General Equilibrium model for Scotland used in this chapter. The method chosen for the introduction of learning by-doing in the model is also discussed. Section 3 describes the simulations reported in this chapter. All simulations represent a production subsidy to the marine electricity sector, but the definition of learning-by-doing differs in each simulation. Eight simulations are conducted to address the major variations identified in the literature review in Chapter 3. Section 4 reports and compares the results of these alternative simulations, by focusing on the optimal representation of learning-by-doing in the model. Section 5 provides conclusive comments, as well as policy and modelling recommendations in terms of the choice of assumptions regarding learning-by-doing.

2. The CGE Model for Scotland

Computable General Equilibrium (CGE) models have become standard tools for policy analysis, as they offer a balanced combination of strong theoretical foundations from neoclassical economics and empirical grounding through real economic data requirements. In this section, I first give a brief account of the theory and structure underlying CGE modelling. This section then introduces the AMOS (A Micro-Macro Model of Scotland) modelling framework used in the thesis (Harrigan et al., 1991). After a general description of the model, the modifications implemented in this thesis to introduce endogenous technological change are discussed.

2.1. Computable General Equilibrium modelling

Originating in the work of Walras (1874), the concept of General Equilibrium is the theoretical foundation underlying CGE models. The Walrasian General Equilibrium mathematically refers to a system of simultaneous equations representing the economy in a state of equilibrium, where market prices are set so that demand equals supply for all commodities simultaneously. The mathematical foundations of general equilibrium theory were further developed in the work of Arrow and Debreu (1950), Debreu (1959) and Arrow and Hahn (1971), and the concept began to attract attention for applied policy analysis. CGE modelling, or Applied General Equilibrium modelling, developed in the 1960s and 1970s, incorporates actual economic data about specific regions or countries into this mathematical equilibrium representation of the economy, in order to provide insights into the welfare impacts of policy decisions.

In general terms, a CGE model is based on a mathematical framework representing an economy. This framework is defined as a set of equations characterizing the behaviour of economic agents and institutions, as well as their interactions on a given number of markets. Generally consistent with neoclassical theory, CGE models incorporate the assumptions of utility-maximizing consumers and profit-maximizing producers, which constitute the basis for setting demand and supply respectively. Households maximize their utility from consumption of goods and services according to their preferences under a budget constraint, determined by the income received as owners of the factors of production, namely wages and capital rental. Producers determine the optimal output to supply to the market in order to minimize costs and maximize profits. Output is produced with a combination of factors of production (labour and capital, purchased or rented from households) and intermediate inputs (purchased from other producers). Some CGE models also include a government sector, which produces and purchases public goods, as a tool to induce policy shocks. The government can interact with both consumers in producers; it receives income through the collection of taxes and redistributes this income through subsidies, transfers and direct consumption of goods and services.

Finally, external transactors are included models to represent trade with other regions or nations. Firms can choose to import some of their intermediate inputs, while consumers (and government) can choose to consume some imported goods. Import (or export) decisions are determined by the relative price of domestic goods compared to their foreign equivalent. Most models incorporate an Armington assumption which reflects product differentiation between domestic and foreign goods, operationalised through the use of an elasticity of substitution (Armington, 1969). Overall, the behaviour of each agent described above is determined in each CGE model by the choice of specific functional form (for example, Leontief, Cobb-Douglas and Constant Elasticity of Substitution are commonly-used functional forms in production). The model closure is determined by defining the sets of exogenous and endogenous variables, as constrained by the number of equations to solve in the model. CGE models differ greatly in the way they represent agent behaviours, their level of disaggregation, as well as their model closure. These are mostly determined by the intended use of the model, and often depend on data availability.

Once the mathematical framework of the model has been determined, it is then calibrated using a benchmark of real economic data for one specific year. This benchmark dataset consists of a Social Accounting Matrix (SAM), which represents all the transactions and transfers that take place within an economy. A SAM takes the form of a square matrix, incorporating all economic agents (households, producers, government, external trade partners). It details the income and expenditures of each of these agents for a given year. A SAM incorporates production data from Input-Output tables as well as disaggregated demand data from national accounts, data on public revenues and expenditures from government accounts, and import and export data from trade accounts. Through the structural relationships defined by the imposed functional forms, the SAM data, and existing literature are used to assign exogenous values to parameters describing the behaviour of agents (e.g. elasticity parameters). This complete SAM dataset and new parameter values, represent a snapshot of the economy in a given year and are used to calibrate the model as an initial benchmark equilibrium. Once defined mathematically and calibrated using real data, CGE models can be used to simulate exogenous changes determined by policy decisions or external shocks. The simulations are often conducted by exogenously changing the value of a policy instrument or variable of interest. The model is then solved to produce a new equilibrium following this shock, which can be compared to the benchmark equilibrium. Alternative simulations can be compared by changing the exogenous shock or changing the model configuration.

CGE models have been widely used as tools for policy analysis in a wide range of fields, but they are particularly favoured tools in the evaluation of environmental and energy policy. They have been used extensively to model the impact of a variety of policy instruments, principally in the context of GHG reductions and climate change mitigation. Numerous CGE modelling application exists looking at the carbon tax, emission permits, emission trading schemes, taxation of fossil-fuels, energy efficiency measures, or the rise of renewable energy sectors. Several goods reviews of this literature can be found in Bhattacharyya (1996), Conrad (1999) and more recently Bergman (2005). As pointed out in Sue Wing (2007), the popularity of CGE models for energy and environmental policy analysis lies in the multi-sectoral possibilities of the framework. As energy constitutes a standard input in production as well as an important component of final demand, policies affecting the quantities or prices of energy goods are likely to propagate across a large number of markets. CGE models are designed to represent economy-wide interactions and allow for the identification of these propagation effects. While CGE models have become a standard tool in this context, there are few examples of such models that have implemented endogenous technological change. A brief review of top-down model with endogenous technological change was presented in chapter 2, and differentiated between R&D and learning-by-doing as the two methods. Examples of environment and energy-focused CGE models with endogenous technological change include R&D-driven models (Sue Wing, 2003; Goulder and Schneider, 1999) and learning-by-doing models (Rasmussen 2001; Goulder and Mathai, 2000). Chapter 3 provided a review of the models incorporating learning-by-doing.

2.2. The CGE model for Scotland – AMOS

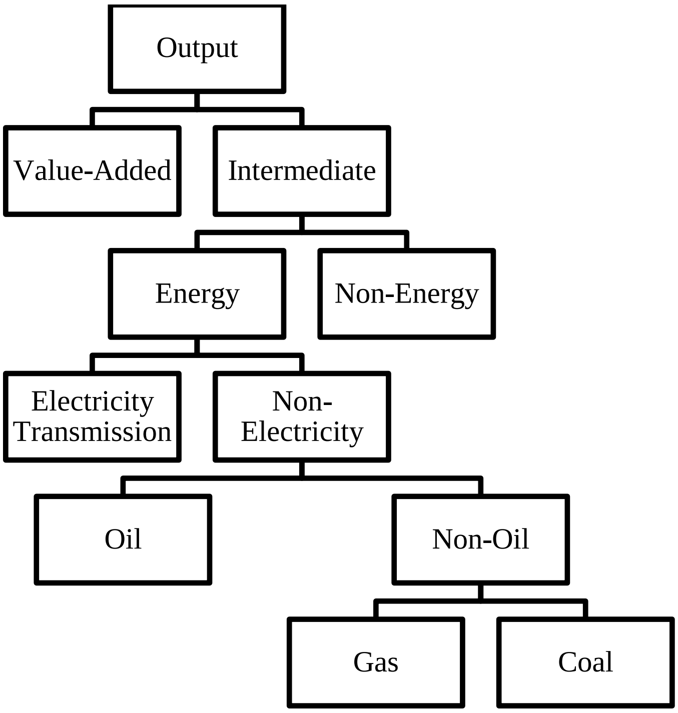
The model used in this thesis is a version of the AMOS model (A Micro-Macro Model of Scotland). The AMOS model is a computable general equilibrium framework which allows a great deal of flexibility in functional form, parameter values and assumptions concerning different markets (Harrigan et al., 1991). The standard AMOS model, its extended environmentally-focused version, and its extended UK version, have all been used for a number of energy or environmental policy-focused studies including the impact of energy efficiency improvements and rebound effects (Hanley et al. 2006; Hanley et al. 2009; Turner, 2009) the development of new renewable energy sectors (Allan et al. 2008) and the introduction of a carbon tax (Allan et al., 2014, Winning et al., 2012). This chapter is the first attempt to introduce endogenous technological change in the AMOS framework.

In AMOS, there are three domestic transactor groups, namely households, firms and government, as well as two external transactors: the rest of the UK (RUK) and the rest of the world (ROW). The version of the model used in this chapter is multi-sectoral and highly disaggregated at the energy level. Based on the electricity disaggregated Input-Output tables for Scotland in 2000 (Allan et al. 2007a), the model includes 17 sectors, of which 13 are energy related-activities, including three fossil-fuel sectors and 10 electricity sectors. The 10 electricity sectors include nine electricity generation sectors and one electricity transmission sector embodying all electricity transmission and distribution activities. This structure offers a more realistic representation of the electricity system, where all the generation sectors feed into the transmission sector, which is responsible for distributing electricity to the intermediate and final demands[45]. Thus, the transmission sector stands as an intermediate sector between electricity generation activities and the rest of the economy, and reflects the homogenous characteristic of electricity as a commodity. A list of all sectors in this model can be found in Appendix B.

In terms of production structure, firms in all these sectors are cost-minimizing and subject to nested Constant Elasticity of Substitution (CES) production functions. For all sectors of activity, the nested structure of the production function is represented in Figure 4.1, except for the electricity transmission sector which is subject to a specific structure shown in Figure 4.2. The trade structure for inputs to production is presented separately in Figure 4.3 for simplification.

[45] This details of the sectoral disaggregation of energy activities and the construction of the dataset can be found in Allan et al. (2007).

Figure 4.1: Production Structure (16 sectors)

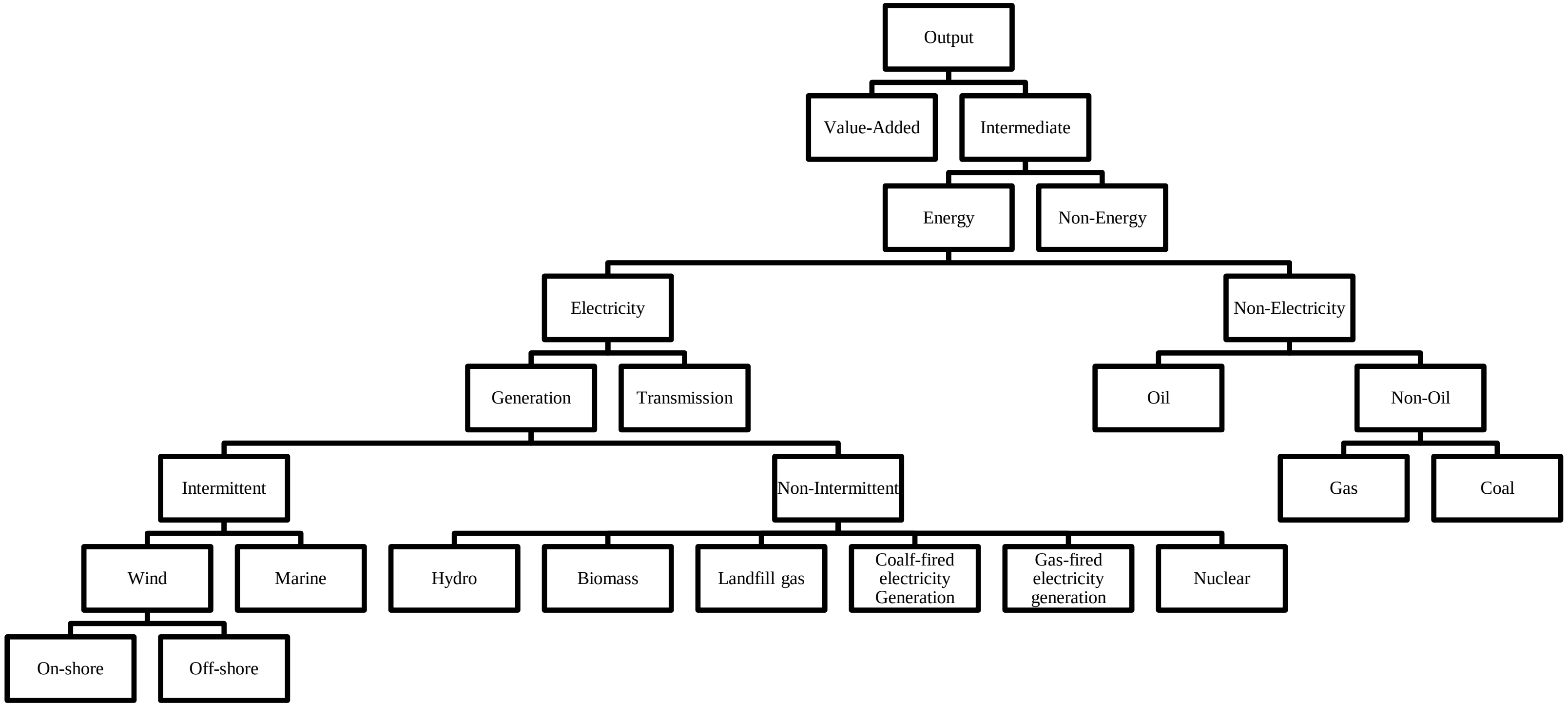


In each sector, output is a CES combination of a value-added composite (CES of capital and labour) and intermediate inputs. Intermediate inputs are an aggregate of energy and non-energy inputs. The question of where energy ought to enter the production structure is still widely debated in the modelling literature. Lecca et al. (2011) systematically examine the sensitivity of the CGE model results to assumptions about the structure of the KLEM production function (Capital, Labour, Energy and Materials). In a simple demand shock exercise, simulation results are compared where energy enters the nested CES production function either as in the intermediate inputs composite or is combined with capital inputs to enter the value-added composite. When there are different elasticities of substitution at different nests in the production function, and relative prices are allowed to change, the results are highly sensitive to the production structure. In our case, energy is considered as a produced commodity; thus it is introduced in the intermediate input composite, instead of with factors of productions in the value-added composite.

The energy composite is itself a CES combination of electricity and non-electricity (fuel) commodities. Non-electricity energy is a composite of oil and non-oil sectors, which comprise coal and gas. All sectors represented by Figure 4.1 (all sectors other than electricity transmission) receive their electricity inputs through the transmission sector only.

The entire output of electricity generation sectors feeds into the electricity transmission sector. Electricity generation sectors have no other forward links with the rest of the economy or between each other. Figure 4.2 details the production structure of the transmission sector and shows how electricity generation technologies enter the multi-level CES production function. Electricity generation is a CES combination of intermittent and non-intermittent generation technologies. Three intermittent generation technologies are identified: marine (including wave and tidal), onshore wind and offshore wind. These are combined into a separate composite, to reflect the fact that the electricity output they produce is variable with the intermittent renewable resource they use. Of the six non-intermittent generation technologies, three are based on renewable resources as well: hydropower, biomass and landfill gas. They are combined with two fossil-fuelled generation technologies (gas and coal) and nuclear generation. The choices of structure and elasticities of substitution between the electricity generation technologies will be of importance for the results of the modelling exercise and are discussed below.

Figure 4.2: Production structure of the transmission sector



Elasticities of substitution at every point in the CES production functions take a default value of 0.3, with the exception of substitution between energy inputs which are higher. The substitution between electricity and non-electricity intermediate inputs, and oil and non-oil is 2, to reflect more flexible substitution between fossil-fuels energy and electricity generation. This is done to reflect the policy objective of replacing fossil-fuel use with cleaner technologies in the energy system. In addition, in production structure of the transmission sector, the elasticity of substitution between electricity-generation technologies is set to 5 to further emphasize the relative homogeneity of electricity as a commodity[46]. Table 4.1 provides a summary of the elasticities of substitution used at each level of the production function.

Table 4.1: Elasticities of Substitution

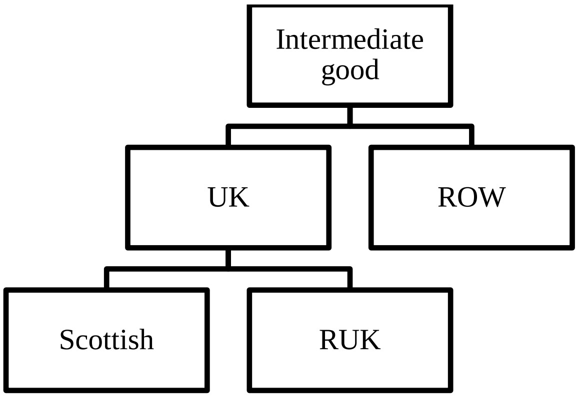
Nod in CES function	Elasticity of Substitution
Electricity and Non-electricity	2
Oil and Non-oil	2
Transmission and Generation	2
Intermittent and Non-intermittent	5
Between Intermittent	5
Between non-intermittent	5
All other CES nods	0.3

Firms in each sector sell their output on competitive markets. Intermediate demand represents the inter-sectoral purchases and is determined by the backward linkages, identified in the Input-Output tables. Firms can substitute between imported and domestic intermediate goods to produce their output. Imports and exports are

[46] Although we are conscious that this assumption can be contested in light of the intermittency of electricity output from technologies relying on variable renewable resource (e.g. wind).

sensitive to changes in relative prices between endogenous domestic prices and exogenous RUK and ROW prices. The trade structure is represented in Figure 4.3 and is subject to standard CES Armington relationships (Armington, 1969). The Armington link is applied to both interregional and international trade with an elasticity of 2 (Gibson, 1990).

Figure 4.3: Trade



In addition to the external transactors (RUK and ROW), there are three other components of final demand, namely consumption, investment, government expenditures. In this modelling exercise, government demand is considered exogenous. Consumption is defined as a linear homogenous function of real income. The model is run on a period-by-period basis, allowing for the progressive updating of the labour and capital stocks. Within each period for which the model solves, the total capital stock and its sectoral composition are fixed. Investments between periods adjust the capital stock according to a simple mechanism: investment demand is determined by the difference between actual and desired capital stock, and depends on a speed of adjustment parameter. Desired capital stock is a function of output, nominal wage and the user cost of capital, while actual stock reflect last period's stock, adjusted for depreciation and gross investment. The economy is assumed initially to be in long-run equilibrium, where desired and capital stocks are equal. In the long run, capital stock is optimally adjusted as well.

Although the AMOS framework allows for a variety of closures of the labour market, we choose just one for this modelling exercise. Our representation of the Scottish labour market is a single market characterized by perfect sectoral mobility. Wages are assumed to be determined in a regional-bargaining process, where the regional real take-home wage is inversely related to regional unemployment rate (Blanchflower and Oswald, 1994; Minford et al, 1994). Endogenous migration is incorporated in the model, so that population is also updated between periods. We take net migration to be positively related to the real wage differential and negatively related to the unemployment rate differential between Scotland and the RUK, in accordance with the econometrically estimated model reported in Layard et al. (1991). The net migration flows in each period are used to update population at the beginning of the next period, in a manner equivalent to the updating of the capital stock. The regional economy is initially assumed to have zero net migration and ultimately net migration flows re-establish this population equilibrium. A formal description of the version of AMOS used in this chapter is provided in Appendix C.

The dataset informing the model is a 2000 Social Accounting Matrix for Scotland, which augments the I-O tables by introducing transfers and payments between the production side of the economy, the three transactor groups and the two external transactors.

2.3. Introducing endogenous technological change

As the objective of this chapter is to explore the impact of learning-by-doing on simulation results, the model must be augmented to allow for the possibility of endogenous technological change. As stated in Chapter 3, the theoretical foundations of top-down models in macroeconomics require an interpretation of the LBD process, in order for it to be introduced directly into the production function. To follow previous examples of top-down models with endogenous technological change, learning-by-doing in this chapter is assumed to lead to improvements in the productivity of factors, and therefore is introduced directly in the value-added production function.

Learning-by-doing refers to the process of costs reductions with experience accumulation. In the case of CGE models, the costs of production are embodied in the costs of inputs into production. With constant factor prices, a reduction in the costs of production is therefore equivalent to changes in technology which lead to improvements in the productivity of factors (capital and labour). However, several possibilities can be explored when determining where the LBD process should enter the value-added production function (Arrow, 1962a). In this exercise, using a standard CES function, value-added is determined in the following equation:

$$VA_t = A_t\left[B_t\delta_K K_t^{\rho} + C_t(1-\delta_K)L_t^{\rho}\right]^{-\frac{1}{\rho}} \tag{4.1}$$

where VA(t) is the value-added at time t, A(t) is a technology parameter, referring to Total Factor Productivity (TFP). K (t) is the capital stock, L(t) is labour inputs, δ_K represents the capital intensity in production and ρ is the elasticity of substitution between capital and labour. B and C represent the efficiency of capital and labour inputs respectively. By changing the value of A, B or C, it becomes possible to change the productivity of all factors of production, and capital or labour separately.

In previous modelling exercises, the value-added function used in AMOS has only reflected exogenous changes in technology, by introducing exogenous shocks on the efficiency parameters A, B or C. If technological progress is introduced through changes in A, improvements in efficiency will be Hicks-Neutral (Hicks, 1932), i.e. the TFP will increase, and for given input prices, i.e. the ratio of marginal product of capital to labour remains unchanged. In this chapter, the simulations presented are typically run using this Hicks-neutral technological change assumption. Some results will also be presented exploring the change from Hicks-Neutral to capital-augmenting technological progress.

The major contribution of this chapter is the introduction of endogenous technological change through transforming the efficiency parameter (generally Total Factor Productivity) into a function of *experience*, as suggested by the learning-by-doing literature. Total Factor Productivity (TFP) becomes endogenous to the model and an increasing function of experience. Several equations and choices for the experience proxy will be explored in the simulations and are detailed in the next section.

2.4. Alternative specifications of LBD

Several simulations are run in the CGE model, which differ with the specification of the learning-by-doing process. Reflecting the differences in specifications identified in Chapter 3, this chapter also explores alternative ways to define learning-by-doing in order to determine how it should be best represented in the CGE model for Scotland. Differences in specifications explored in this paper fall into four main categories. First, two major equation forms (describing the learning-by-doing process) are compared, namely the engineering and economic learning curves, as identified in Chapter 3. Secondly, simulations are compared with alternative variables representing cumulative experience. Third, different values for the economic learning curve returns to knowledge parameter are compared. Finally, the variable impacted by improvements in experience is changed from TFP to the efficiency of capital, reflecting a change from Hicks to Solow-neutral technological change. Each of these variations will be explored in a number of simulations presented in Section 3. In this chapter, each specification is adapted to best fit the CGE model for Scotland notation.

3. Simulations

All the simulations presented in this chapter combine a targeted policy support scheme to the marine electricity generation sector with endogenous sectoral technological progress. Specifically, each simulation is run for a 10% production subsidy on the marine electricity generation sector, which is also the only sector subject to learning-by-doing This enables us to identify both the aggregate and the sectoral impacts of changing the endogenous LBD specifications. For each simulation with endogenous technological change, a default value of the learning rate is chosen at 20%, as a regular estimate in the LBD literature.

The model is solved period-by-period for 25 years in all cases. In each time period, the model is solved as a set of simultaneous equations, to find a set of prices that clears all markets: the supply of each produced good equals its demand. In period 1, representing the short-run, the labour supply and the capital stock are fixed to their base-year values. The assumption is relaxed from period 2 onwards, and the capital and labour market can adjust through investment and migration. The results presented in the final period (i.e. period 25) do not correspond to the long-run results[47]. This is due to the exponential nature of the endogenous technological change used in some specifications, which make it impossible to run the model for longer. These results however illustrate the modelling difficulties associated with more complex representation of technological progress[48].

Each simulation differs from the others in the treatment of the LBD process. When possible, a simulation was run for each combination of equation form (engineering or economic learning curve) and experience proxy (cumulative gross investment, cumulative output or capital stock). Additional simulations were run with the economic specification when changing the value of the returns to knowledge parameter. The results of eight selected simulations are presented in this chapter and provide useful insights in the modelling of endogenous technological change in AMOS.

Simulation 1 corresponds to the base case simulation, where the marine electricity sector receives the subsidy but there is no endogenous learning-by-doing in the model. This simulation corresponds to running the model in its original form, with constant (exogenous) factor efficiency parameters. This simulation is then compared

[47] In the long-run, the model will have reached a new equilibrium following the shock, both capital and employment levels will be at their optimal levels and the real wage and unemployment rate return to their original values.
[48] This reflects limitations of this type of top-down model using certain specifications from the literature. This is discussed further in the results section.

to seven simulations where factor efficiency is endogenous (either through TFP or capital efficiency).

Simulations 2, 3 and 4 correspond to the engineering specification of the learning curve but with three alternative proxies for experience, namely gross investment, output and capital stock. Comparing these three simulations can therefore provide insight into the importance of the choice of variable as experience proxy on modelling results. The three specifications, under the engineering learning curve specification are repeated in Equations 4.2, 4.3 and 4.4 below.

$$A_t = A_0 \left(\sum_{i=1}^{t} GI_t \right)^{\alpha} \tag{4.2}$$

$$A_t = A_0 \left(\sum_{i=1}^{t} Q_t \right)^{\alpha} \tag{4.3}$$

$$A_t = A_0 K_t^{\alpha} \tag{4.4}$$

In equation 4.2, TFP is an exponential function of cumulative gross investments GI(t). In equation 4.3, TFP is an exponential function of cumulative output Q(t). In equation 4.4, it is an exponential function of the capital stock K(t).

Three simulations are also run using the economic specification of learning-by-doing, i.e. the equation form identified in top-down economic models. For these three simulations, only one experience proxy is selected: gross investment. Each of these specifications is based on the equation form, shown in equation 4.5:

$$A_t = A_{t-1} + (GI_t)^{\alpha} . A_{t-1}^{\phi} \tag{4.5}$$

Effectively, following the endogenous growth literature, technological change is represented through the period-by-period accumulation of a knowledge stock. The difference between Simulation 5, 6 and 7 resides in the value of the returns to knowledge parameter ϕ, determining how the past accumulation of knowledge may impact future efficiency gains. Simulation 5 uses the economic learning curve equation form with a ϕ value of zero. In this case, the past accumulation of knowledge neither facilitates nor hinders future efficiency gains. This specification enables a straight forward comparison with Simulation 2, to determine the influence of equation form on modelling results. It can also be compared to Simulation 6 and 7 which correspond to the cases of fishing-out and standing-on-shoulders respectively. Simulation 6 uses a negative value for ϕ, making it harder to improve factor efficiency as the stock of knowledge increases. Simulation 7 corresponds to the opposite case of a positive ϕ, where past knowledge accumulation facilitates future gains in efficiency.

Finally, an additional simulation is included in the modelling of this chapter, where the efficiency parameter affected parameter is capital efficiency only, rather than total factor productivity. Simulation 8 is configured so that it is optimal to compare it with Simulation 2 as well, as shown in equation 4.6.

$$B_t = B_0 \left(\sum_{i=1}^{t} GI_t \right)^{\alpha} \tag{4.6}$$

B(t) is the capital efficiency parameter in the value-added production function defined in equation 4.1. It becomes endogenous in simulation 8, while A remains unchanged. B(t) is an exponential function of cumulative investments. This specification suggests that the capital factor becomes more efficient in production.

This has a combined effect of costs reduction and substitution in the value-added production function. Production costs reduce as capital becomes more efficient (with constant labour inputs, less capital is required to produce the same amount of value-added) but substitution also occurs in favour of the more efficient factor (away from labour).

Details of each simulation in terms of equation form, experience proxy, value of the returns to knowledge parameter and efficiency parameter affected by learning are summarized in Table 4.2.

Table 4.2: Simulations

	Simulations	**Equation form**	**Experience proxy**	**Value of ϕ**	**Efficiency parameter**
1	No_learning	N/A	N/A	N/A	N/A
2	EngGI	Engineering LC	Gross Investment	N/A	TFP
3	EngQ	Engineering LC	Cumulative Output	N/A	TFP
4	EngK	Engineering LC	Capital Stock	N/A	TFP
5	Econϕ=0	Economics LC	Gross Investment	0	TFP
6	Econϕ<0	Economics LC	Gross Investment	-0.5	TFP
7	Econϕ>0	Economics LC	Gross Investment	0.5	TFP
8	EngB	Engineering LC	Gross Investment	N/A	B (Capital)

4. Results

In each simulation described above, the shock to the model is a 10% production subsidy on the marine electricity generation sector. Designed to represent the mechanisms of renewable obligation certificates, this subsidy reduces production costs for firms generating electricity from marine technologies (tidal and wave powered). Effectively, this subsidy incentivizes the production of electricity from the renewable resource. We expect the introduction of learning-by-doing on the same sector to further decrease the costs of productions, through improvements in factor efficiency as experience in the sector increases. Each simulation is run on a multi-period basis, and Table 4.3 reports the impact of the shock on key macroeconomic variables for the last period considered (period 25). All results are presented as changes from base year values and expressed in percentage points. Additionally, the results for energy sector outputs in period 25 are summarized for all eight simulations in Table 4.4.

Table 4.3: Macroeconomic Results – Period 25

	1	2	3	4	5	6	7	8
Simulation	**No LBD**	**Eng. GI**	**Eng. Q**	**Eng. K**	**Econ.**	**Econ. ϕ<0**	**Econ. ϕ>0**	**Eng. B**
Efficiency gains	n/a	44.55	59.81	35.41	53.52	8.78	138.49	38.86
GRP Income measure	0.39	0.91	0.93	0.79	0.91	0.59	1.13	0.78
Consumer Price Index	-0.09	-0.18	-0.18	-0.16	-0.18	-0.12	-0.21	-0.16
Unemployment Rate	-0.06	-0.24	-0.36	-0.27	-0.32	-0.11	-0.51	-0.19
Total Employment	0.34	0.82	0.84	0.72	0.83	0.54	1.03	0.71
Nominal Gross Wage	-0.09	-0.16	-0.14	-0.12	-0.14	-0.11	-0.15	-0.14
Real Gross Wage	0.01	0.03	0.04	0.03	0.04	0.01	0.06	0.02
Replacement cost of capital	-0.53	-1.15	-1.24	-1.04	-1.20	-0.71	-1.54	-0.98
Labour supply	0.33	0.80	0.80	0.69	0.80	0.52	0.97	0.69
Households Consumption	0.20	0.52	0.54	0.46	0.53	0.35	0.67	0.45
Net investment	0.50	1.23	1.34	1.12	1.30	0.76	1.69	1.04
Capital Stock	0.46	1.06	1.08	0.92	1.07	0.69	1.31	0.91
Export RUK	0.23	0.60	0.58	0.51	0.58	0.40	0.69	0.52
Export ROW	0.25	0.56	0.55	0.48	0.55	0.38	0.64	0.49

Table 4.4: Energy Sectors Output – Period 25

	1	2	3	4	5	6	7	8
Energy Sector output	**No LBD**	**Eng. GI**	**Eng. Q**	**Eng. K**	**Econ.**	**Econ. ϕ<0**	**Econ. ϕ>0**	**Eng. B**
Coal	0.43	0.60	0.56	0.50	0.57	0.41	0.65	0.52
Oil	0.33	0.70	0.70	0.60	0.69	0.46	0.84	0.60
Gas	0.27	0.66	0.66	0.57	0.66	0.44	0.79	0.57
Transmission	0.52	1.22	1.25	1.07	1.23	0.79	1.54	1.04
Nuclear Generation	0.29	0.66	0.61	0.55	0.62	0.47	0.71	0.58
Coal Generation	0.12	0.30	0.24	0.23	0.26	0.23	0.27	0.27
Hydro Generation	-0.18	-0.31	-0.36	-0.29	-0.34	-0.17	-0.48	-0.25
Gas Generation	-0.08	-0.11	-0.19	-0.13	-0.16	-0.03	-0.27	-0.08
Biomass Generation	-0.67	-1.36	-1.50	-1.26	-1.45	-0.82	-1.93	-1.15
Wind Onshore Generation	0.35	0.76	0.71	0.64	0.73	0.54	0.84	0.67
Wind Offshore Generation	0.23	0.53	0.48	0.43	0.50	0.37	0.56	0.46
Landfill Generation	-0.55	-1.11	-1.22	-1.02	-1.17	-0.67	-1.56	-0.93
Marine Generation	23.72	69.87	81.43	61.87	76.82	34.66	120.54	54.45

As expected, the production subsidy in the marine electricity sector has an expansionary effect on the Scottish Economy. In all simulations, GDP has increased in period 25. Household consumption, investment, employment and net exports have all been stimulated as a result of the policy. The subsidy reduces the cost of marine electricity generation, leading to a drop in the output price of the marine sector and stimulates the demand for its output. In all simulations the increase in marine electricity generation can be seen clearly in Table 4.4, where marine output increases much more than in any other sectors. Because marine electricity is combined in production with other generation technologies, the prices of other electricity composites drop as well, leading to a reduction in the consumer price index. This increases competitiveness, and leads to an increase in net exports. Consumption and intermediate demand are also stimulated. The percentage changes in aggregate economic results presented in this illustrative comparison of different LBD specifications are relatively small due to the relative size of the sector shocked for the analysis. However the large variations in these small numbers reveal the sensitivity of model results to equation form, variable choice and parameter values, as explored in the next few sections Focusing on simulation 1, which does not include learning-by-doing, first conclusions can be drawn from the modelling of the policy.

4.1. Results without learning

Simulation 1 represents the result of the subsidy only, and the marine electricity sector is not subject to any technological progress. In period 25, the production subsidy leads to an increase in the output of the marine generation sector of 23.72% from the base year. Indirectly, other sectors are affected by the supply shock in marine electricity production. Figure 4.4 shows the sectoral output changes for the 16 sectors (other than marine generation) for Simulation 1.

In the first few periods, the increase in the marine sector output has to be sustained by increases in employment and investments in the sector. Due to the limited availability of factors in the short-run, this leads to upward pressure on the real wage and some sectors are initially crowded-out by the expansion of marine generation. From the SAM data, the marine generation sector is relatively value-added intensive. The output of most sectors falls in the short-run as the results of this crowding-out effect. After a few periods, the supply constraints are slowly relaxed as investment and migration adjust the desired and actual levels of factors of production. After 24 periods, all but four sectors are actually stimulated by the expansion, due to indirect demand effects from the backward linkages of the marine sector, as well as changes in price. A closer look at the electricity generation sectors in particular reveals that they are differently affected by the shock. Figure 4.5 presents the sectoral output changes separately for the eight electricity generation sectors other than marine[49].

The only four sectors that are still negatively affected by the shock in period 25 are electricity generation sectors. The shock to the marine sector displaces some generation from traditional technologies, towards the newly subsidised sector. Hydro, gas, biomass and landfill electricity generations are crowded-out by the growing marine sector.

[49] Marine output is excluded here for an easier interpretation of Figure 4.5.

Figure 4.4: Simulation 1 No learning – output changes

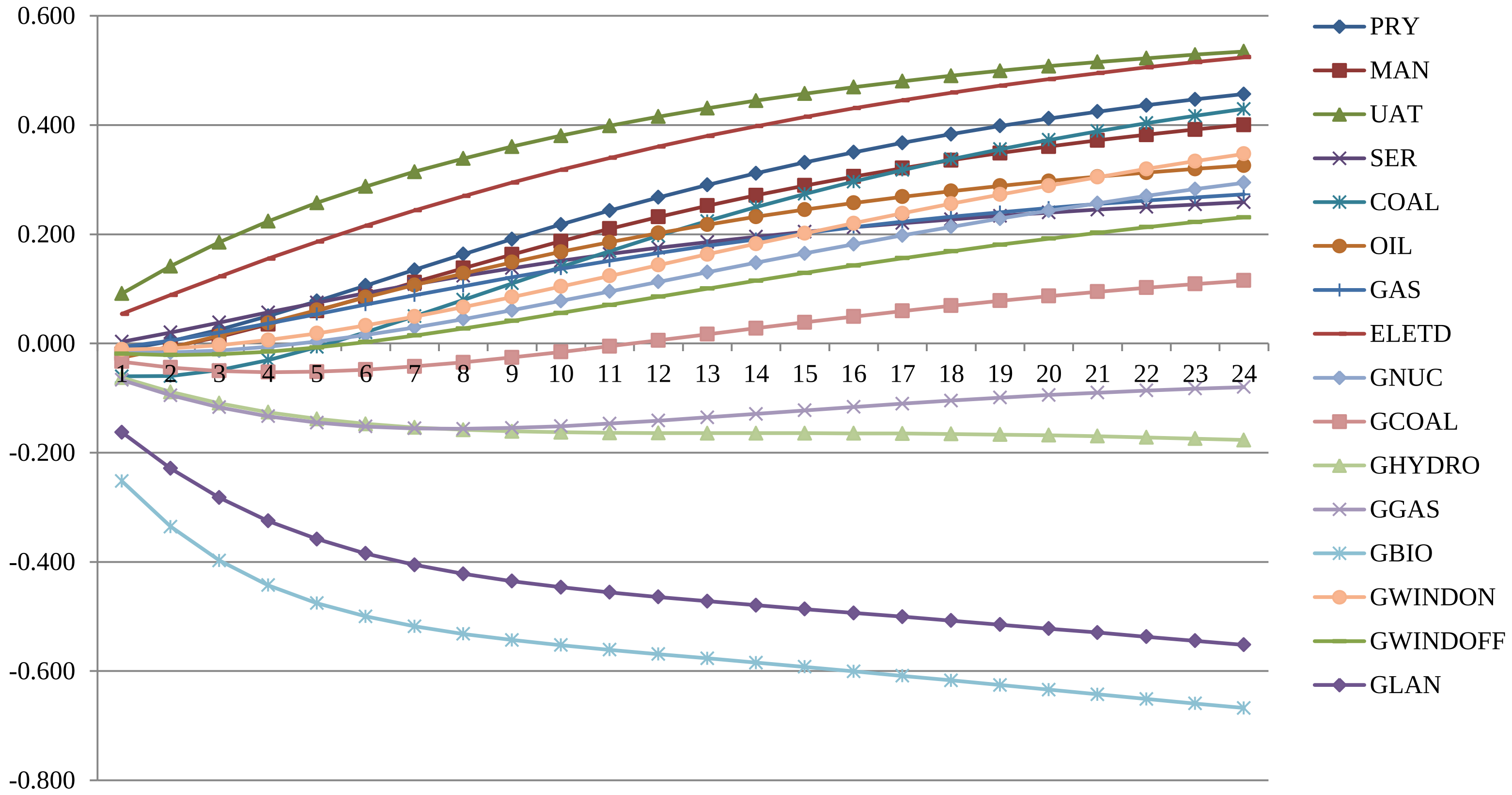
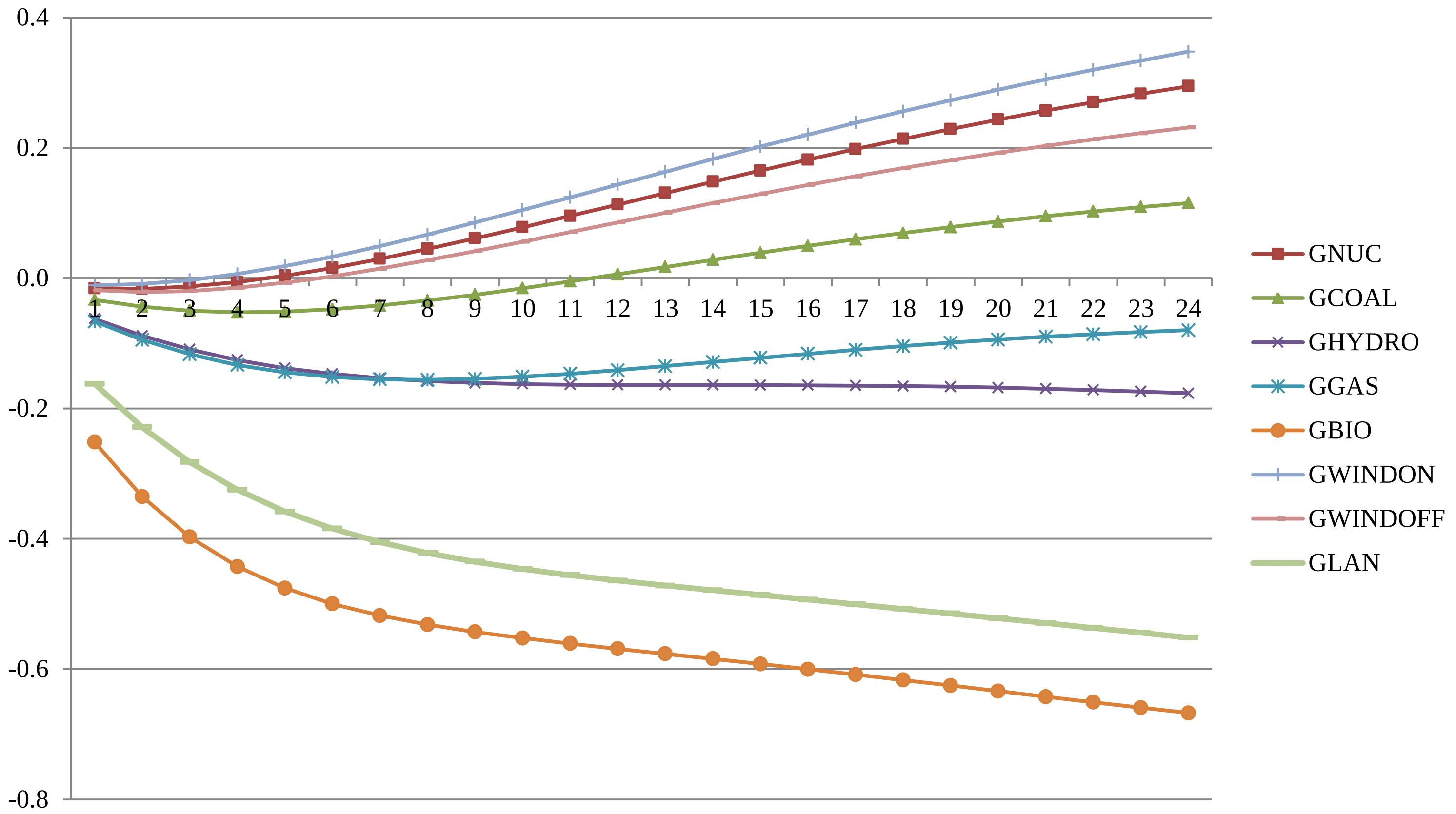


Figure 4.5: Electricity generation sectors output changes



On the other hand, some generation sectors actually beneficiate from the shock and are stimulated in the long run. Onshore and Offshore wind generation is stimulated, and so is generation from coal and nuclear technologies.

These differences in sectoral results reflect a number of effects. First, sectors which provide a large portion of inputs to the marine electricity sector are positively affected by the shock. There are few sectors that are directly linked to marine generation. As for every other electricity generation sectors, the output of marine generation is sold entirely to electricity transmission. On the other hand, its domestic inputs are limited to the manufacturing and utilities and transport sectors. The utilities and transport sector is directly stimulated by the shock from period 1 (see Figure 4.4). Another determinant of differences in sectoral output changes is the choice of nested production structure, as well as the elasticities of substitution chosen at different nods. As wind generation and marine generation form one composite of intermittent electricity generation, some generation is initially displaced from wind towards marine, but after a few periods, wind generation increases, benefiting from the price reductions in the intermittent electricity composite.

Non-intermittent technologies effectively act as substitutes for intermittent generation, and since the elasticity of substitution in the CES function has been set to high value, generation is displaced from traditional generation towards marine and wind. However, this substitution effect is mitigated by the overall expansionary impact of the shock on the economy. The sectoral differences amongst non-intermittent generation sectors require deeper analysis. Landfill gas and biomass generation are the most negatively affected, their output fall continuously over the longer time horizon to stabilize in the long-run around -0.70% and -0.80% respectively. Gas and hydro generation are also negatively affected by the shock, but stabilize in period 25 at higher levels (-0.30% and -0.10% respectively). In contrast, coal and nuclear generations are stimulated in the long-run by 0.15% and 0.45% respectively. These differences can be explained by the input composition of these sectors. As the marine generation sector is stimulated, upward pressure is put on wages, and the most labour-intensive sectors suffer from this rise. Landfill and biomass generation are the most labour-intensive sectors in the model (approximately 40% of total inputs). In contrast, highly capital-intensive sectors, after an initial period of crowding-out in the short-run, beneficiate from the drop in the replacement cost of capital. Nuclear and coal are highly capital intensive generation sectors (with more than 62% and 41% of total inputs respectively).

This observation of sectoral differences has large implications for renewable energy policy-makers. If less-developed energy sectors (often renewable-based sectors) suffer crowding-out effects from policy support targeted at one technology, renewable policies should be developed to jointly encourage the development of several less-developed technologies, in the hope of displacing traditional (generally more polluting) generation. These general findings about the impact of targeted policy support to marine generation through a production subsidy can be further explored in the context of endogenous technological change. Simulations 2 to 8 introduce learning-by-doing in a variety of forms to improve factor efficiency in marine electricity generation.

4.2. Introducing learning-by-doing

The introduction of endogenous learning-by-doing has a large impact on the simulation results. The expansionary effect of the subsidy on the Scottish economy is reinforced by the efficiency gains in marine electricity generation, which further reduce the production costs for the sector. The increase in marine generation output is higher in all simulations including learning than in Simulation 1. Accordingly, the change in GDP in period 25 (from the base year) increases from 0.39% in Simulation 1 without learning, to levels between 0.59% and 1.13% in Simulations 2 to 8. All the aggregate and sectoral effects discussed above are deepened. The decrease in production cost decreases the price of marine generation and in most sectors in the long-run.

The larger costs reduction from endogenous learning increases the boost to competitiveness, to consumption and to investment. The lasting crowding-out of some generation sectors is also deepened with learning effects. These results support the generally accepted view that policy support is more beneficial when targeted at sectors with high technological progress potential. However, these results also differ from a shock where the marine sector would have been subject to an exogenous improvement in production technology.

In this chapter, technological change is introduced as an endogenous process, and this has implications. The learning-by-doing effects will have implications for the speed and path of adjustment of the model, depending on the actual specification of the process. Next, the results of each simulation are compared to others according the criteria identified previously in Chapter 3: in terms of equation form, returns to knowledge assumptions and experience and performance proxies[50].

4.3. The equation form

In order to compare the engineering and economic learning curves in their simplest form, we must look at Simulations 2 and 5. They both use the same variable to embody

[50] The results are presented in this way to be easily compared to the results of the micro-simulations in the previous chapter.

experience: cumulative gross investment; the same variable to embody performance or technology (TFP); and Simulation 5 uses the economic learning curve with no returns to knowledge. The first observation from this comparison is that the economic learning curve in Simulation 5 generates larger gains in total factor productivity (TFP) than the engineering learning curve (53.52% against 44.55%).

Despite the differences in TFP improvement, the aggregate macroeconomic results are remarkably similar between simulations 2 and 5. Increases in GDP are of the same magnitude. The economic learning curve leads to slightly larger increases in employment, consumption and net investment, while the engineering learning curve leads to very slightly larger increases in exports. The sectoral results in period 25 reveal more significant differences between the two specifications than the aggregate results (Tables 4.3 and 4.4). The increase in marine output reaches 76.82% with the economic learning curve, against 69.87% for the engineering learning curve.

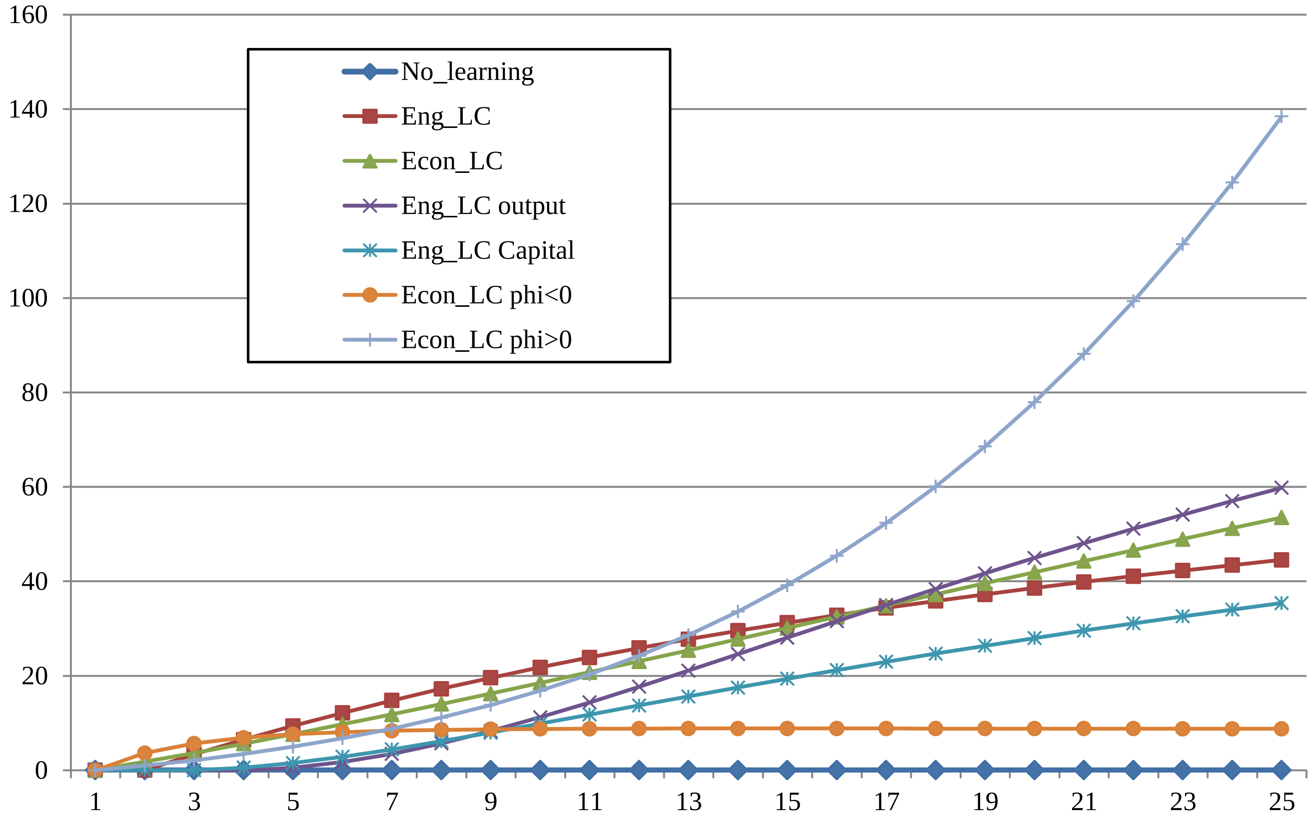
As shown, in Chapter 3, the flow-updating form of the economic specification explains this difference between the two specifications. It generates larger LBD gains when the learning elasticity is smaller than 1 (here $\alpha = 0.32$, corresponding to a learning rate of 20%). The adjustment paths of TFP and marine output are shown in Figures 4.6 and 4.7 respectively, for all simulations.

Although the final period results are relatively close on the graph for the two simulations, the paths of adjustments of TFP and marine sectoral output are different. The engineering specification initially creates faster growth in TFP and output, while the economic specification appears slower at bringing efficiency improvements, but eventually overtakes the engineering specification. The path of TFP with the economic learning curve is more linear (as confirmed in the micro-simulations of chapter 3) and therefore continues to increase after period 25[51], whereas the engineering learning curve leads to concave TFP path and seems to converge towards a long-run equilibrium value. The adjustment path of the marine sector output roughly corresponds to that of the TFP adjustments.

The economic learning curve leads to larger and steady marine sector growth after 25 periods, while the simulation with the engineering learning curve leads to a decreasing rate in marine sector growth overtime. These results confirm that the engineering learning curve is designed to represent the difficulties associated with further doubling of experience over time. The simple economic specification, when ignoring potentially negative returns to knowledge, ignores this difficulty and is equivalent to assuming that unlimited learning-by-doing improvements are achievable, as long as investments continue to grow.

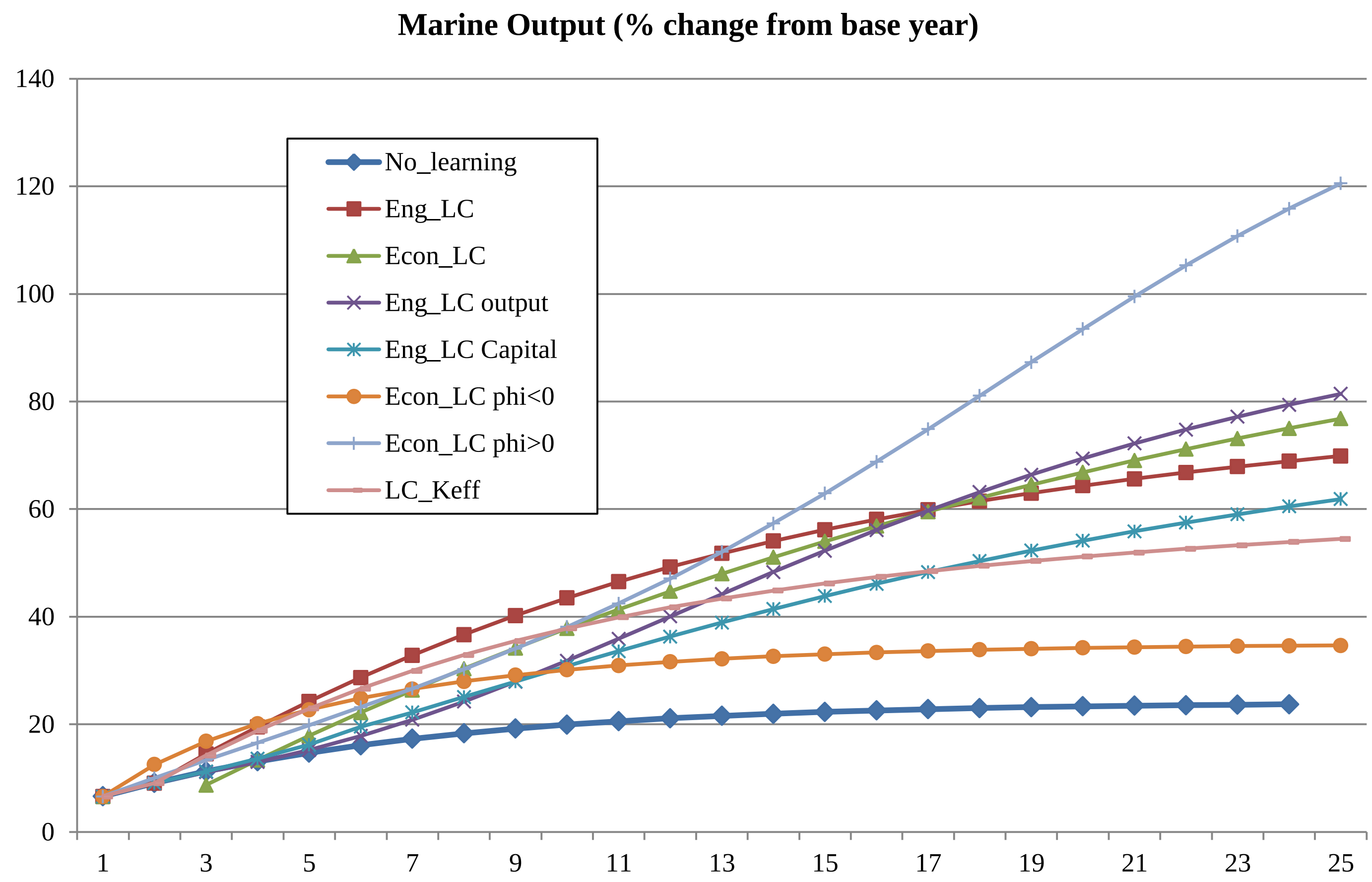
[51] Although it is not perfectly linear, since the sequence of investment shocks predicted by the model is not linear, as opposed to the fixed investment shocks in Chapter 3.

Figure 4.6: TFP (% Change from base year)- Simulations 1 to 7[52]



[52] Note: Simulation 8 is excluded from this graph as the parameter impacted by learning-by-doing is capital efficiency, and not TFP.

Figure 4.7: Marine Output (% change from base year) – Simulations 1 to 8



4.4. Returns to knowledge in the economic learning curve

Simulations 5, 6 and 7 illustrate the comparison of alternative returns-to-knowledge, and thus focus only on the economic specification of the learning curves. Three cases are analysed, which vary with the value of the parameter ϕ (in equation 4.5.). The case of "fishing-out" is shown in Simulation 6, where past increases in efficiency make future efficiency gains more difficult. In this simulation, TFP improvements in early periods reduce the possibility for future TFP gains. This suggests the limited availability of learning potential for a technology. With "standing-on-shoulders", Simulation 7 presents the opposite case, and refers to a situation of increasing returns to efficiency gains. Here, early gains in TFP actually increase the future possibilities for more technological progress. In other words, there is an infinite potential for learning improvement, and "the more you learn, the more you can learn". Both simulations are compared to the case of no external returns to knowledge, with ϕ=0 in Simulation 5.

The value of parameter ϕ has significant implications for modelling results. In the case of fishing-out, the expansionary economic impact of the subsidy is the most limited of all the scenarios introducing learning-by-doing. Implementing decreasing returns to knowledge weakens the economic specification, which shows a concave shape. As pointed out in Chapter 3, this specification produces adjustment paths that are qualitatively similar to the engineering learning curve, although the parameterisation chosen leads to smaller quantitative results. TFP increases by 8.8% and marine output increases by 34.6%. In contrast, the case of standing-on-shoulders leads to exponential improvements in TFP. At the end of period 25, it has increased by 138.5% and Figure 4.6 shows that growth in TFP continues to accelerate over time. This huge positive competitiveness shock leads to an increase of 120.5% in marine output and the largest GDP increase of 1.13%. The economic specification with standing-on-shoulders leads to very different shapes of adjustments in total factor productivity gains. These do not resemble the existing empirical findings of learning-by-doing. The case of fishing-out appears to be the economic learning curve specification with results that are closest to the empirically defined learning curve from the engineering literature. This simulation exercise suggests that the choice of returns-to-knowledge parameter should be kept within negative values in economic models with endogenous learning, to ensure that the concave shape of learning-by-doing improvement is respected. This should also lead to further research in estimation of learning rates using alternative functional forms. The exact value of the returns to knowledge parameter should be the object of specific estimation exercises. The objective would be to determine an “economic” learning rate and corresponding returns to knowledge parameter that would best fit the data on costs reductions and experience gains.

4.5. The experience proxy

Focusing on the engineering curve, different experience proxies can be compared, to determine the impact of the choice of variables on modelling results. Simulations 2, 3 and 4 represent the engineering specification where experience is embodied in cumulative gross investment, cumulative output and capital stock respectively.

Using cumulative output (Simulation 3), rather than cumulative investments (Simulation2) to account for experience increases the total factor productivity gains in the results, and therefore enhances the positive aggregate economic impact and the displacement of electricity generation towards the marine sector. The aggregate economic impact remains of similar magnitude, although the growths in marine sector TFP and output are much larger in simulation 3 than simulation 2 (with 59.81% and 44.55% respectively for TFP and 81.43% and 69.87% respectively for output). This result is mainly driven by the fact that in the model, cumulative output always grows more than cumulative investment in the CGE model.

The adjustment paths in Figure 4.6 and 4.7 also reveal new observations (absent from the micro-simulations of Chapter 3), reflecting the more complex structure of the CGE model, than the partial framework of Chapter 3. When using cumulative output to proxy for experience, marine output and total factor productivity follow an S-shape adjustment path. The increase in TFP is initially slower with cumulative output, as the sector begins to respond to the shock. It then accelerates as output increases with TFP and TFP increases with output. This feedback effect leads to fast TFP and output growth. Finally, the growth in TFP appears to slow down again, as the doubling of cumulative output becomes more and more difficult to achieve. At this threshold, the growth in marine sector output slows down. This finding is interesting as it coincides with the economic theory of the s-shaped diffusion of innovation (Davies, 1979). While not specific to economics research, the S-shaped diffusion theory suggests that innovations are successively adopted by different groups, and will different stage of maturity, during which the speed of adoption changes. Innovations ultimately reach a maturation stage, where it has reached its maximum adoption or market-share. Interestingly, the output-driven learning specification is the only one to bring an s-shaped output adjustment path in the model.

Both the cumulative investment and cumulative output (Simulations 2 and 3) results show larger aggregate impacts than the third case, where experience is embodied in capital stock (Simulation 4). The increase in TFP is smaller at 35% and accordingly, the increase in GDP is also smaller (at 0.79%). However, using capital stock as a proxy for experience produces qualitatively similar results as cumulative gross investment. As expected, the adjustment paths for TFP and output follow roughly the same pattern as with cumulative investment, but lower at any point. Capital stock grows with gross investments in each period but also includes depreciation. This corresponds to depreciating the stock of experience, thus using capital stock reduces the speed and magnitude of TFP gains.

Overall these results suggest that the choice of experience proxy matters greatly, in particular depending on the model type. Cumulative output offers a qualitatively different proxy for experience, due to the reciprocal growth effects between output and TFP. In a CGE model, using output as a proxy for experience might over-estimate the increase in total factor productivity, as output is produced in every period, regardless of a shock to the sector. In contrast, increases in gross investment in marine is only triggered by a shock, otherwise gross investment stays constant to replace depreciated capital stock (in equilibrium). The use of capital stock as a proxy for experience tends to decrease the potential for TFP improvements, as depreciation of capital is made equivalent to depreciations to the stock of knowledge. However, when using capital stock, this assumption should be carefully informed by estimates of learning-by-doing depreciation in the industry in question. To my knowledge, estimates of knowledge depreciation in renewable energy sectors are not yet available.

4.6. Efficiency of Capital

Finally, an additional simulation in included in this chapter, illustrating the impact of changing the parameter affected by LBD. In the engineering learning curve discussed previously (Simulations 2 to 4), TFP increases with experience. In the additional simulation (Simulation 8), a new parameter is chosen to embody technological change: here, the efficiency of capital in the production of value-added (B) increases with experience. This simulation is best compared with Simulation 2, which also uses gross investment to embody experience.

Simulation 8 is motivated by the economic assumption that costs reductions from experience are embodied in new capital. Thus, as experience increases with cumulative gross investments, the efficiency of the capital stock increases, which also reduces the costs of production in the marine sector, further than just the subsidy. However, the efficiency of labour in that sector remains unchanged. This has two impacts. First, the cost of value-added reduces less than in previous simulations, because labour is not more efficient. Second, there is a degree of crowding-out in the value-added function. The increase in employment is reduced in Simulation 8 compared to Simulation 2. This will reduce the expansionary impact of the shock.

The same shapes of adjustment paths in marine sector output are observed in Figure 4.6 whether TFP or capital efficiency is improved with LBD. TFP and capital efficiency are increased through the same functional form, with the same proxy for experience. However, learning in capital efficiency leads to a smaller expansionary economic impact than learning in TFP, as suggested above. The aggregate results also show a smaller increase in all key macroeconomic variables. The increase in capital efficiency is smaller than the increase in TFP, due to the smaller increase in cumulative gross investments. The smaller increase in employment has reduced the induced effects from the shock; the positive impact on consumption is smaller, which lessen the potential for positive returns to learning-by-doing on the whole economy.

5. Conclusions

Assumptions about learning-by-doing in terms of equation form, variable choices and parameter values have been shown to have vast implications for modelling results. In a first attempt to introduce endogenous technological change in a CGE model for Scotland, this chapter explores alternative specifications of the learning-by-doing process, informed by findings of Chapter 2 and 3.

The AMOS model used in the Chapter is modified to enable the introduction of endogenous technological change in the value-added production function. This way, cost reductions in production from learning effects can be modelled through improvements in factor productivity (capital and labour). In order to model policy support to a new renewable energy sector, as implemented with the Scottish Government's banded Renewable Obligation Certificates, a production subsidy in the marine electricity generation sector is simulated in the model.

A set of simulations are presented in a multi-period analysis. Simulations all represent the same production subsidy shock but differ in their definition of learning-by-doing, in that they use different equation forms, experience proxies, parameter values or performance proxies (TFP or the efficiency of capital only). The simulation results highlight several major observations. First, the economic learning curve inspired from endogenous growth theory leads to larger efficiency gains than the traditional engineering learning curve, due to its flow adjustment form. Top-down models using this specification are likely to find lower compliance costs to climate policies or larger benefits from LBD than bottom-up models. Second, the introduction of decreasing returns-to-knowledge in the economic learning curve weakens the specification and leads to results qualitatively closer to the engineering learning curve, despite being quantitatively smaller. The case of fishing-out appears consistent with the hypothesis that learning-by-doing opportunities decrease as the technology develops. In contrast, the introduction of increasing returns-to-knowledge in the standing-on-shoulders case completely alters the behaviour of the learning-by-doing function, and leads to exponential growth in efficiency. These results illustrate the need for a more detailed a throughout testing of these specifications using econometric estimation techniques. This exercise might be limited by the availability of data for a number of energy technologies. Third, the use of cumulative gross investments or capital stock as a proxy for cumulative experience is strongly backed by economic theory insisting that technological change is embodied in new capital. However, the simulation using cumulative production, as argued in early models of learning-by-doing, generates different results and is the only case where marine output shows an S-shape adjustment path, which coincides with S-shape diffusion curve referred to in the economic literature on innovation diffusion. This also suggests the need for further research in the estimation of learning curves for energy technologies.

These results have implications for the CGE model for Scotland and for the broader EEE modelling literature that introduces LBD. The engineering specification is a preferred method for incorporating learning-by-doing due to the simplicity of its equation and the decreasing returns associated with it, providing the possibility for adjustments towards a long-term equilibrium. The economic specification is theoretically preferable to introduce in a CGE economic model, and can also lead to a long-term equilibrium but only in the case of fishing-out. The cases of constant returns to knowledge and standing-on-shoulders lead to ever-expanding experience gains, which destabilise the model in the long run. Finally, the choice of variable embodying experience is of relatively modest importance, although the use of cumulative production appears consistent with the literature on the s-shape diffusion curve. This chapter highlights the high sensitivity of modelling results with regards to assumptions in the learning-by-doing process. Policy modellers need to clearly identify these assumptions and their impact on results and policy conclusions. Technological change is a complex process of interactions between technological, economic and policy-driven influences. The development of more complex estimation tools are required to fully encompass these interactions and identify an optimal representation of learning-by-doing.

Part B: The UK Roll-out of Smart Meters, Efficiency Gains in Electricity Consumption and Rebound Effects

The UK government has announced its commitment to a mass roll-out of smart meters, set to equip all British homes and small businesses with electricity and gas smart metering devices by the end of 2020. This commitment takes place in the larger policy context of transitioning to a low-carbon energy system. Smart meters are expected to play an important role in reaching ambitious CO2 emission reductions targets, through promoting efficiency gains in energy consumption. In addition, they are crucial to the large-scale development of a national smart-grid, which would introduce flexibility into the demand-side management of the energy sector. The UK commitment to smart meters is largely influenced by recent extensions to European legislation on energy efficiency and smart grid requirements for member states. As part of the "Third Package" of EU legislation on the liberalization of electricity and gas markets published in August 2009 (OJEU, 2009), EU member countries must ensure that at least 80% of electricity consumers are equipped with intelligent metering devices by 2020. Additionally, in its 2012 directive on energy efficiency (2012/27/EU), the European Union restates its target of a 20% reduction in annual primary energy consumption by 2020 compared to projections. Among its general guidelines for member states to contribute to this target with energy efficiency measures, the directive highlights the need for the diffusion of informative metering technologies. The installation of these "smart meters", providing accurate information on actual energy consumption and time-of-use, is regarded as a necessary step towards reductions in final electricity consumption (OJEU, 2012).

The UK target for the adoption of smart meters is more ambitious than EU recommendations and the plan is to equip all domestic and non-domestic customers (30 million homes and small businesses) by 2020[53]. This programme has been subject to a series of evaluations and consultations conducted by DECC, assessing the costs and benefits of such a policy, as well as addressing policy concerns such as data use and consumer privacy. The latest impact assessment in April 2012 estimates the net present value of the roll-out at £4.8 billion up to 2030, with costs and benefits of £10.9 billion and £15.7 billion, respectively (DECC, 2012). The installation and operation costs of the new meters and communication equipment make up the largest share of the total costs of the roll-out, and are to be borne by the suppliers. The estimated benefits are largely driven by assumptions about savings on three counts. These are suppliers' cost savings (through eliminating the need for bill estimates, visits for meter readings and reducing the volume of customers' enquiries), consumer energy savings and associated carbon savings (driven by improvements in energy efficient behaviour).

These impact estimates have been the object of significant interest from both academic and popular press, due to the uncertainty surrounding the scale of the energy savings and the distributional impacts of the roll-out. Consumer concerns gravitate around data privacy and the risk that suppliers might pass the costs of the meter onto customers' bills, while denying costs savings to be passed on as well. In addition, some question the ability of smart meter technology to generate energy savings on their own without accompanying policy to develop time-of-use pricing (Thomas, 2012).

[53] The original target of 100% of meters installed by the end of 2019 has been pushed to the end of 2020 as of 10 May 2013, reflecting the industry's need for a longer testing period (DECC, 2013).

There exists a growing body of literature showing that smart meters can contribute to the reduction of household energy consumption, through a better understanding of energy use and bills[54]. However, despite evidence of energy savings, there is continued uncertainty about the scale of household response to the new technology and about the actual channels through which these reductions will take place. The household energy savings from the adoption of smart meters is assumed to originate in energy efficiency gains in consumption and should lead to reductions in household bills. However, these efficiency gains are also likely to have wider economic consequences by reducing household electricity and overall electricity demand in the UK, leading to changes in prices and in turn to further demand adjustments. In particular, efficiency gains in household electricity consumption might lead to rebound effects in household and total UK electricity use, through a decrease in the effective price of electricity services in consumption. These issues are best addressed in an economy-wide framework.

Part B of this thesis is devoted to explore these rebound issues using modelling tools that can identify the economy-wide effects of a change in household energy technology on the rest of the economy. Chapter 5 explores the household and total rebound in electricity use in an Input-Output framework. Chapter 6 extends the analysis to a Computable General Equilibrium model, to identify the added-value from endogenizing prices and income in the economy-wide rebound analysis.

[54] This literature is reviewed in Chapter 5.

Chapter 5: An Input-Output Analysis of the Rebound Effects from Efficiency Gains in Household Electricity Consumption

1. Introduction

The UK Government mass roll-out of smart meters is planned to equip all domestic energy customers with the technology by 2020. This policy is mostly targeted at improving the demand-side management of the energy system, and in particular, at improving consumers' visibility of their energy consumption. It has been shown in the literature that with a better access to information about their energy consumption, households tend to reduce their overall consumption (see for example Darby, 2006 for a review[55]). These energy savings are assumed to originate in energy efficiency improvements that enable households to enjoy the same "energy services" with lower consumption of energy in natural units. While these households' energy savings have been an area of debate in the literature, little (or no) attention has been given to the knock-on effects of this policy on the rest of the energy system, the economy and the environment. By inducing an improvement in household energy efficiency, this policy is likely to have wider implications for the overall economy, the rest of the UK energy demand, the supply side of the energy system and in turn on the UK emissions of greenhouse gases.

The aim of this chapter is to explore the economy-wide impacts of an efficiency gain in household electricity consumption from the mandated roll-out of smart meters[56]. This

[55] This literature is reviewed in more details in Section 2 of this chapter.
[56] This Chapter focuses on an efficiency gain in electricity consumption only, as there has been limited evidence linking gas savings to smart meters.

analysis is framed in the context of rebound effects from an efficiency gain in household electricity consumption. While the rebound effect has been extensively studied in the context of energy efficiency gains in the production side of the economy (see Turner, 2013 for a review), there are relatively few studies that have looked into the rebound effects from efficiency gains in household consumption. These studies have mostly focused on direct rebound effects, i.e. the rebound in household energy use only (e.g. Dubin et al., 1986; Frondel et al., 2008; Greene et al., 1999; Klein et al., 1985 and 1987; Schwarz & Taylor, 1995; West, 2004). By focusing on the direct rebound only, these studies ignore the potential economy-wide impacts of efficiency gains in energy consumption. The use of Input-Output analysis in this chapter is largely motivated by this gap in the literature. To our knowledge, multi-sectoral modelling has only tackled efficiency improvements in household energy use as a whole: Druckman et al. (2011) and Freire-Gonzalez (2011) use Input-Output analysis to examine the direct and indirect rebounds from efficiency improvements in energy consumption, whilst Lecca et al. (2014) generalise this research by identifying the value-added of using a Computable General Equilibrium model to investigate this phenomenon.

This chapter uses an Input-Output (IO) model for the UK to estimate the total rebound effects from efficiency gains in household electricity use from the adoption of smart meters. This exercise is innovative in several ways. First, this work represents the first attempt to estimate the economy-wide impacts of the large scale deployment of smart meters in the UK. This is the first time that IO analysis is used to determine the direct, indirect and induced economic and environmental impacts of efficiency gains in household electricity consumption. It is also the first attempt at determining the extent of the economy-wide rebound in electricity from this policy. Additionally, the chapter addresses a range of other innovative issues relating to the policy, such as:

- the general relationship between the direct and total rebound in the context of efficiency gains in household electricity consumption
- the impact of disaggregating the electricity sector on electricity rebound results
- the sensitivity of the rebound to assumptions about substitution possibilities in household energy expenditures (by extending our modelling method to incorporate econometric work on household energy consumption)

The remainder of the chapter is organised as follows. Section 2 reviews the literature estimating the impact of the introduction of smart meters on household consumption behaviour. In addition to highlighting the major uncertainties surrounding the issue of the impact of smart meters, this review is employed to identify a value for the efficiency gain in household electricity consumption, which is used to parameterize the exogenous efficiency shock in our simulation exercise. Section 3 focuses on the definition of rebound effects in this thesis. Based on the energy rebound literature, it defines household and total rebound effects by differentiating between household and total electricity use. Section 4 details the methods and the IO framework used for the analysis. It also introduces the definitions of the direct, indirect and induced effects of the efficiency shock, to define the total Type I and Type II total rebound effects in electricity use. Section 5 presents the first results of the IO analysis of the rebound effect from an efficiency gain in household electricity consumption. The results are shown in terms of direct, Type I and Type II sectoral and economy-wide impacts on output and CO2 emissions. The corresponding direct, Type I and Type II rebounds are calculated as well. In Section 6, the electricity sector is disaggregated to differentiate between generation and transmission and distribution activities. The new IO tables are used to discuss the impact on the rebound results of the aggregation of all electricity activities into one sector. Section 7 compares the results of a set of simulations illustrating how consumption substitution possibilities between energy commodities affect the rebound results. This exercise uses findings from the econometric estimation of substitution in household energy consumption. It compares scenarios where gas and electricity are substitutes and complements in household consumption. Section 8 concludes the chapter and discusses the need to extend this modelling exercise of the roll-out of smart meters, using a Computable General Equilibrium framework, which is the focus of Chapter 6.

2. Smart meters and feedback on energy consumption

In the UK, as in most countries, domestic energy meters are often placed out of sight. Therefore, household consumers are typically unaware of the energy that is used in running domestic appliances. The impact of providing enhanced information to households on their energy use has been the focus of a number of surveys and pilot studies since the 1970s. This literature, which refers to this enhanced information as "improved feedback", generally argues that improving the information communicated to consumers about their energy use leads to a better control over their consumption and ultimately leads to energy savings (Fisher, 2008). This section reviews the major findings of this experimental literature about the level of savings by households when subject to improved feedback[57].

[57] Many of these studies have looked at the impact of feedback on energy consumption in combination with the impact of time-of-use pricing methods. Due to the scope of the chapter, the literature review only reports findings relating to energy savings.

Darby (2006) presents the first review of this literature and includes 38 feedback studies conducted between 1979 and 2006. The evidence gathered in the review largely confirms the potential for energy savings resulting from the use of technologies that improve customer feedback. While improved feedback consistently appears to lead to energy savings, the degree of response varies with the type of informative feedback considered in the studies. Direct feedback, such as in-home displays, leads to savings in the range of 5-15%, while the impact of indirect feedback (e.g. monthly billing or comparative feedback) is more modest at 0-13%. A later review by Fisher (2008) includes 26 studies but restricts the analysis to studies designed exclusively to determine the impact of feedback on consumption. It largely confirms the findings in Darby (2006) with typical savings of around 5-12% and concludes that computerized feedback is a regular feature of successful programs. Other factors determining the success of the feedback in reducing consumption include an interactive element, an appliance breakdown[58] and a high feedback frequency (daily or more). A more recent review funded by the European Smart Metering Industry Group (Stromback et al., 2011) regroups and analyses the results of 100 pilot studies from Australia, Canada, Europe, Japan and the U.S.A. Through a direct comparison of different feedback methods, this report concludes that In-Home-Display (IHD), which provides direct and easily accessible reading possibilities to consumers in their homes, is the most efficient method. On average it reduces energy consumption by 8.68%, as compared to informative billing (5.90%) or web feedback (5.13%). This international review highlights a number of factors which impact on the results. For example, they observe stronger response to feedback in European countries, and find that longer pilots tend to

[58] Feedback with appliance breakdown details energy use for each appliance in the home.

have longer lasting effects (suggesting some habit formation). In terms of feedback content, they conclude that In-Home-Displays are more effective when they provide real time consumption, real time bill information and/or historical comparison, whereas comparative feedback can have a negative impact on savings. A recent meta-analysis of information-based energy conservation experiments reviews the results of 156 published field trials between 1995 and 2012 (Delmas et al., 2013). The results of the meta-analysis confirm the potential for information campaigns to reduce household energy usage. These results validate the use of new technologies, such as smart meters, that can provide low-cost feedback on energy consumption and are likely to lead to energy savings. While the results of the meta-analysis show an average reduction in electricity consumption of 7.4%, they also provide a quantitative comparison of alternative information-based strategies, such as historical or real-time feedback, information about energy saving approaches, normative strategies or strategies involving monetary incentives[59]. Their findings confirm the superiority of real-time feedback strategies when compared to comparative feedback or monetary incentives.

In addition to reviews that compare all types of feedback, a number of recent papers and reports focus specifically on real-time feedback (Faruqui et al., 2010, Foster and Mazur-Stommen, 2012, Houde et al., 2013). This type of feedback gives households real-time information about their energy use (level of consumption, cost, carbon emission, etc.) and is the closest to the information that smart meters will deliver in the UK. These studies confirm the advantage of In-Home Displays technologies (IHDs) compared to other feedback methods in delivering savings. Focusing on this IHD technology itself,

[59] Historical feedback corresponds to information about past energy usage, energy costs, etc. Real-time feedback is information about current or near-present energy usage, energy costs, energy price, etc. Normative strategies refer to comparative feedback based on social norms

Faruqui et al. (2010) review 12 pilot studies and find energy savings in the range of 3-13% with an average of 7%. A report by the American Council for an Energy Efficient Economy (Foster and Mazur-Stommen, 2012) over 9 real-time feedback studies finds a range of energy savings of 0-19.5% with an average of 3.8%. The report also reveals that the more advanced the IHD technology, the more customers engage, which leads to more energy savings. Additionally, they observe that real-time costs and real-time consumption are the most relevant information to consumers in terms of delivering savings. Houde et al. (2013) conduct an experiment looking at the impact of a new Google device that graphically displays historical and current electricity consumption at 10 minute intervals. They find that exposure to this feedback leads to an average 5.7% electricity consumption reduction.

The UK also conducted its own pilot studies funded by the regulator Ofgem in collaboration with four energy suppliers (EDF ENERGY, E.ON, Scottish Power and Scottish and Southern Energy). These studies were conducted over the period 2007-2010 for a total of 61,344 household including 18,370 equipped with smart meters. The findings suggest that no consumption reductions occur in interventions without smart meters (e.g. more informative billing or consumer engagement strategies). Smart meters are found to work best in combination with IHDs, confirming the findings from other studies and reviews. The reported estimated electricity savings were however, smaller than previous estimates with an average 3% reduction in consumption, while little evidence of reduction in gas consumption is discovered (AECOM, 2011).

This literature seems to converge on the success of real-time feedback to reduce electricity consumption through the use of smart meters and IHD technologies. The recent UK Energy Demand Research Project estimate of 3% savings on electricity consumption from the introduction of smart meters (AECOM, 2011) appears as a reasonable value to use to calibrate the efficiency shock in the simulations conducted in this chapter. This value is chosen as it is estimated for the UK and relates to the same (or similar) technology that will be deployed during the mass roll-out. This value of 3% is relatively conservative compared with the average energy saving findings in the literature as a whole.

3. Rebound effects

As shown in the previous section, it is generally expected that improving feedback to consumers about their energy use will lead to conservation behaviour. Through the introduction of smart meters, UK households will receive real-time information about their electricity use, and from this feedback, they are likely to reduce their consumption. This conservation behaviour can be explained by improvement in efficiency in electricity consumption, i.e. households use electricity units more efficiently when more information about their usage becomes available to them. This chapter attempts to model the efficiency gain in household electricity consumption and determine the extent of the rebound it will generate, both in terms of household and total UK electricity use. First, it is necessary to define formally the concept of rebound effects from efficiency gains in electricity consumption[60].

The rebound effect corresponds to the difference between the change in electricity use and the change in electricity efficiency. In effect, the proportionate decrease in

[60] In this thesis, the rebound effects are defined and discussed only in the context of electricity use, and not energy in general. This is due to the policy focus on reductions in electricity consumption from the introduction of smart meters. The impact on gas use and CO_2 are also discussed but not in terms of rebound.

electricity use will be smaller than the proportionate increase in efficiency when it is mitigated by a *rebound effect*.

An increase in efficiency in household electricity consumption can be assimilated to a change in "consumption technology", through which households can extract more energy services from each physical unit of electricity. This implies that following an efficiency gain in electricity consumption, households can, *ceteris paribus,* maintain their previous level of utility with lower electricity consumption in physical units. This efficiency gain should in principle reduce household electricity consumption, but this conservation mechanism has been shown to be mitigated by a rebound effect: the efficiency gain in electricity consumption essentially reduces the price of electricity services in efficiency units for households. The price of electricity in efficiency units P_e is defined as follows:

$$P_e = \frac{P_n}{1 + \gamma} \tag{5.1}$$

where P_n is the price of electricity in natural units and γ is the shock to efficiency in household electricity consumption. Following the increase in efficiency, there is an implicit reduction in the electricity price in efficiency units and households substitute electricity in efficiency units for other consumption goods. In effect, the reduction in electricity consumption is mitigated by this *household rebound effect*, and will be smaller than the improvement in efficiency. The household rebound effect R_H, from an efficiency gain (γ) is formally defined in equation 5.2:

$$R_H = \left(1 + \frac{\dot{E}_C}{\gamma}\right).100 \tag{5.2}$$

where $\dot{E}_C$ is the proportionate change in household electricity consumption in natural units. When the proportionate decrease in household electricity consumption equals the proportionate increase in efficiency, the household rebound is zero. However, when the decrease in household consumption is lower than the increase in efficiency, there is a partial household rebound effect ($0 < R_H < 100$). Finally, if household consumption actually increases in natural units, then $R_H > 100$ and we have the case of backfire[61].

In this economy-wide analysis, the household electricity rebound represents only one element of the impact of efficiency gains. The economy-wide impact of the efficiency gains must be measured through the *total rebound in electricity use*. The total rebound is calculated using the change in total UK electricity use, as given in equation 5.3:

$$R_T = \left(1 + \frac{\dot{E}_T}{\alpha\gamma}\right). 100 \qquad (5.3)$$

where $\dot{E}_T$ is the proportionate change in total electricity use, and α is the initial share of household electricity consumption in total UK electricity use.

Although the rebound effect has been defined here in relation to efficiency improvements in household's electricity consumption, it is a well-documented phenomenon arising from efficiency gains in energy use in general. It is commonly accepted that any improvement in energy efficiency will be subject to a rebound effect. The possibility that energy savings from efficiency gains can be reduced by the rebound effect (or more than offset, in the case of backfire) has widely debated, depending on

[61] Sorrell (2007) and Saunders (2008) also identify the theoretical possibility of a case of "super-conservation", corresponding to a negative rebound, where energy use decreases by more than the efficiency gain. However, no empirical evidence exists to support the existence of super-conservation in practice.

the definition used. For good reviews of this literature, see Greenings et al. (2000), Dimitropoulos (2007) and Sorrell (2007).

4. Input-Output Analysis

4.1. The Input-Output Model

In this chapter, Input-Output (IO) is chosen as a method of analysis to explore the direct, indirect and induced effects from the efficiency gains in household electricity consumption from the adoption of smart meters. In this chapter, a demand-side IO analysis is performed to model the total impact of households' consumption switching behaviour following the efficiency shock in electricity consumption.

The 2004 UK industry-by-industry IO tables are used to show the impact of a decrease in household final demand for electricity. While the focus of this chapter is mainly to determine the magnitude of rebound effects in total electricity use, another major issue of interest is the impact of this demand change on aggregate CO2 emissions. Thus, the UK 2004 IO tables are aggregated from the original 123 sectors into 67 sectors, in order to reflect the availability of CO2 data by industry[62]. The list of sectors used in this chapter is presented in Appendix D, with the corresponding IO and Environmental Accounts sector classifications. CO2 emissions are attributed to each sector's output according to the CO2-intensity derived from the Environmental Accounts. Among the 67 sectors, 2 are energy commodities, namely electricity and gas.

In the simulations, we represent the introduction of smart meters in British homes as an efficiency gain in household electricity consumption. The direct effect from this

[62] The 67 sector aggregation is driven by the sectoral classification of the Environmental Accounts, as explained in Hermannsson and McIntyre (2013)

efficiency gain is represented as an exogenous change in household final demand for electricity consumption. In order to calibrate the reduction in household electricity consumption in natural units, the empirical estimates from Section 2 are used. The introduction of smart meters in UK households is estimated to produce a 3% reduction in electricity consumption. This corresponds to a £286.87m reduction in household demand for the electricity sector in the 2004 UK IO accounts. This reduction in household electricity consumption is compensated by a corresponding redistribution of expenditures towards all other consumption sectors[63].

In this demand-driven IO analysis, the objective is to determine the impact of a change in final demand on the rest of the economy, through the determination of direct, indirect and induced effects. This analysis is conducted under the general IO assumption of passive supply. Under this assumption, supply is able to fully satisfy changes in final demand, i.e., there are no supply-side constraints on factors of production. The IO tables can be read as a set of simultaneous equations representing how each sector's output is used by other sectors or agents in an economy. The matrix form of the IO tables enables a clear representation of the complex interdependencies between industry and final demand, as well as the inter- and intra-sectoral linkages. The advantage of IO analysis is the possibility of relatively simply transforming this system of equations to determine the "knock-on" impacts of a change in final demand for one sector on all other sectors, and thus on the economy as a whole.

[63] A number of assumptions about the redistribution of expenditures to non-electricity sectors are explored in this thesis, particularly with regard to substitution between electricity and gas. These assumptions are embodied in several scenario analyses and are clearly stated in the next sections.

The conventional model can be formulated in order to express the output as a function of the exogenous final demand:

$$X = (I - A)^{-1}Y \tag{5.4}$$

where X, I, A and Y are respectively the vector of output, the identity matrix, the matrix of input coefficients and final demand. $(I - A)^{-1}$ is the Leontief inverse matrix that summarises the economic structure of a country. The elements of the Leontief matrix identify the backward linkages of each sector. If sector *j* increases its output, there will be increased demand from sector *j* (as a purchaser) for other sectors whose goods are used as inputs to production in *j*. This is the direction of causation in the usual demand-driven model and the term backward linkage is used to indicate the interconnection of a particular sector with those sectors from which it purchases inputs. Equation (5.4) illustrates the dependence of sectoral output on final demand components (Miller and Blair, 2009). This relationship is used to determine the Type I (direct and indirect) and Type II (direct, indirect and induced) impacts of a change in final demand on sectoral output.

The direct effect is the initial adjustment to the change in final demand. This impact corresponds to the adjustment of supply in response to a direct change in demand for one or several sectors' output. In turn, the demand for inputs by these sectors changes as well, resulting in further adjustments in sectoral outputs. This is the indirect effect. While the direct impact only represents the change in outputs in the sectors which are subject to the change in final demand, the indirect impact reflects the backward linkages of the directly impacted sector. For example, if final demand for the electricity sector decreases, the direct impact is the decrease in electricity output to adjust to the change in final demand. However, other sectors in the supply-chain of the electricity sector will be negatively impacted by the decrease in electricity output. These sectors' output will decrease as an indirect impact, thus the total negative impact on the economy will be larger than the initial direct impact. The total Type I impact represents the sum of direct and indirect impact and can be calculated using Type I multipliers. Multipliers are defined as the sum of elements in each column of the Leontief inverse.

In addition, Type II multipliers can also be derived, in an open Leontief model, to include induced effects. Induced effects are obtained from changes in households' income, as a result of the change in final demand. As sectoral outputs adjust to the new vector of final demands, households' income (payment for labour inputs into production) adjusts as well. This change in income results in a change in household final consumption, a component of final demand. The induced effects are obtained in the model by incorporating the employment-output multipliers in the calculation of the Leontief inverse.

Once the Type I and Type II sectoral impacts have been calculated using the multipliers, we can determine the associated impacts on sectoral and total CO2 emissions using CO2-output multipliers. Using equation (5.4) the impact of an exogenous increase in final demand Y on total output X can be formulated as follows:

$$\Delta X = (I - A)^{-1} \Delta Y \tag{5.5}$$

This model is based on a number of assumptions. The supply side is passive, so that the final demands drive economic activity. Prices are assumed to be fixed and therefore no crowding-out effects occurs. This approach assumes excess capacity; therefore the economy can expand without putting any upward pressure on wages and prices. This means that the supply side of the economy reacts passively to changes in demand. In the simulations performed in this chapter, it is assumed that production technology (the Leontief coefficients), and thus the cost structure of each economic activity, do not change over time. Therefore, the results described here provide estimates for the economic impact in the absence of structural change in the economy over the period under consideration. All the results tables for this chapter are presented in Appendix E.

4.2. Direct, Indirect and Induced Rebound

In the IO context of this chapter, three major components of the rebound effect are investigated. These components correspond to the three effects that are identifiable from the IO analysis: namely the direct, indirect and induced rebound. These components are defined and explained below in the Input-Output context of this chapter.

4.2.1. The Direct Rebound

Following the typology of the rebound proposed by Greening et al. (2000), the direct rebound in this thesis refers exclusively to the rebound at the micro-level, which corresponds to the direct increase in household electricity consumption from the reduction in the price of electricity services. Effectively, the direct rebound represents the adjustment of household electricity consumption in efficiency units following the decrease in the price of electricity services. Because the analysis of this chapter is based in an Input-Output framework with fixed prices (in natural units) and fixed income in the Type I analysis, the direct rebound is equivalent to the household rebound defined in Section 3[64].

[64] The household rebound will be different than the direct rebound in the next chapter which employs a Computable General Equilibrium approach.

The direct rebound in this chapter is defined in the same way as household rebound (in equation 5.2.). It represents the household response to the implicit decrease in electricity price following the efficiency shock. Thus, the direct rebound is assumed to be fully defined by the price elasticity of household electricity demand (η_e).This corresponds to the simplest definition of the direct rebound (Khazzoom, 1980, Sorrell and Dimitropoulos, 2007)[65].

The price elasticity is defined in equation (5.6), as the proportionate change in household electricity demand in efficiency units, $\dot{E}_e$ following a change in the electricity price in efficiency units, $\dot{P}_e$:

$$\eta_e = \frac{\dot{E}_e}{\dot{P}_e} \tag{5.6}$$

In other words, in this IO analysis, the household rebound is equal to the direct rebound, which is also equal to the own price elasticity of household electricity demand, as shown in equation 5.7:

$$R_D = R_H = \eta_e . 100 \tag{5.7}$$

If the direct rebound is positive but lower than 100, households decrease their electricity consumption following the efficiency shock. This is the case that is expected in the analysis of this chapter, since the literature review reveals a decrease in household consumption following the introduction of smart meters.

[65] although the estimates of the elasticities of energy demand may be biased depending on the trends of energy prices at the time of estimation. Time series estimates during periods of rising energy prices could overestimate the rebound (Sorrell and Dimitropoulos, 2007).

4.2.2. Indirect Rebound

In addition to the direct rebound in household electricity consumption, the analysis aims to determine the impact of efficiency improvements on the change in total electricity use. Following the efficiency shock in household electricity consumption, the change in household electricity consumption is determined by the extent of the direct rebound. With a direct rebound lower than 100, household electricity consumption decreases and this will impact the demand for other goods, through consumption-switching effects.

This consumption-switching in turn changes the total demand for electricity as it is used as an intermediate input in production. The indirect rebound measures this embodied electricity effect. The sign and magnitude of the indirect rebound is therefore influenced by the relative level of electricity-intensity of the preferred goods and services for household consumption, as compared to the electricity commodity itself. If households switch their consumption from the electricity sector towards more electricity-intensive goods, the indirect rebound will be positive. Conversely, if consumption switches towards less electricity intensive goods, the indirect rebound will actually be negative.

This can be expressed formally in the following system: A change in household expenditures on electricity consumption (ΔE) is fully redistributed towards the consumption of non-electricity goods (ΔNE), and can be expressed as a function of total household expenditure C, as in equation 5.8:

$$\Delta E = -\Delta NE = C\left(\frac{R_D}{100} - 1\right)\lambda\gamma \tag{5.8}$$

Where λ is the share of electricity in total household expenditures

The combination of direct rebound in household consumption and indirect rebound from embodied-electricity effects give a measure of the Type I total rebound in electricity in the economy. Given the fact that the electricity sector is highly energy (electricity) intensive, shifting consumption towards non-electricity goods is likely to generate a negative indirect rebound, and thus to reduce the total rebound.

4.2.3. Induced Rebound

Induced effects are also considered in the analysis. As households demand changes through consumption-switching effects, sectoral activity adjusts, leading to further adjustments in income for households and in turn further adjustments in total consumption. The total rebound which includes direct, indirect and induced effects is defined as the Type II total rebound effect. If households' income increases as a result of indirect effects, there will be an induced increase in household consumption, which will increase total electricity use. In this case, the Type II total rebound, which incorporates indirect and induced effects, will be larger than the total Type I rebound which only includes indirect effects. In the reverse case, a decrease in household income will lead to a decrease in total UK electricity use, and a smaller total Type II rebound effect.

4.2.4. Total Rebound

The total rebound measures the rebound in total electricity use(in both consumption and production). It was defined in equation 5.3 in Section 3 using the proportionate change in total electricity use $\dot{E}_T$. It can also be defined in terms of the absolute change in total electricity use ΔE_T, defined in equation 5.9

$$\Delta E_T = \Delta E\ (1 + m_E^E) + \Delta NE\ (1 + m_N^E) \tag{5.9}$$

E_T, the total Type I (or Type II) change in UK electricity use is determined by the electricity embodied directly and indirectly (and induced) in the change in household consumption of electricity and non-electricity goods. Here, m_E^E represents the embodied-electricity in the electricity commodity and m_N^E the electricity-intensity of non-electricity goods.

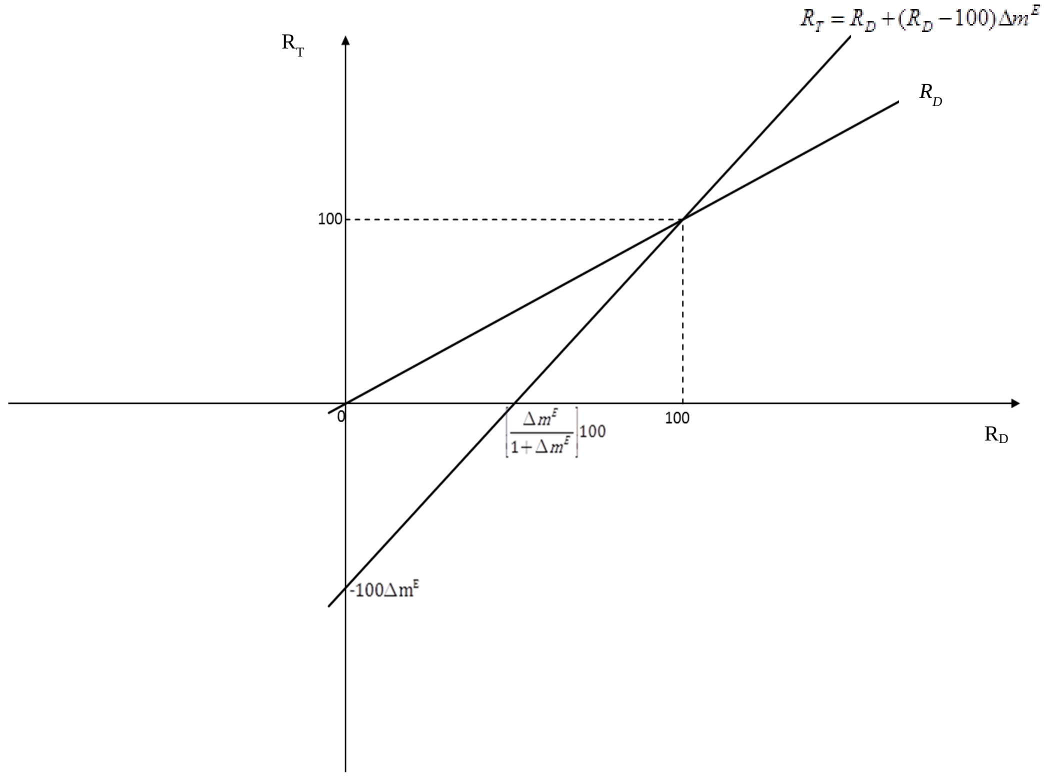
The relationship between direct rebound (in household consumption) and total rebound (incorporating economy-wide effects) is determined by the difference between the embodied-electricity in the electricity commodity and non-electricity goods, Δm^E, as shown in Equation 5.10:

$$R_T = R_D + (R_D - 100)\Delta m^E \tag{5.10}$$

where $\Delta m^E = m_E^E - m_N^E$. If the electricity commodity is more electricity-intensive than other goods, then Δm^E is positive, and the relationship between the direct and total rebound is shown in Figure 5.1.

Several observations about the rebound can be drawn from this graph. First, if the direct rebound is 100 (R_D = 100), there is no change in the household use of electricity following the efficiency gain. In this case, there is no consumption-switching behaviour, and no adjustment to production. Therefore the total rebound is equal to the direct rebound, and equals 100. If direct rebound is larger than 100, households increase their consumption of electricity because of the efficiency gain. This is the case of backfire. In this situation, households spend a larger share of their income on electricity, and the relative electricity-intensity of consumption increases, leading to positive indirect rebound from production effects. The total rebound is larger than the direct rebound.

Figure 5.1: The relationship between direct and total rebound



Source: Lecca et al. (2014)

In contrast, if direct rebound is lower than 100, then households reduce their electricity consumption and redirect their consumption towards less (electricity-intensive) non-electricity goods. In this case, the indirect rebound is negative and the total rebound is lower than direct rebound. Finally, it is theoretically possible for the total rebound to be negative, if the negative indirect rebound is large enough to more than offset the positive direct rebound. Formally, this corresponds to a direct rebound $R_D < \Delta m^E / 1 + \Delta m^E$.

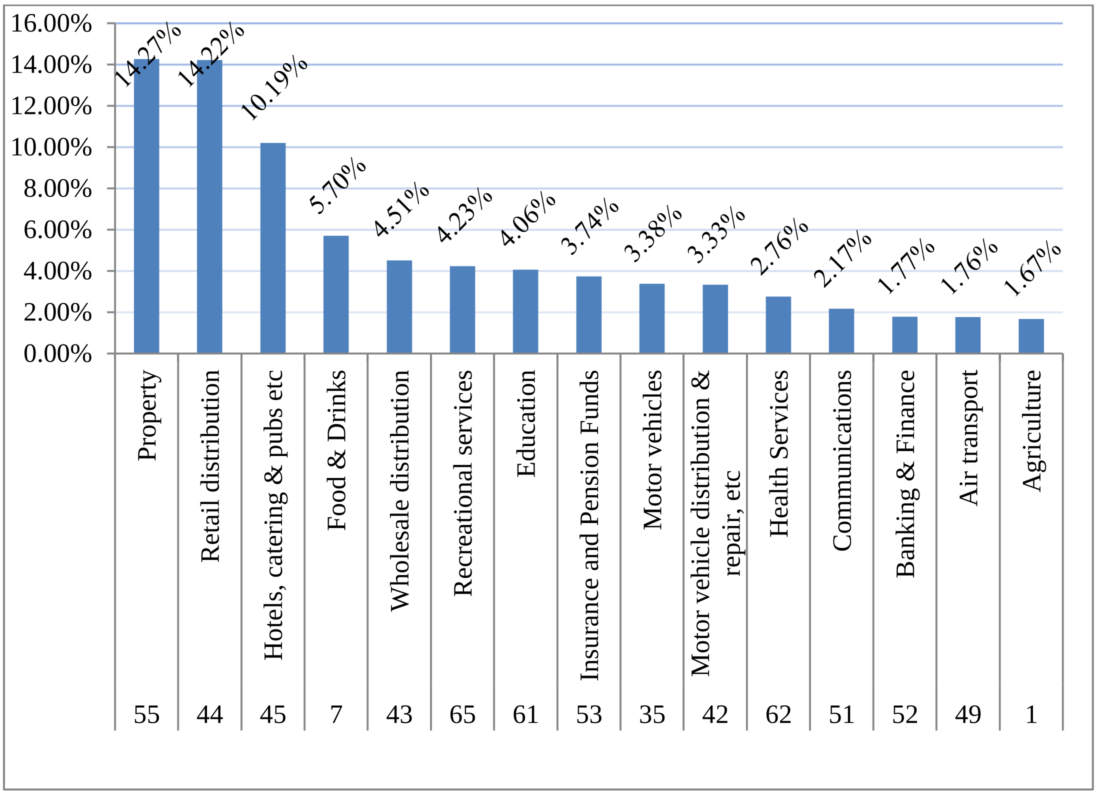
If the value of total rebound equals 100, the efficiency gains in household consumption from the introduction of smart meters are fully offset by the increase in total electricity use in the economy. If $0 < R_T < 100$, the roll-out generates some savings in total UK electricity use. Input-Output analysis is chosen as a useful tool to examine the implications of the above observation that indirect (and in turn total) rebound is highly dependent on the electricity-intensity of consumption goods, and thus highly dependent on inter-sectoral linkages in the economy. Using the total Type I or Type II change in the electricity output by shocking the IO model, it is possible to calculate the change in total UK electricity use, and therefore to calculate the total Type I or Type II UK rebound from the efficiency gain.

5. "Base-Case" Scenario: BASE67

In the first simulation, the IO tables are shocked with a 3% reduction in electricity demand, corresponding to a £286.87 reduction in household expenditure on electricity. It is assumed that this 3% reduction in household consumption is observed (as noted in Section 2) and therefore already takes into account the direct rebound on household electricity consumption.

Assuming no change in household preferences, the reallocation of consumption expenditures away from electricity and towards non-electricity goods and services is solely determined by the initial distribution of household consumption given in the IO tables. The results of the base case simulation, referred hereafter as BASE67 are presented using this reallocation principle. The newly available household income from savings in electricity consumption is redistributed to all other sectors according to their initial shares of household consumption. These shares are shown in Figure 5.2 for the top 15 sectors in household consumption. The five dominant sectors, namely Property, Retail Distribution, Hotels, Catering and Pubs, Food and Drink and Wholesale Distribution together make up about 50% of total household consumption.

Figure 5.2: Sectoral shares in household consumption (Top 15 Sectors)



5.1. IO results – BASE67

The aggregate results of simulation BASE67 are presented in Table 5.1. The table summarizes the direct, Type I and Type II impacts in terms of changes in: total output, output of the electricity sector, aggregate output of non-electricity sectors and total CO2 emissions[66]. The "Direct" results correspond to the effect of the direct shock, i.e. the reduction in electricity demand, and the simple reallocation of household expenditures to the other sectors. Households save 3% of their electricity consumption as a result of the introduction of smart meters. The corresponding £286.87m saved by households in the Electricity Production and Distribution sector are redistributed as expenditures on the 66 non-electricity sectors. In the direct effect, there is no change in total household

[66] The rebound results are also presented in Table 5.1 but will be discussed further in Section 5.2.

expenditures, but only consumption-switching effects. All non-electricity sectors are directly stimulated by the shock, in proportion to their share in household consumption.

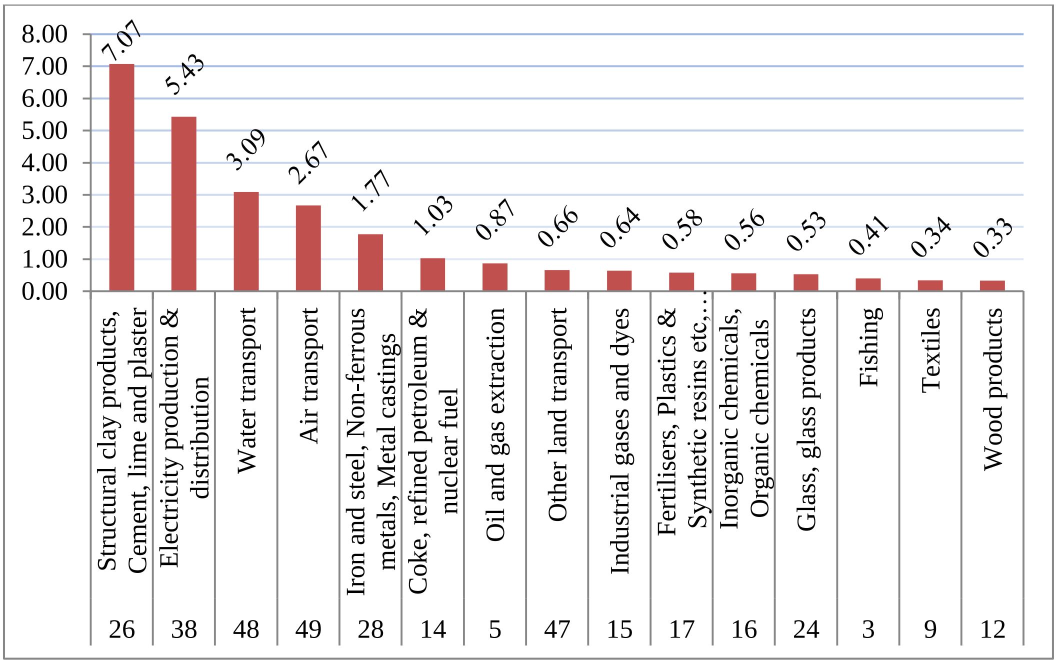
Table 5.1: BASE67 Aggregate Results

	Direct	Type I	Type II
Total Output (£ms)	0.00	-163.99	-80.73
Electricity Output (£ms)	-286.87	-407.68	-405.94
Total non-electricity output (£ms)	286.87	243.70	325.21
CO2 emissions (000ts)	-1,517.93	-2,230.34	-2,208.95
Change in household electricity use (%)		-3.00%	-3.00%
Change in total electricity use (%)		-1.24%	-1.24%
Household rebound		75.80	75.80
Indirect Rebound		-10.72	-10.72
Induced Rebound			-0.15
Total Rebound		65.09	65.23

Table E1 (in Appendix E) presents the detailed sectoral output results of the shock for this first simulation. These figures represent the changes in output (in £ms) for each of the 67 sectors. The five dominant sectors identified previously experience large increases in demand, such as £41.51m for Property or £41.36m for Retail Distribution. Other significant sectors in household consumption include Recreational Services, Education, Insurance and Pension Funds. These sectors are also stimulated significantly by the shock.

The reallocation of household expenditure also has a significant impact on CO2 emissions. In essence, the redistribution of household consumption will lead to an increase (or decrease) in total CO2 emissions where stimulated sectors are more (or less) CO2-intensive than the electricity sector. Figure 5.3 ranks the Top 15 sectors in terms of CO2 intensity. Appendix F.1 presents the full list of CO2-output coefficients by sector. Electricity Production and Distribution is the second most CO2 intensive sector, after Cement & Clay. Other CO2-intensive sectors include transportation sectors (Water Transport, Air Transport, Other Land Transport), manufacturing processes (e.g. Iron and Steel, Industrial Gases and Dyes, Glass products, Textiles) or resource extraction (Oil and Gas Extraction). These sectors do not account for a large share of household consumption; therefore they should not be significantly stimulated by the direct redistribution of expenditures, and thus we would not expect CO2 emissions to increase as a result of the direct shock.

<u>Figure 5.3: CO2-Output coefficients (Top 15 Sectors)</u>



As expected, the redistribution of expenditures away from the CO2-intensive Electricity Production and Distribution sector leads to a large direct reduction in total CO2 emissions of 1.52 mT. This is explained by the relatively high CO2-intensity of the electricity sector compared to other sectors of activity, which is likely driven by the high emissions from traditional electricity generation technologies, such as coal, gas and oil-fired power plants[67]. Table E2 in appendix summarizes the sectoral CO2 results for the base case scenario (BASE67). The largest sectoral increase in CO2 emissions is attributed to the Air Transport sector at 13,000 tons but is very small compared to the reduction of 1.56 mT of CO2 from reduced activity in the Electricity Production and Distribution Sector.

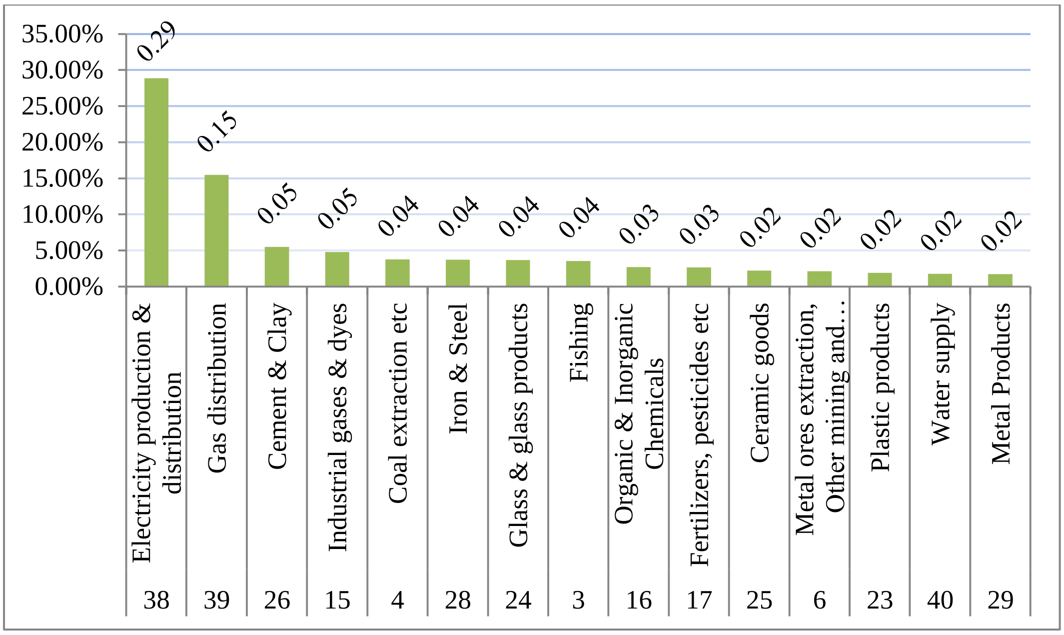
In addition to the direct impact of the shock, indirect effects can be derived as the changes in intermediate demand as a result of the direct shock. The combination of direct and indirect effects (i.e. Type I) are presented in column 2 of Table 5.1, while the detail sectoral impacts are shown in appendix. The direction and size of indirect output changes are determined by the backward linkages of sectors and are embodied in Type I output multipliers. The total Type I impact on industrial output is negative at -£164m, and can be disaggregated between some negative and some positive sectoral output changes. While most sectors are indirectly stimulated by the shock as intermediate inputs to non-electricity consumption sectors, there are 10 sectors for which the output indirectly falls.

Given that electricity is the only sector whose direct output decline, any subsequent decline in non-electricity sectors suggests that these sectors have strong indirect links with electricity. In particular, all energy-related sectors experience an indirect fall in output including: Coal Extraction, Gas and Oil Extraction, Gas Distribution and Electricity Production and Distribution. The Electricity sector is the most affected by

[67] These generation sectors are part of the Electricity Production and Distribution sector. The role of generation sectors in the rebound and in the carbon impact of smart meters is explored in more details later in this Chapter.

the intermediate negative demand shock, confirming the strong internal linkages within the sector itself between electricity generation, transmission and distribution activities. Using the Input-Output table, the electricity intensity of each sector can be derived with the electricity-output coefficients[68]. Appendix F.2 details the electricity-output coefficients for all 67 sectors. The top 15 sectors' coefficients are ranked by electricity intensity and presented in Figure 5.4. The electricity sector is highly electricity-intensive with about 30% of its input sourced internally. However, none of the major household consumption sectors listed previously ranks highly in terms of electricity-intensity, explaining the indirect decline in total output.

Figure 5.4: Sectoral Electricity Intensity (Top 15 Sectors)



The increase in demand for electricity as an intermediate input to consumption sectors is fully offset by the indirect fall in demand by the electricity sector itself. Overall total

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68 These coefficients represent the direct share of electricity inputs in each unit of the sector output. They are the direct input-output coefficients in the A Matrix. In other words, they embody the electricity requirements of each sector.

industrial output is reduced by the shock due to the large negative shock on the electricity sector, and major internal linkages within the sector. Correspondingly, when incorporating indirect effects, total CO_2 emission reductions are larger than when only the direct effect is included. The total type I CO_2 emission reductions equal -2.23mT.

Finally, Type II output and CO_2 results can be computed by incorporating induced effect. Induced effects represent the impact of the changes in household income and consumption from the indirect effects. While the direct shock is a simple reallocation of expenditures, the indirect effects adjust sectoral demand for intermediate inputs, ultimately affecting payments for factors of production, i.e. household income. As a result of the increase or decrease in income, household consumption will be affected. Column 3 in Table 5.1 summarizes the Type II results of the shock. (Appendix E.1 and E.2 show the Type II changes in output and CO_2 respectively for each sector). Larger numbers in Column 3 compared to Column 2 reflects an increase in household income and their corresponding increase in expenditures in all consumption sectors. Overall, there are small positive induced effects from the efficiency shock. While the indirect effects on output and CO_2 were negative, induced effects are positive. This is shown in a Type II output change of -£80.73m and CO_2 change of -2.20mT (less negative than Type I results). This result suggests that the sectors indirectly stimulated by the shock are more highly labour intensive than the sectors that are negatively affected. Thus, households' income increases from the indirectly stimulated sectoral outputs. This is confirmed in the IO tables, where services and retail industries appear more labour intensive when compared to manufacturing and energy sectors.

5.2. Rebound Results – BASE67

From the results of the IO analysis on output, the total Type I (direct and indirect rebound) and Type II (direct, indirect and induced) rebound effects in electricity consumption can be computed in an economy-wide framework. The total Type I or Type II rebound effect determines whether electricity use in the UK will decrease (RT < 100), stay constant (RT=100) or actually increase (in the case of backfire, RT >100). The rebound results for BASE67 are presented in Table 5.1.

As stated previously, the direct rebound corresponds to the increase in household electricity consumption from the implicit fall in the price of electricity in efficiency units. It is assumed to be fully determined by η_e, the price elasticity of household electricity demand. Household energy expenditures have been the focus of a large number of econometric studies, which have often produced estimates of the own-price elasticity of household electricity demand (Jamasb and Meier, 2010). In this analysis, the Baker et al. (1989) estimates of this elasticity for the UK are chosen. This estimate is $\eta_e = -0.758$. Thus, a direct rebound of 75.8 is assumed in the analysis.

In this case, we are assuming a positive direct rebound which is lower than 100. Therefore the simulation corresponds to a negative demand shock on the electricity distribution sector. The magnitude of the efficiency shock required to obtain the 3% reduction in household electricity consumption from the literature is calibrated to include the 75.8 rebound. Rewriting the definition of the household rebound in equation 5.2, to express the efficiency shock, we find:

$$\gamma = \frac{\dot{E_N}}{(R_D/100 - 1)} \tag{5.11}$$

Using Equation (5.11), a 3% reduction in household electricity consumption, which incorporates a direct rebound of 75.8, corresponds to an efficiency shock of 12.40%[69].

The rebound results are summarized in the last four rows of Table 5.1. The indirect rebound is negative at -10.72, corresponding to the overall indirect decrease in UK electricity use from backwards linkages. Combining direct and indirect rebound, the Type I total rebound equals 65.09, and is lower than the direct rebound of 75.80. The direct rebound is mitigated by the negative indirect rebound in electricity demand. This negative indirect rebound is driven by the large negative indirect shock on the Electricity Production and Distribution sector, as an intermediate input in its own production. Through a decrease in household electricity demand, the need for electricity as an intermediate input falls, generating a lower Type I total rebound effect compared to the household rebound.

The induced rebound is small and positive 0.15, as the income effect slightly increases electricity demand overall. This induced effect leads to a Type II total rebound of 65.23. Overall, the results show that despite a positive rebound in the total use of electricity, the benefits from the introduction of smart meters might go further than originally expected. In addition to the 3% reduction in household electricity consumption, industrial use of electricity will decrease, leading to a smaller economy-wide rebound. However, these results are strongly driven by the size and internal linkages of the electricity sector as it incorporates a variety of activities from generation to distribution. The large negative indirect effect on electricity demand is mainly driven by the high electricity-intensity of the electricity sector itself. This observation is explored further

[69] This value will be used in subsequent simulations in the next chapter to calibrate the efficiency shock.

through replicating the base simulation in a UK Input-Output table where the electricity sector is disaggregated between generation, transmission and distribution activities.

6. Disaggregated Electricity Sector

6.1. Disaggregating generation, transmission and distribution

In order to observe how the composition of the Electricity Production and Distribution sector impacts the rebound results, the sector can be disaggregated in the IO tables by differentiating between generation, transmission and distribution activities. First, electricity transmission and distribution network activities are separated from the generation activities. Generation activities are then disaggregated into 9 technologies, namely Nuclear, Coal, Oil and Gas, Hydro, Biomass, Wind Onshore, Wind Offshore, Marine and Solar, and other technologies. The disaggregation of the electricity sector follows the methodology used for disaggregating the Scottish IO tables in Allan et al. (2007a) referred to in Part A of this thesis. Following this methodology, the disaggregation of electricity activities is repeated in Winning (2012) for the UK tables, and the same disaggregation of electricity sectors is used in this chapter. The model is now composed of 76 industrial sectors including 10 electricity-related sectors. Electricity generation sectors sell the totality of their output to the Electricity Transmission and Distribution sector that redistributes electricity to the rest of the economy. Through this disaggregation, households have no direct purchases of electricity from the generation sectors, so all household electricity expenditures are made in the Electricity Transmission and Distribution sector. Using the newly disaggregated tables, the same simulation of a 3% reduction in household electricity expenditures is conducted to represent the introduction of smart meters. The major difference in simulation in the DISAG76 scenario compared to BASE67 is that the household efficiency gain, and the corresponding £286.87m reduction in household expenditures, is applied only to the Electricity Transmission and Distribution sector. In this simulation, this expenditure is again redistributed to all other sectors according to their initial share in household consumption.

6.2. IO Results – DISAG76

The aggregate results of the simulation are presented in Table 5.2. Again, the detailed sectoral results are presented in Appendix E (in Table E3 and E4 for output and CO2 emission respectively). Using the same reallocation principle as in BASE67, the direct impact from the shock is neutral on total output, as the saved electricity expenditures are redistributed to non-electricity sectors.

Table 5.2: DISAG76 Aggregate Results

	Direct	**Type I**	**Type II**
Total Output (£ms)	0.00	-164.04	-96.97
Electricity Output (£ms)	-286.87	-305.79	-304.66
Total non-electricity output (£ms)	286.87	141.75	380.73
CO2 emissions (000ts)	-51.90	-2,230.96	-2,215.08
Change in household electricity use (%)		3.00%	3.00%
Change in total electricity use (%)		-1.24%	-1.23%
Household rebound		75.80	75.80
Indirect Rebound		-1.97	-1.97
Induced Rebound			-0.10
Total Rebound		73.83	73.93

There is no redistribution of household income to the newly disaggregated generation sectors, since households have no direct purchase in these sectors. The direct redistribution of expenditures to non-electricity sectors is therefore identical to the BASE67 simulation. Every non-electricity sector is stimulated in the same proportion after disaggregation (see appendix E for sectoral details).

Although the direct change in total output is zero in both simulations, the disaggregation of the electricity sector impacts the magnitude of Type I and Type II impacts. Although the total Type I impact of the shock in DISAG76 is negative at -£164.04m and very similar to the BASE67 results (-£163.99m), the sectoral results reveal some large differences. The indirect impact of the shock on the electricity sectors can now be disaggregated between different activities. The Electricity Transmission and Distribution sector is still negatively impacted by the indirect shock (-£305 m), as it is still an important direct input to its own production, but less drastically than when the electricity sector was fully aggregated (-£407m).

However, the newly created generation sectors are also negatively impacted by the indirect shock, as they represent more than 30% of intermediate inputs to the Electricity Transmission and Distribution sector. The negative indirect shock on generation sectors is proportional to their share of total generation. Oil and Gas generation experiences the largest decrease in outputs with -£42m, followed by Coal generation (-£34m), nuclear generation (-£20m) and finally by renewable generation sectors. By aggregating the negative indirect impact on both generation and distribution activities, we obtain the negative indirect impact on the aggregated electricity sector of the BASE67 simulation. In this disaggregation exercise, we can observe the actual impact of household efficiency gains between different electricity sector activities.

In all non-electricity sectors, the indirect impact on output is similar to this of the BASE67 simulations, except in a few sectors, which are affected by the altered backward linkages of the electricity sectors. For example, the output of the Metal Product sector indirectly decreases less (-£1.76m) with the fall in Electricity Transmission and Distribution than in BASE67 (-£2.21m).

The induced effects after disaggregation are still positive overall. The total Type II change in output is -£96m, which is larger than the total Type I output change. This result confirms the observation from the BASE67 simulation, that households' income, and thus consumption increases when considering induced effects. However, the positive impact of induced effects on output is lower in DISAG76 than in BASE67. This suggests that some electricity generation sectors are actually relatively labour intensive, and that their indirect decrease in output generates some loss of income for households. This is the case for the Biomass Generation and Other Generation sectors.

6.3. Impact on CO2 Emissions

An interesting finding arises when comparing the direct, Type I and Type II changes in CO2 emissions before and after disaggregation. In addition to the change in total CO2 emissions shown in Table 5.2, the sectoral CO2 emissions changes for DISAG76 are presented in Table E4 (in appendix).

While the direct sectoral output results are the same in both simulations, the direct CO2 results are different. The decrease in CO2 emissions associated with a reduction in Electricity Transmission and Distribution output is lower than when the sector was aggregated with generation activities. Figure 5.5 presents the new sectoral CO2 intensities once the electricity sector has been disaggregated (for the top 15 sectors).

The complete list of 76 sector CO2 intensity is included in Appendix F.3. Fossil-fuel electricity generation sectors now dominate the list in terms of CO2-output coefficients. Coal Generation is the most CO2 intensive followed by Gas and Oil Generation.

When all electricity activities were aggregated, the Electricity sector was the most CO2 intensive. After disaggregation, the Electricity Transmission and Distribution sector is now the 17th most CO2 intensive sector (and consequently is not shown in Figure 5.5) with a coefficient of 0.32. The reduction in output from the Electricity Transmission and Distribution sector reduces CO2 emissions by 91,560 tons which are partially offset by the direct reallocation to other sectors. Total direct CO2 emission reductions amount to 51,900 tons in DISAG76, compared to 1.52mTs in BASE67.

Figure 5.5: DISAG76-Sectoral CO2 intensity (Top 15 sectors)

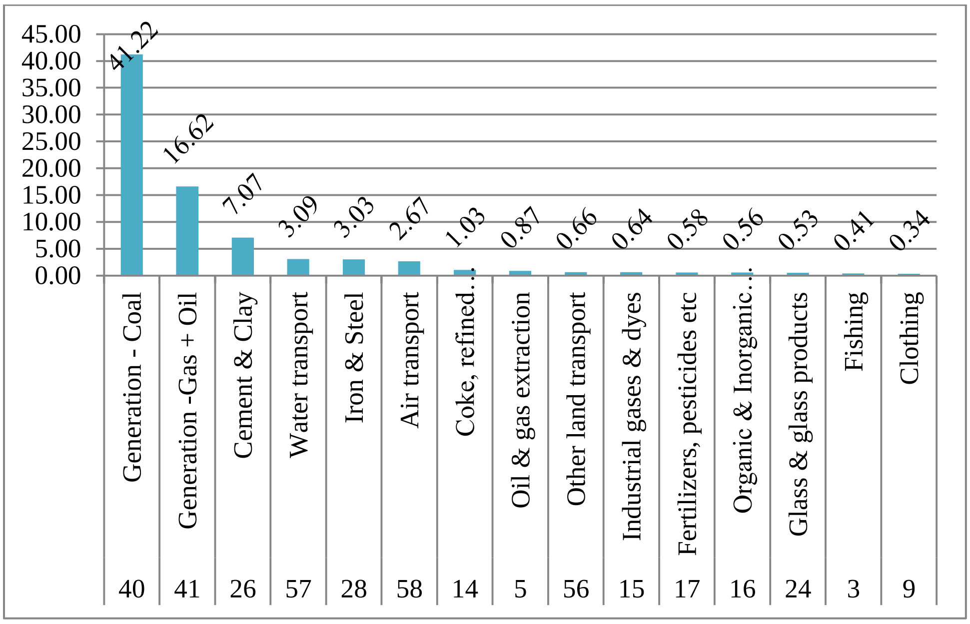
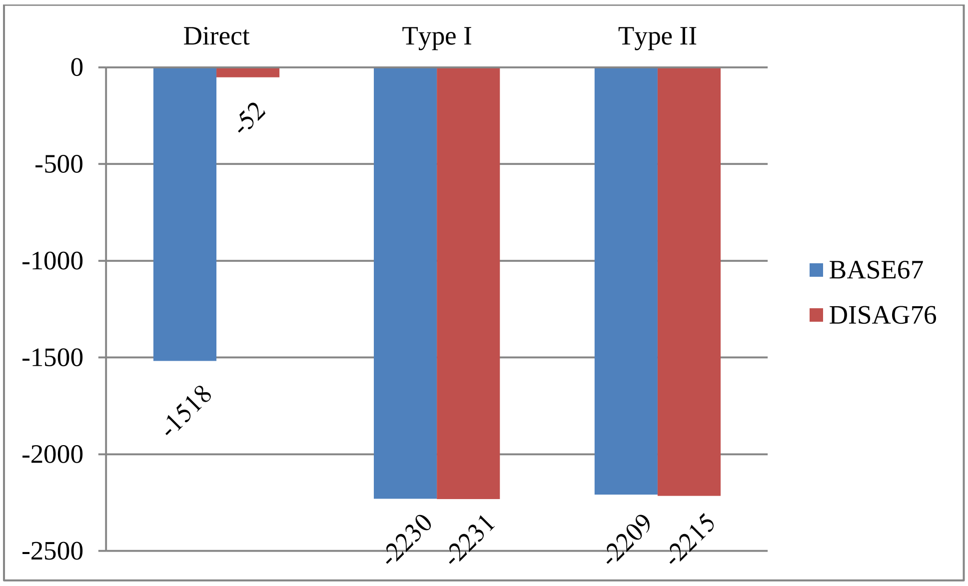


Figure 5.6 represents the comparison of direct, Type I and Type II CO2 emission changes for the two simulations. The total Type I CO2 emission reductions in DISAG76 are extremely close to these of BASE67. As the generation sectors outputs have

adjusted indirectly to the shock, emissions from generation sectors have decreased in the indirect impact. The decrease in Coal Generation and Gas and Oil Generation outputs contribute to the largest CO2 emission reductions with 1.42mTs and 0.70mTs respectively.

Similarly, the total Type II CO2 emission changes are similar whether or not the IO table is aggregated. The induced increase in CO2 emissions in DISAG is slightly smaller than the induced increase in BASE67 (approximately 16,000 tons vs. 21,000 tones). This slight difference in Type II CO2 emission changes reflects the output results. In DISAG76, there is a slightly smaller induced positive impact from the shock.

Figure 5.6: Total CO2 emissions changes (BASE67 and DISAG76)



Overall, the impact of disaggregation on total Type I or Type II CO2 emission changes results is minor. The impact of the disaggregation is however significant on sectoral output results, and it is likely that it will significantly impact rebound results in electricity use. This is discussed in Section 6.4.

6.4. Rebound Results – DISAG76

Rebound results for the 76 sectors simulation are summarized in the last four rows of Table 5.2. The rebound is calculated on the Electricity Transmission and Distribution sector results only, reflecting more precisely the changes in the use of electricity in the economy. The direct rebound is the same in both simulations BASE67 and DISAG76, since we consider the direct rebound to be already incorporated in the 3% reduction in household electricity consumption and determined by the price elasticity.

However, the total Type I and Type II rebounds differ significantly between the two simulations. In the aggregated tables (BASE67), the total type I rebound was reduced by a large negative indirect rebound (-10.19, see Section 4.3). This negative impact on the electricity sector was largely triggered by the strong internal linkages within the electricity sector itself. In DISAG76, the indirect rebound is also negative but with a smaller value of -1.97, reflecting the decrease in electricity use by industries. This translates into a total Type I rebound of 73.83, which is larger than in BASE67. The backwards linkages of the Electricity Transmission and Distribution sector within itself are still strong (negative indirect rebound) but they are largely mitigated by the disaggregation. Externalising the generation activities from the sector drastically reduces these internal linkages, and leads to a larger Type I rebound overall.

The total Type II rebound in UK electricity use can also be computed. The induced rebound (from households' income adjustments) is still positive at 0.10 but is smaller than in the BASE67 simulation. As pointed out in the analysis of the IO results, household income increases as a result of the direct and indirect stimulations of relatively labour-intensive sectors. However, after disaggregation, some individual electricity generation sectors are relatively more labour intensive than the aggregated electricity sector. These sectors being indirectly negatively affected by the shock mitigate the increase in household income and in turn mitigate the induced rebound.

Overall, Type I and Type II rebound effects are larger after disaggregation (73.83 and 73.93 respectively). With a more disaggregated electricity sector, the indirect negative effect is reduced and the difference between direct and total (either Type I or Type II) rebound is smaller. Overall, these results confirm that the efficiency gains from the introduction of smart meters could still lead to further reductions in electricity use when considering economy-wide effects (total rebound is still smaller than direct household rebound), but the negative indirect rebound in industrial use of electricity is reduced when disaggregating the electricity sector.

7. Substitution in Household Energy Consumption

Up to now, the IO simulations have been conducted as a simple consumption reallocation exercise, by redistributing household's expenditures away from electricity to all other consumption sectors according to their initial shares of consumption. Effectively, this assumption suggests that households substitute between electricity and all other consumption goods in the same way, using the same elasticity. One major issue that is ignored in the previous analysis is the particular nature of the substitution possibilities between energy sources in household consumption. Household energy demand is often a composite of several fuels, such as electricity and gas. It is likely that substitution between these fuels is different from substitution between energy and non-energy goods. In particular, as households' electricity consumption is changed through efficiency gains, it is likely that their consumption of gas will be impacted in a more direct fashion than their consumption of other goods.

7.1. Cross-price elasticity

In the simple microeconomic sense, the impact of a change in electricity consumption on gas consumption is determined by the value of the cross price elasticity between these two goods. The cross-price elasticity of gas consumption with respect to the electricity price ($\eta_{g,e}$) represents the change in household demand for gas ($\dot{G}_D$) as a result of a change in the electricity price. It is defined as follows:

$$\eta_{g,e} = \frac{\dot{G}}{\dot{P}_e} \qquad (5.12)$$

If the cross-price elasticity $\eta_{g,e}$ is positive, gas and electricity are substitute goods in consumption. In other words, a decrease in the price of electricity in efficiency units leads to a decrease in gas consumption, as households substitute electricity for gas in consumption. Alternatively, if the cross-price elasticity is negative, gas and electricity are complements. If the price of electricity decreases in efficiency units, household consumption of gas and electricity will rise together in this case.

Whether gas and electricity are complementary or substitute goods in household consumption is not a straight-forward question. While gas and electricity are used by households to deliver similar energy services, such as heating or cooking, the substitution possibilities between them is highly dependent on existing installations and appliances in the home. The cross-price elasticities of household energy demand have been estimated in a number of econometric studies. Baker et al. (1989), which was previously used in this chapter to calibrate the efficiency shock to the own price elasticity, presents estimates of cross-price elasticities for gas and electricity demands. The results show that the cross-price elasticity of household electricity demand to the gas price is low and positive at $\eta_{e,g}$= 0.185. This suggests that households increase their electricity demand when the price of gas increases. This corresponds to the case of substitute goods, households substitute electricity for gas when gas prices increase.

However, the econometric findings on gas demand show complementarity with electricity. The cross-price elasticity of gas demand to the electricity price is negative at $\eta_{g,e}$= -0.373. The findings of complementarity are confirmed in Baker and Blundell (1991) and Jamasb and Meier (2010), although little explanation is provided.

In light of this evidence, the substitution possibilities in household energy consumption appear to be more complex than other consumption goods. This section aims to incorporate the findings from this econometric literature into the determination of the household electricity rebound. This work represents the first attempt to examine the impact of substitution elasticities in household electricity and gas consumption in a system-wide analysis of the electricity rebound effects[70].

7.2. Substitutes Case – SUBS76

The first substitution case analysed in this section, is the case of gas and electricity being substitutes in consumption. As opposed to the first two simulations where the reduction in household electricity consumption is redistributed directly to all other consumption sectors including gas, this new simulation requires us to treat the gas sector differently from other consumption goods when determining the direct sectoral

[70] Due to the scope of the thesis, the issue of other consumption fuels is not discussed here. Although oil and coal represent 24% and 1% of all household energy expenditures (2004 IO Tables). These sectors will be treated differently from other non-energy goods in the CGE analysis of Chapter 6, where they are included in a separate nest of the consumption function.

impacts of the efficiency gain ex-ante. In the following simulations, the change in household gas consumption is determined as a function of the change in the price of electricity in efficiency units[71]. Once the changes in household electricity and gas consumption are determined, they are summed to determine the total change in household energy expenditures. This is then reallocated to other non-energy goods according to their initial shares in household consumption.

Equation 5.12 can be re-formulated to express the change in gas demand as a function of the cross-price elasticity, $\eta_{e,g}$ and the change in the price of electricity in efficiency units $\dot{P}_e$:

$$\dot{G} = \eta_{e,g}.\ \dot{P}_e \tag{5.13}$$

In the case of fixed prices, (assuming a constant price of electricity in natural units), the decrease in the electricity price in efficiency units for households is equal to the increase in efficiency in electricity consumption:

$$\dot{P}_e = -\gamma \tag{5.14}$$

Using the cross-price elasticity estimates in Baker et al. (1989), it is now possible to determine the change in household demand for gas following the change in household electricity demand in efficiency units.

In the case of substitutes, it is assumed here that the cross-price elasticity of gas demand to the electricity price is positive, and we use the Baker et al. (1989) estimate of the cross-price elasticity of electricity demand to the gas price. In other words, $\eta_{g,e} =$

[71] Effectively, this assumes that electricity and gas form a separate nest in the consumption function. This will be explored formally in Chapter 6.

$\eta_{e,g}$ =0.185. Substituting this value into equation 5.13 (and calibrating the efficiency shock at γ= 12.40%[72]), the change in household gas demand is calculated and we find $\dot{G_D}$ = -2.29%.

From the Input-Output tables, this corresponds to a decrease in household gas consumption of £120m. As electricity demand in efficiency units increases from the efficiency gain (the direct rebound), households substitute electricity for gas, i.e. they consume more of the efficient commodity. Using the 76-sector IO tables, the direct, indirect and induced impact of the shock can be calculated to determine the total rebound effects of the introduction of smart meters in the case of increased substitution between gas and electricity[73]. The aggregate results of the simulation where gas and electricity are complements, called SUBS76, are summarized in Table 5.3.

In this simulation, the overall direct change in households' energy consumption is the sum of the reduction in household electricity consumption in natural units with the reduction in household gas consumption. This corresponds to a decrease in household energy expenditures of £406.98m. This is redistributed to non-energy consumption sectors according to their initial share of household consumption (excluding electricity and gas). Like for previous simulations, the detailed sectoral results are presented in Appendix E, Tables E5 and E6, for output and CO2 emissions respectively.

[72] as explained in Section 4.4
[73] Relative to the equi-proportionate change in consumption of non-electricity goods analysed in earlier sections

Table 5.3: SUBS76 Aggregate Results

	Direct	Type I	Type II
Total Output (£ms)	0.00	-189.79	-92.95
Electricity Output (£ms)	-286.87	-327.21	-325.58
Gas Output (£ms)	-120.11	-164.39	-163.48
Total non-electricity/gas output (£ms)	406.98	301.82	396.12
CO2 emissions (000ts)	-55.62	-2,403.43	-2,380.51
Change in household electricity use (%)		3.00%	3.00%
Change in total electricity use (%)		-1.32%	-1.32%
Household rebound		75.80	75.80
Indirect Rebound		-3.81	-3.81
Induced Rebound			-0.14
Total Rebound		72.00	72.14

As households substitute electricity in efficiency units for gas, their consumption of gas decreases as a results of the efficiency shock[74], whereas before it has increased like other consumption goods. Like in the previous simulations, the reallocation of expenditures to other consumption goods stimulates the activity of large consumption sectors like Property and Distribution sectors, etc. Electricity Transmission and Distribution, and Gas Distribution are the only two sectors negatively impacted by the direct shock. Again, the indirect impact is fully dependent on the backward linkages of each sector. The overall negative impact on output is -£190m. Energy-related sectors, such as fuel extraction sectors or electricity generation sectors are negatively impacted by the indirect shock as they represent a large share of the electricity and gas

[74] The price of electricity in efficiency units decreases, leading to an increase in electricity consumption in efficiency units (direct rebound), which in turn leads to a decrease in gas consumption.

distribution sectors' inputs. The Electricity Transmission and Distribution sector is again the most negatively impacted with -£327m in output while the Gas Distribution sector also has a large Type I reduction in output of £164m. Both of these indirect drops in output are larger than in the previous simulations due to indirect effects driven by the high interdependency between these two sectors. Both sectors are highly gas and electricity intensive, and therefore have strong internal linkages, as well as strong linkages with each other. The direct drop in output in both of these sectors leads to larger indirect decreases in output in these two sectors compared to DISAG76. Also worth noting in this analysis is the larger drop in the Oil and Gas Extraction sectoral output compared to previous simulations; this sector represents the second major intermediate input to the gas distribution sector, after Electricity Transmissions and Distribution. Most other sectors are positively impacted in the indirect shock.

In terms of induced effect, the sectoral results for the total Type II effect are close to those of the Type I. But there is once again an overall positive induced impact, leading to a smaller reduction in total Type II output compared to total Type I output. The positive induced effect is larger in SUBS76 than in DISAG76. This result is explained by the larger redistribution of expenditures to non-energy sectors, which contribute to a larger increase in household income. Overall the total Type II impact on output is -£92m.

The impact of substitution on CO2 emission changes is discussed in comparison with the case of increased complementarity in section 6.3, while the rebound results are also shown and explained comparatively in Section 6.4.

7.3. Complementarity Case – COMP76

As stated previously, despite the fact that households have the opportunity to choose between electricity, gas or a combination of both for their energy needs, there is econometric evidence of complementarity in household energy expenditures. Baker et al. (1989), Baker and Blundell (1991) and Jamasb and Meier (2010) find evidence of this complementarity in UK households' energy expenditures.

Although a positive cross-price elasticity of household electricity demand to the gas price is found, the cross-price elasticity of household demand for gas to the electricity price is found to be negative, with a value $\eta_{g,e} = -0.373$. In this scenario, households increase their demand for gas, alongside their demand for electricity when the price of electricity falls. This suggests a complementarity in the use of gas and electricity in UK homes. As a result of an efficiency shock in electricity consumption, households increase their demand for electricity in efficiency units. To explore the case of complementarity in electricity and gas consumption, a simulation is run with the negative cross-price elasticity estimate, called COMP76.

The direct impact on household gas demand from the shock can be determined in equation 5.12, as shown in Section 6.1. Combining the negative cross-price elasticity with the 12.40% efficiency shock, we find that household gas demand increases by 4.62%, as a result of the efficiency gain in electricity consumption. This corresponds to an increase in household gas consumption of £242m. As in the previous simulation, the direct shock corresponds to the combined shock on total household energy expenditures (gas and electricity). Thus the direct shock in COMP76 corresponds to a large decrease in electricity consumption combined with a large increase in gas consumption, which amounts in total to a small decrease in household total energy consumption (gas and electricity). The change in total household energy expenditures is a decrease of £44.69m, which is redistributed to all non-energy consumption sectors according to their initial share of consumption. The aggregate results of this simulation (COMP76) are presented in Table 5.4 while sectoral results are shown in Appendix E, Tables E7 and E8 for output and CO2 emissions respectively.

Table 5.4 COMP76 Aggregate Results

	Direct	Type I	Type II
Total Output (£ms)	0.00	-113.55	-104.85
Electricity Output (£ms)	-286.87	-263.78	-263.63
Gas Output (£ms)	242.18	239.66	239.74
Total non-electricity/gas output (£ms)	44.69	-89.43	-80.95
CO2 emissions (000ts)	-44.61	-1,892.80	-1,890.74
Change in household electricity use (%)		3.00%	3.00%
Change in total electricity use (%)		-1.07%	-1.07%
Household rebound		75.80	75.80
Indirect Rebound		1.62	1.63
Induced Rebound			0.00
Total Rebound		77.43	77.44

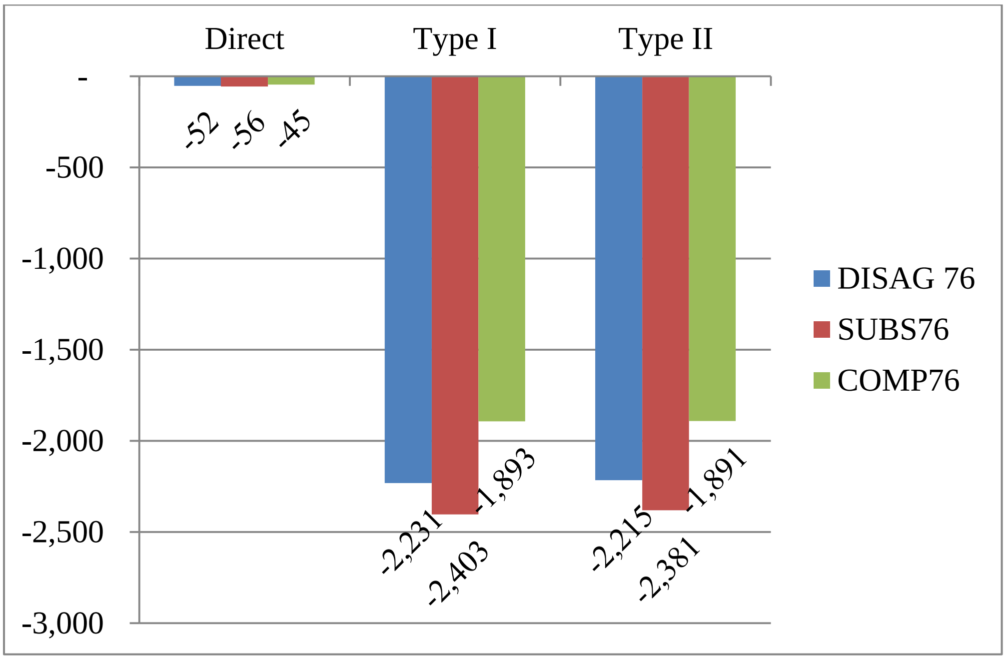
The direct positive impact on all non-energy consumption sectors is smaller than in previous simulations, as the fall in electricity expenditures is partly offset by the increase in gas expenditures. Correspondingly, the indirect effect is negative overall, once again driven by the backward linkages of the Electricity Transmission and Distribution sector. But in this case, the overall indirect effect is the smallest negative impact on output (-£113m) of all the conducted simulations, due to the offsetting effect of the positive shock on Gas Distribution. Although Gas Distribution is stimulated by the direct increase in households' gas expenditures, the indirect effect on Gas Distribution is slightly negative, as explained by the backward linkages of the electricity sectors. As electricity-related industries are negatively impacted by the efficiency shock, the Gas Distribution sector experiences an indirect drop in demand as an intermediate input in these sectors. This indirect effect partially offsets the direct rise in Gas Distribution output, but the Type I impact on the sector is still largely positive. On the basis of a similar reasoning, the Type I shock on Electricity Transmission and Distribution is the least negative in this simulation, due to the mitigation from the positive indirect shock in demand for electricity as an intermediate input to the Gas Distribution sector.

Once again, the total induced impact on output is slightly positive, but to a lesser exent proportions than in SUBS76. The negative Type II impact on total output is greatest in COMP76, and is very close to the Type I overall impact (-£104m). This small induced effect in the case of complements is explained by the relatively low stimulation of non-energy sectors. Since the reduction of household energy expenditures is the smallest when gas and electricity are complement in consumption, non-energy sectors receive a smaller reallocation of expenditures. The increase in non-energy sectors output still stimulates household income, but in lower proportions than in previous simulations. This leads to a reduced positive induced impact, and an overall larger Type II decrease in total output.

7.4. Substitution and CO2 emission changes

When the substitution possibilities between energy sources change, the direct, Type I and Type II impacts on output change as well, as illustrated in Sections 7.1 and 7.2. This will have an impact on the CO2 emissions changes resulting from adoption of the new technology. The CO2 emission results, summarized in Figure 5.7, show that in the simulation with higher substitution between gas and electricity (SUBS76), there is a larger drop in CO2 emissions (-2.38 mTs), than the standard case (DISAG76). This result is mainly driven by the negative shock on the Gas Distribution sector. In SUBS76, households reduce their gas consumption, as they substitute for the more efficient fuel (electricity). This reduces emissions directly (as gas is a CO2-intensive sector) and also indirectly; by negatively impacting the output of all energy-related and generally CO2-intensive sectors.

Figure 5.7: A comparison of CO2 emission changes



The results also show that the case of complementarity in household energy consumption limits the reduction of CO_2 emissions from the efficiency shock. In COMP76, the Electricity Transmission and Distribution sector exhibits the smallest reduction in output, and the output of Gas Distribution actually increases. Thus CO_2 emission reductions only reach 1.89m tons compared to 2.21m tons and 2.38m tons in the DISAG76 and SUBS76 scenarios respectively.

7.5. Substitution and Electricity Rebound

In determining the impact of the introduction of smart meters on total UK electricity use, it is useful to compute the electricity total rebound and compare it with alternative substitution possibilities. Table 5.5 summarizes the electricity household and total rebound results for each of the three simulations in the 76 sector tables, namely DISAG76, SUBS76 and COMP76.

Table 5.5: The impact of energy substitution possibilities on rebound results

	DISAG76	SUBS76	COMP76
	Standard IO	*Substitutes*	*Complements*
Direct Rebound	75.80	75.80	75.80
Total Type I Rebound	73.83	72.00	77.43
Total Type 2 Rebound	73.93	72.14	77.44

While it is assumed here that the direct rebound is the same for all three simulations and determined by the price elasticity of electricity demand for households, the indirect and induced rebound effects are determined by the changes in electricity use in the UK as a whole, and depend on sectoral output changes.

Although household demand for gas increases in both DISAG76 and COMP76 simulations, the results in terms of total Type I and Type II rebounds are different. In the base case scenario with the disaggregated IO tables (DISAG76) gas consumption is treated as all other non-electricity consumption sectors. The indirect rebound in this case is negative. Indirect effects have reduced the total UK electricity use, and the total Type I rebound is smaller than the direct rebound. Still in DISAG76, the induced rebound effect is small and positive at 0.10 representing a slight increase in electricity use when considering positive household income effects from the stimulated sectors (non-electricity sectors). Overall the total Type II rebound is 73.93.

In the case of complementarity (COMP76), gas distribution is treated differently from other non-energy sectors, and gas consumption is considered complementary to electricity consumption for households. In consequence, household gas consumption increases as consumption of electricity increases in efficiency units. While it also increased in DISAG76, the increase in household gas consumption in COMP76 is approximately 100 times larger than in DISAG76, as it is calculated before the redistribution to non-electricity sectors. Due to the large positive shock on the gas distribution sector, the total Type I rebound in UK electricity use is larger in COMP76 than in DISAG76 (77.43 against 73.83). The indirect rebound is actually positive in COMP76, where the large stimulation to the Gas Distribution sector leads to a significant indirect boost in electricity consumption. The positive indirect rebound is mainly driven by the high interdependencies between electricity and gas sectors. The induced rebound is still positive but very small, reflecting the relatively smaller re-distribution to non-energy sectors. As gas consumption increases in the complement case, other sectors are less stimulated than in DISAG76, leading to a smaller increase in induced consumption, and a smaller induced positive rebound on electricity use. Incorporating direct, indirect and induced effects, COMP76 shows a total Type II rebound of 77.44, the highest rebound effect in the three simulations presented.

When gas and electricity are substitute goods in consumption in SUBS76, the rebound results are again different from the base case. The increase in efficiency in household electricity consumption leads to a decrease in household gas consumption, combined with the decrease in electricity consumption. Households consume less energy and as a result redistribute their expenditures towards non-energy goods. Because of the high internal linkages within and between the electricity and gas distribution sectors, the indirect impact from the shock reduces the total UK electricity use, reflecting in a negative indirect rebound effect of -3.81. The total Type I rebound is 72.00 in SUBS76, and is the smallest Type I rebound recorded in the table. The SUBS76 simulation also shows a small positive (although the largest of the three simulations) induced rebound as household income rises from the large reallocation of expenditures to non-energy sectors. When energy sources are substitutes in household consumption (SUBS76), the total Type II rebound is the lowest of all simulations at 72.14. This is explained by the fact that the Electricity Transmission and Distribution sector experiences the largest reduction in output, due to the joint decrease in the output of the Gas Distribution sector.

These results show the sensitivity of the rebound in electricity to assumptions about the substitution possibilities in household energy consumption. If gas and electricity are more easily substitutable in household consumption, then the total electricity rebound will be smaller. In this case, the total reduction in electricity use in the UK from the adoption of smart meters might go further than the estimated direct reduction in household consumption. If, on the contrary, households consider gas consumption as a complement to electricity consumption, gas consumption might increase as a result of the introduction of smart meters, and the total rebound on UK electricity use could be larger, and mitigate this projected 3% reduction in household electricity consumption.

8. Conclusions

The mass roll-out of smart meters mandated for all British homes by DECC is expected to bring energy savings of an estimated 3% in household consumption. While in the presence of efficiency gains from new technologies, some reductions in household electricity consumption may be expected, the rebound effect literature predicts that these reductions could be mitigated by the rebound effect. As households consume electricity more efficiently, the price of electricity in efficiency units will drop and consumption will readjust to this new price. The magnitude and sign of the rebound is determined by several factors, including the price elasticity of household electricity demand. More importantly, the overall impact of smart meters is not limited to change in households' electricity consumption, and is likely to have further impacts on the rest of the economy as household redistribute their total consumption. The impact of this new technology should be assessed in an economy-wide framework. In this Input-Output analysis, inter-sectoral linkages are incorporated to estimate the total rebound in UK electricity use from the adoption of smart meters. The use of CO2 emissions data by industry also enables the modelling of changes in CO2 emissions as a result of the shock on household efficiency in electricity consumption. The simulations conducted in this chapter consist of reducing household expenditures on electricity, and reallocating these expenditures across all other sectors according to their initial share in household consumption.

Once the direct impact of this reallocation is determined, indirect and induced effects on sectoral and total output (and CO_2 emissions) are calculated through the use of Type I and Type II output multipliers (and CO_2-output coefficients). With these results, the total Type I (direct and indirect) and Type II (direct, indirect and induced) rebounds are calculated to determine the economy-wide rebound from the adoption of smart meters. This simulation was conducted on both a 67 sector and a disaggregated 76 sector IO tables for the UK (BASE67 and DISAG76 respectively). While the overall impact on output and CO_2 emissions are similar before and after disaggregation, the magnitude of the indirect rebound is greatly decreased when the electricity-sector is disaggregated between transmission and distribution and generation activities.

Overall, the simulation on the 76 sector IO tables (called DISAG76) shows a negative indirect rebound effect from the shock, driven by the internal linkages of the Electricity Transmission and Distribution sector. The large direct decrease in this sector output also translates to a large indirect decrease in output when considering backwards linkages. Combined with a relatively small but positive induced effect, the total Type II rebound amounts to 73.93, which is smaller than the direct rebound (on household consumption only of 75.80). These results suggest that despite a positive rebound effect, the reduction in total UK electricity use could be larger than the 3% reduction in household consumption due to economy-wide effects. Although it is generally expected that total rebound should be larger than direct rebound, this analysis shows that this is not always the case. Because of the strong internal linkages within the electricity sector, the indirect rebound is found to be negative, and total rebound is smaller than household rebound. This analysis also considers CO_2 emissions changes in the UK economy. In addition to CO_2 reductions from a decrease in household electricity consumption, the overall change in emissions is further reduced by the indirect sectoral linkages and this leads to significant reductions in CO_2 in the economy as a whole.

The IO 76 sector tables were also used to explore the role of the interactions between gas and electricity use in household consumption on the total rebound results. The simple reallocation simulation (DISAG76) was compared with two simulations with special treatment of gas consumption. Using UK cross-price elasticity estimates for the responsiveness of household demand for gas to the electricity price, the change in gas consumption was estimated in two alternative scenarios. In SUBS76, electricity and gas consumptions were treated as substitutes, so that gas consumption decreased as a result of the efficiency gain in household electricity consumption. In COMP76, the rebound was determined in the case where electricity and gas are complements in consumption, as suggested by some estimates on UK energy demand. When gas and electricity are complementary goods, household gas consumption actually increases as a result of the efficiency gain in electricity consumption. The results of the comparative exercise show the sensitivity of the total electricity rebound to assumptions about the substitution possibilities in household energy consumption. If gas and electricity are preferred substitutes in household consumption, then total electricity rebound is reduced. If, on the contrary, households consider gas consumption as a complement to electricity consumption, gas consumption might increase as a result of the introduction of smart meters, and the total rebound on UK electricity use would be larger.

This analysis highlights the need for estimating the impact of a new technology like smart meters in an economy-wide framework. In a case of a large-scale policy such as the UK mandated roll-out of meters, the consideration of inter-sectoral linkages is crucial to determine the impact on the total use of electricity. Rebound effects are commonly accepted as a consequence of efficiency shocks in both production and consumption. In the case of efficiency gains in household electricity consumption from the adoption of smart meters, this chapter finds that total rebound effects are lower than the direct rebound due to the size and strong backwards linkages of the electricity sector. Additionally, substitution possibilities between household energy sources are a crucial determinant of the total rebound, suggesting the need for more precise estimates of price elasticity in household energy demands.

This chapter has focused on calculating the economy-wide impact of a gain in efficiency in household electricity consumption using a demand-driven Input-Output model. In this context, the rebound is calculated assuming a fully passive supply-side of the economy and fixed prices. However, in practice, as household demand for electricity changes, the sectoral supply adjustments are likely be constrained by the availability and distribution of factors or production. This will lead to relative price variations, and further adjustments in both the consumption and production sides of the economy. The IO framework is unable to capture these effects, though these are likely to be important in determining the total economy-wide rebound. This issue is addressed in Chapter 6 which explores the impact of the roll-out of smart meters in a CGE model of the UK.

Chapter 6: Rebound effects from efficiency gains in household electricity consumption: The value-added from General Equilibrium Modelling

1. Introduction

In line with the concept of rebound detailed in Chapter 5, efficiency gains in electricity consumption, brought to UK households through the adoption of smart meters, are likely to generate a rebound effect, both in household consumption, and in total UK electricity use. The Input-Output framework used in Chapter 5 has in effect provided a partial equilibrium analysis of the household and total rebound effects. While the household rebound was determined entirely by the responsiveness of electricity consumption to the decrease in the price of electricity in efficiency units[75], the total rebound was calculated by incorporating the direct and indirect (and often induced) changes in sectoral outputs, and determined fully by the backward linkages of the electricity sector. A major finding from Chapter 5 was that, although it is generally expected that total rebound should be higher than household rebound, it was shown that the strong internal linkages within the electricity sector tend to reduce the total rebound compared to the household rebound. While the IO analysis provided helpful insights into the structure of UK sectoral linkages, and their implications for the size of the electricity rebound, it has imposed the restrictive assumption of fixed prices and has often assumed fixed incomes. These assumptions are imposed by the nature of Input-Output modelling as a static exercise with no supply constraints.

[75] In effect, in the input-output model, the household rebound was considered and defined as equivalent to the direct rebound.

However, it is likely that household electricity consumption and total UK electricity use will both be highly dependent on the relative price changes, which would certainly occur in reaction to the efficiency shock. In order to observe the impact of endogenous prices on the rebound results, a Computable General Modelling framework is used in this chapter[76]. Because supply constraints are incorporated in the CGE model, a drop in demand for electricity would lead to excess capacity in electricity-supplying sectors, which would decrease the price of the electricity output. This relative price change will impact household and total rebound. For example, while households' electricity consumption is expected to rebound as a result of the fall in the electricity price in efficiency units, this rebound could be reinforced by a fall in the relative price of electricity in *natural units*. Further, a decrease in the price of electricity in natural units would improve competitiveness and increase export demand for electricity, while it would also boost industrial demand for electricity. Thus, a drop in the price of electricity could increase total electricity use, and increase the scale of the total rebound effect. Using the more encompassing CGE modelling framework, the analysis of the rebound can be extended to fully encompass "economy-wide" rebound effects, which will arise from changes in relative prices and income.

An additional issue explored in the IO chapter is the impact of substitution possibilities between gas and electricity in household consumption on the rebound results. In the CGE model, this issue can also be addressed in more detail by formalising a new consumption structure, where gas and electricity can be substituted directly and independently from other goods. In this representation, household electricity rebound

[76] CGE models have been widely used in the energy rebound literature, but mostly in the analysis of efficiency gains in production (for a good review, see Allan et al., 2007b). Lecca et al. (2014) introduces efficiency gains in household energy consumption.

will not only be determined by the change in electricity price in efficiency units but also by the elasticity of substitution between electricity and gas.

In this chapter, these issues are addressed using a version of the AMOS framework (Harrigan et al., 1991) described in Part A of the thesis, but this one is adapted and calibrated to UK data[77]. Section 2 summarizes the main attributes of the model. Special attention is given to model features that differ from the version used in Chapter 4. Section 3 describes the shock simulated in the model: the efficiency gains in household electricity consumption. Alternative scenarios are defined following those of Chapter 5 in the sense that a direct link is identified between the household demand for gas and electricity. Simulation using different elasticities of substitution between gas and electricity are implemented. Section 4 presents and compares the results of these simulations. Section 5 provides a discussion of these results of the CGE modelling and offers general conclusions on the second part of the thesis.

2. The UKENVI Model

The UKENVI model is a multi-sectoral, energy-economy-environment computable general equilibrium model of the UK. It is based upon the AMOS framework (Harrigan et al., 1991), like the regional version used in Chapter 4 of this thesis. The two models share a number of similarities. They are both built on the same broad framework (allowing for great flexibility in functional form and parameter values) with a structure that emphasises the energy sector. There is however a number of differences in model closures due to the difference in spatial focus. In this chapter, I attempt to model the

[77] The model in Part A looking at learning-by-doing effects was a model of Scotland.

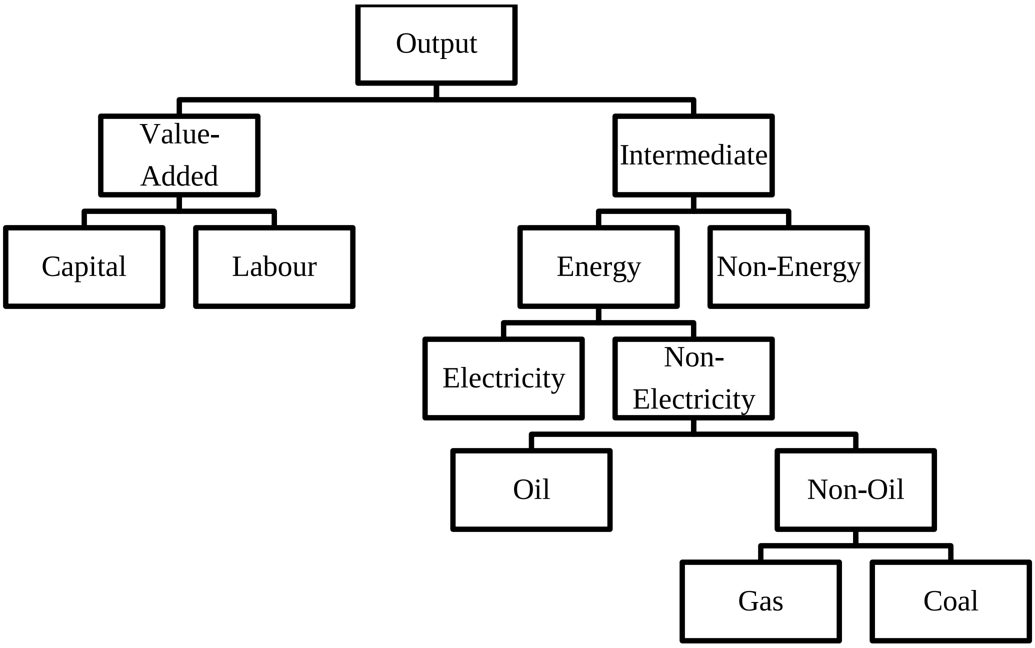
impact of a national policy (the roll-out of smart meters), and therefore I use a national version of AMOS.

The UKENVI model structure is such that final demand has four components: household consumption, investment, government expenditure and exports. There are two external sectors with which the UK trades: Rest of European Union (REU) and Rest of World (ROW). An Armington (1969) link determines the extent of imports and exports to and from the UK; under this assumption, domestic and imported goods are imperfect substitutes and respond to relative prices. In this modelling exercise, government expenditures are assumed to be exogenous and are determined by the initial base-year calibration. In every period, all markets are in equilibrium, with price equal to marginal cost.

2.1. Production

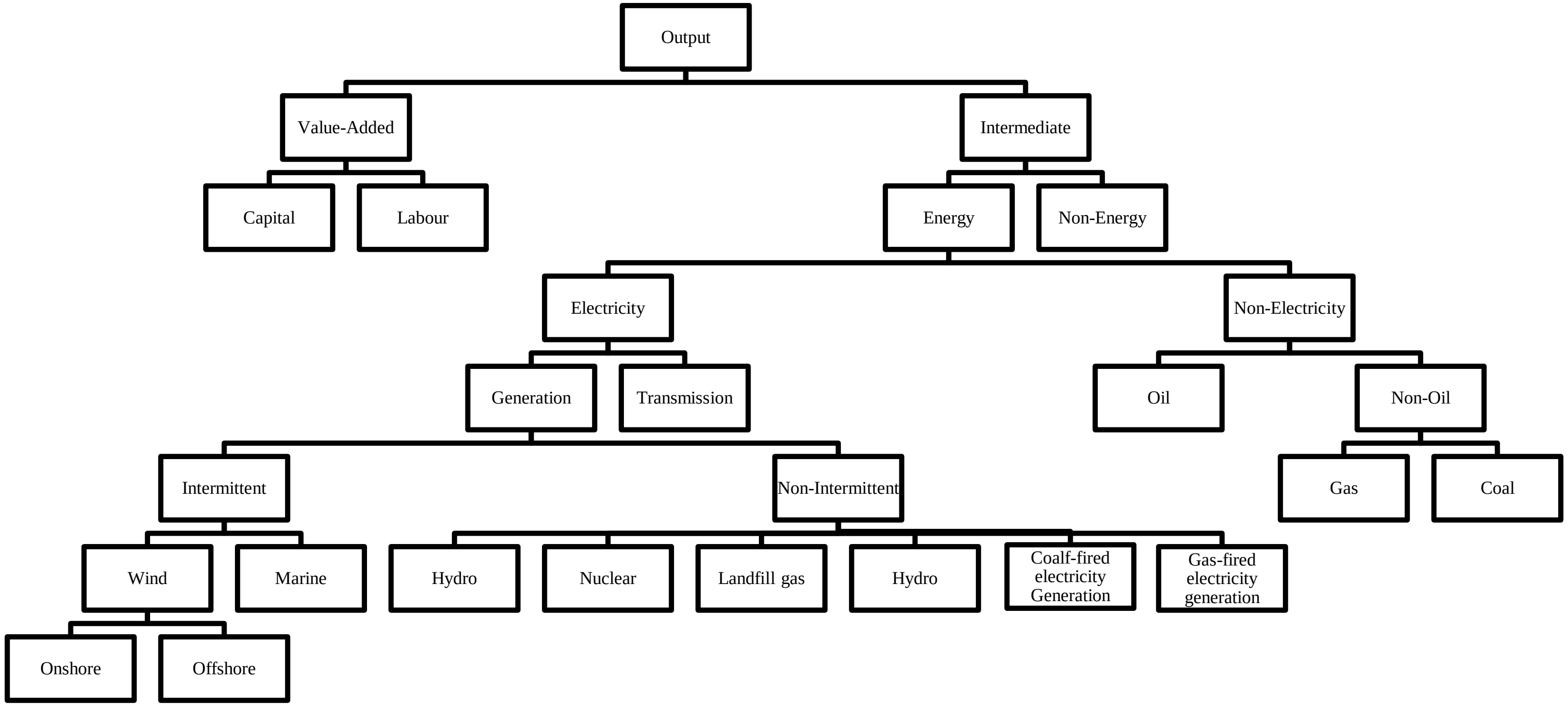
The model consists of multi-level production functions representing cost-minimizing firms producing in competitive markets. For all sectors, the production functions used are Constant Elasticity of Substitution (CES), which allows for input substitution when relative prices change; although Leontief or Cobb-Douglas functional forms are also available. Production structures are the same for all sectors with the exception of the electricity supply sector. This specific treatment of the electricity sector is the same as in the version of the AMOS model previously used for Scotland in Part A. The general production structure and the production structure specific to the electricity sector are both discussed in Chapter 4 of this thesis. They are replicated in Figures 6.1 and 6.2 respectively.

Figure 6.1: General Production Structure



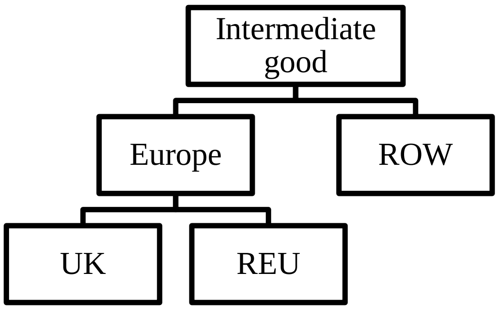
As explained in Chapter 4, by using these different production structures, we require that all sectors purchase their electricity inputs only through the electricity supply sector, which acts as an intermediate sector between electricity generation sectors and the rest of the economy.

Figure 6.2: Production structure of the electricity transmission and distribution sector



Intermediate goods, both energy and non-energy, can either be produced domestically or are imported. Imports from the Rest of the EU (REU) and the Rest of the World (ROW) are determined via an Armington link and are relative-price sensitive (Armington, 1969), as shown in Figure 6.3. The Armington elasticities are set equal to 2 (Gibson, 1990).

Figure 6.3: Trade Structure



Elasticities of substitution at every point in the CES production functions take a default value of 0.3 (Harris, 1989), with the exception of substitution between energy inputs which are higher. The substitution between electricity and non-electricity intermediate inputs, and oil and non-oil are set to 2 to introduce more flexible substitution among fossil-fuels energy and electricity generation. In addition, in the transmission sector production sector, the elasticity of substitution between electricity-generation technologies has been increased to 5. Table 1 provides a summary of the elasticities of substitution used at each level of the production function, which are the same as used in the Scottish model in Chapter 4[78].

[78] Since the simulations in this chapter are based on an efficiency gain in household consumption, the values of the production elasticities are less crucial in this chapter than in the learning-by-doing exercise.

Table 6.1: Elasticities of Substitution in Production

Nests in the CES production function	Elasticity of Substitution
Electricity and Non-electricity	2
Oil and Non-oil	2
Coal and Gas	2
Transmission and Generation	2
Intermittent and Non-intermittent	5
Among Intermittent	5
Among non-intermittent	5
All other CES nests	0.3

2.2. Consumers

The present modelling exercise differs from previous applications of UKENVI, in that it is formulated as an inter-temporal optimization model, where consumption and investment decisions are characterized by perfect foresight (Lecca et al., 2013a). In contrast with the modelling of Chapter 4 where agents' behaviour was myopic (i.e., decisions were determined within each period without consideration of future periods), the modelling of this chapter assumes that investment and consumption decisions are determined through inter-temporal functions and then optimally allocated within periods. The forward-looking model closure has become a standard feature of national CGE models (Lecca et al., 2013a).

In this forward-looking context, households maximize their inter-temporal utility in consumption which takes the following form:

$$U = \sum_{t=0}^{\infty} \left(\frac{1}{1+\rho}\right)^{t} \frac{C_t^{1-\sigma}-1}{1-\sigma} \tag{6.1}$$

where C_t is aggregate consumption at time t, σ is the constant elasticity of marginal utility and ρ is the constant rate of time preference. According to the dynamic budget constraint, the discounted present value of consumption must not exceed total household wealth, *W*. Total wealth is the sum of non-financial wealth (net income from labour plus transfers from institutions) and financial wealth (determined by capital income and accumulated through savings[79]). The inter-temporal utility function determines the optimal path of consumption, which is then allocated for each period.

Within each period, total consumption is disaggregated between different goods through CES consumption functions. As shown in Chapter 5, the way households substitute between energy goods is a major determinant of the rebound. In this chapter, this issue is addressed in a more direct manner by implementing two alternative characterizations of household consumption, capturing different ways in which households can substitute between electricity and non-electricity goods.

Base Case Consumption Function

In our base case scenario, total consumption is defined as a CES combination of electricity and non-electricity goods. In this case, designed to emulate the base case scenario in the IO analysis, gas consumption is considered and represented in the same way as every other non-electricity good. Effectively, to represent this assumption in the CGE model, household consumption is a combination of electricity and non-electricity goods, as shown in equation 6.2.

$$C_T = \left[\lambda(\gamma E_c)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\lambda)NE_c^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{-\varepsilon}{\varepsilon-1}} \tag{6.2}$$

[79] Here the savings rate is exogenous (Lecca et al., 2013a)

where C_T is total household consumption, λ is the share of electricity in total household consumption, E_c and NE_C are household consumption of electricity and non-electricity goods respectively, ε is the elasticity of substitution and γ is the efficiency gain. Consumption of non-electricity goods is a Leontief composite of all other goods, in order to reflect the simple IO assumption of redistribution of expenditures from Chapter 5.

In this structure, an improvement in efficiency in household electricity consumption should in principle reduce household consumption of electricity in natural units (if the direct rebound is lower than 100) and free-up some income for households to spend on non-electricity goods. However, because prices are now endogenous, an increase in efficiency could reduce the relative price of electricity in *natural units*, and therefore lead to more substitution towards electricity consumption. The household rebound will be determined in this endogenous price context, and will therefore differ from the IO analysis.

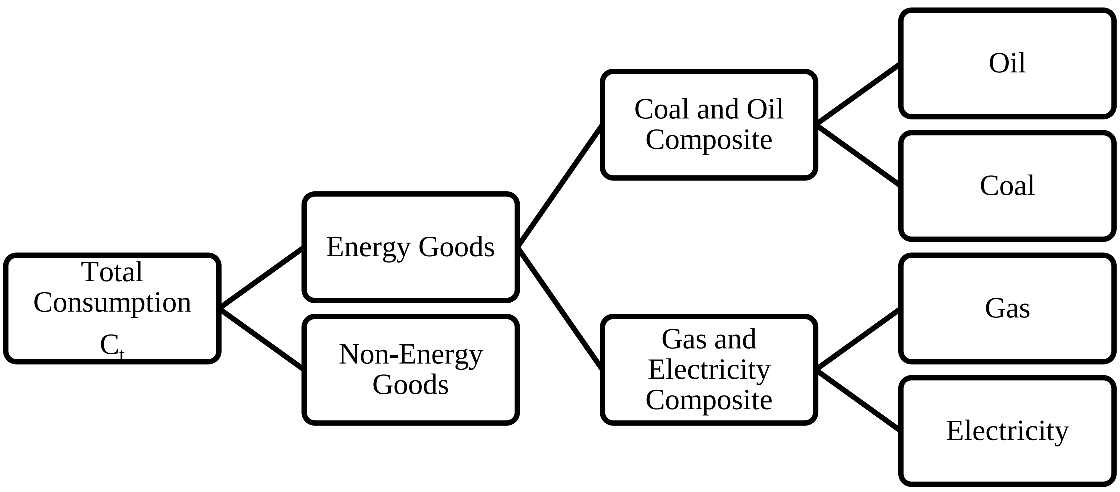
Multi-level CES Consumption Function (Scenario Analysis)

In the previous chapter, it was shown that fuel substitution in household energy consumption is a central determinant of the rebound effect. In an IO context, it was shown that increased substitution between electricity and gas in household consumption would reduce total rebound because gas consumption would decrease as a result of the efficiency shock. In contrast, increased complementarity leads to higher total rebound.

In order to address this issue formally in the CGE model, the consumption structure must be amended to reflect more accurate substitution possibilities in household consumption. The consumption structure used in this case is a nested CES consumption function, differentiating between energy and non-energy goods, as well as between fuels in energy goods consumption. This structure was used in Lecca et al. (2014) to evaluate the rebound effects from household energy efficiency gains and is presented in Figure 6.4.

Total consumption is defined as a CES combination of energy and non-energy goods. The energy good composite is made up of a coal and oil composite (which in the base year represents approximately 25% of total household energy consumption[80]) and a gas and electricity composite.

Figure 6.4: Household Consumption Structure



The gas and electricity composite is of primary importance in this chapter. It is also defined as a CES function as follows:

[80] Oil represents approximately 24% and Coal 1% of total household energy consumption.

$$GE_c = \left[\lambda_e.(\gamma E_c)^{\frac{\varepsilon_{ge}-1}{\varepsilon_{ge}}} + (1-\lambda_e).G_c^{\frac{\varepsilon_{ge}-1}{\varepsilon_{ge}}}\right]^{\frac{-\varepsilon_{ge}}{\varepsilon_{ge}-1}} \tag{6.3}$$

where GE_c is household consumption of the gas and electricity composite, ε_{ge} is the constant elasticity of substitution between gas and electricity and λ_e is the share of electricity in household energy (gas and electricity only) expenditures. In the UK 2004 Input Output tables, electricity represents approximately 64% of household gas and electricity expenditures, so that λ_e = 0.64.

In this CES composite, efficiency improvements in household electricity consumption lead to changes in the price of the gas and electricity composite in the production function. The change in household gas consumption following the efficiency shock is determined the elasticity of substitution. Here, if an efficiency gain generates a relative decrease in the price of electricity, gas consumption will decrease to an extent determined by the elasticity of substitution. Using this new consumption structure, it is possible to vary the elasticity of substitution between electricity and gas to reflect the cross-price elasticity estimates found in the econometric literature on household energy expenditures and discussed in the IO analysis.

However, with this CES specification of the household gas and electricity consumption composite, a major distinction will arise compared to the IO analysis. In the previous chapter, the direct rebound in household consumption was fully determined by the own price elasticity of electricity demand. In the CGE context of this chapter, the household rebound in electricity is determined endogenously, through the CES consumption function described above. The change in household electricity consumption following the efficiency shock will therefore be determined by the substitution elasticity with gas.

It is expected that the higher the elasticity of substitution between gas and electricity, the more households will substitute in favour of the more efficient fuel, leading to an increase in household rebound (and potentially in total rebound). In contrast, with an elasticity of substitution close to zero, households' substitution away from gas will be more limited, and household electricity rebound is expected to be smaller. Several simulations are run in this chapter, which vary this elasticity of substitution to allow us to observe the impact on the rebound results. The simulations are defined in Section 3.

While the elasticity of substitution between electricity and gas is varied systematically among the simulations, other substitution elasticities at the different levels of the nested-CES consumption function are fixed throughout. Their values are listed in Table 6.2. The elasticity of substitution between energy and non-energy goods is set at 0.61. This corresponds to the long-run elasticity of substitution in UK households estimated through the generalized maximum entropy (GME) method, as detailed in Lecca et al. (2011, 2013b). The same elasticity value is set at other energy sub-nests in the consumption function, to remain as close to the IO analysis as possible using this consumption structure, in which households simply reallocate their consumption to non-electricity goods without a change in preference.

Table 6.2: Elasticities of Substitution in Consumption

Nests in CES Consumption function	**Elasticity of Substitution**
Energy and Non-Energy	0.61
Coal and Oil & Electricity and Gas	0.61
Coal and Oil	0.61
Electricity and Gas	Varies in simulations

2.3. Investment

Like household consumption, investment is determined through inter-temporal optimization. Firms, like consumers, have perfect foresight. Following Lecca et al. (2013a), the investment path is obtained by maximizing the present value of firms' cash flow, determined by capital income (or profit π), less investment expenditures, which are subject to adjustment costs $g(x_t)$, as summarized in the following system:

$$Max\ VF = \sum_{t=1}^{\infty} \frac{1}{(1+r)^t} \left[\pi_t - I_t\big(1 + g(x_t)\big)\right] \qquad (6.4)$$

$$\text{With } x_t = \frac{I_t}{K_t}$$

$$\text{Subject to capital accumulation } \dot{K}_t = I_t - \delta K_t$$

The solution to this dynamic problem gives the time path of investments.

2.4. Labour Market

In the AMOS framework, the labour market can be modelled in a variety of ways. In the regional version previously used, the choice of labour market closure was a regional wage bargaining curve where wage was inversely related to unemployment. In addition, endogenous migration was incorporated to reflect inter-regional mobility as a function of the wage rate differential and the unemployment differential.

Here, in order to represent the UK national labour market, another closure is selected. Once again, the labour market is characterized by imperfect competition, and the wage rate is determined through a wage bargaining function (Blanchflower and Oswald, 1994), according to which real wages and unemployment are negatively related:

$$\ln\left(\frac{w_t}{cpi_t}\right) = c - B \cdot \ln(u_t) + D \cdot \ln\left(\frac{w_{t-1}}{cpi_{t-1}}\right) \tag{6.5}$$

where w is the nominal wage rate, cpi is the consumer price index and u is the unemployment rate. Here, although wages are endogenous, labour supply is fixed through population; no endogenous migration is allowed in the model[81]. Adjustments in the labour market only come through changes in the unemployment rate and the wage rate.

2.5. Dataset

The UKENVI model is calibrated on a UK Social Accounting Matrix (SAM) for 2004 (Allan et al., 2007c; and Turner, 2009, Lecca et al. 2014). Based on the same Input-Output tables as the ones used in Chapter 5, the SAM is augmented with information on income transfers between the different agents. Additional data used in the construction of the SAM are drawn mainly from National Statistics (2004).

In this Chapter, the SAM is aggregated into twenty-five intermediate sectors, listed in Table

2, with the corresponding original classification of the sectors. This disaggregation is intended to identify emissions-intensive sectors which are likely to prove important in the analysis. In contrast to the IO where CO2 emissions were calculated simply through sectoral output intensities, emissions in the CGE model are linked to energy use, and thus allows for substitution effects to be captured in the CO2 emission results as well (Allan et al., 2006).

[81] Although migration is currently an issue on UK government policy agenda, it is not allowed to vary endogenously in the model.

Of the 25 sectors in the model, thirteen are energy sectors, which comprise 3 fossil fuel sectors (Coal, Gas and Oil), an electricity supply sector (electricity distribution and transmission) and nine electricity generation sectors, which sell their output only to the electricity supply sector. Originally, this energy disaggregation of the UK 2004 Input-Output tables has been designed to estimate the impact of the introduction of a carbon tax on the UK economy (Winning, 2012). It is used in the present analysis due to the similar focus on energy policy and its economic and environmental impacts.

3. Simulations

The shock introduced in the model is a 12.4% efficiency gain in household electricity consumption. The efficiency shock is calibrated on the projected 3% household electricity demand reduction from the introduction of smart meters, using the econometric estimate of -0.758 for the own-price of electricity demand (see Chapter 5). In this chapter, it is expected that the 12.40% efficiency shock will not produce the same 3% reduction in household electricity consumption, as relative prices will change[82]. However, using the same efficiency shock in both chapters enables the identification of the added-value of allowing for endogenous prices in the calculation of the rebound.

The 12.40% efficiency shock in household consumption is run successively in four scenarios. The first scenario (BASE) uses the basic CES consumption function described in Section 2.2.1. In BASE, households substitute between electricity and all other non-electricity goods, according to their initial share of consumption. The elasticity of substitution between electricity and non-electricity goods in

[82] In other words, the household rebound in the CGE model will not be fully determined by the direct rebound (change in electricity consumption as a result of the decrease in the electricity price in efficiency units), but also by the relative change in price in natural units.

consumption (ε) is derived using the own-price elasticity of household electricity demand, and is given for a CES consumption function as:

$$\varepsilon = \frac{\eta_e - \lambda}{1 - \lambda} \tag{6.6}$$

where η_e is the own price elasticity of electricity demand and λ is the share of electricity in total household consumption (Gørtz, 1977). Using the Baker et al. (1989) econometric estimate of the own price elasticity as in Chapter 5 (η_e= - 0.758), and the share of electricity in total household consumption from the IO tables (λ = 1.62%), the elasticity of substitution is estimated at ε = 0.754. The BASE simulation aims to replicate the IO results, while endogenizing household income and prices[83].

The other three scenarios run in this chapter use the multi-level CES consumption function, where households' substitution in energy goods is disaggregated between fuels. The three scenarios use the same consumption function, but differ in the value of the elasticity of substitution between households' gas and electricity consumption. The three scenarios correspond to three values of cross-price elasticity of household gas demand to the electricity price.

Scenario 1 corresponds to the central case and is parameterized using the default price elasticity of substitution in the UKENVI model (Lecca et al., 2014). It uses the value of 0.61 at every level of the nested-CES consumption function. Scenarios 2 and 3 correspond to the cases of increased complementarity and substitution respectively, and are calibrated using the cross-price elasticity estimates in Baker et al. (1989), which also used in the IO analysis.

[83] Some differences are also expected to arise from the different level of aggregation of the IO tables, from 76 sectors to 25 sectors. However, the disaggregation is identical in the energy sectors, so the differences in rebound results are likely to be limited.

For each scenario, the value of the cross-price elasticity is transformed into the constant elasticity of substitution between gas and electricity in consumption, using the following equation (Ramskov and Munksgaard, 2001):

$$\eta_{g,e} = (\varepsilon_{ge} - 1).\lambda_e \tag{6.7}$$

where ε_{ge} is the constant elasticity of substitution between electricity and gas and λ_e is the share of electricity in household gas and electricity expenditures. In Scenario 1, the 0.61 elasticity of substitution corresponds to a cross-price elasticity of -0.250. In Scenario 2, the cross-price elasticity of -0.373 is used to explore the case of increased complementarity. It corresponds to a low elasticity of substitution of 0.418. Finally, Scenario 3 represents the case of increased substitution between gas and electricity in consumption. It is calibrated using the positive cross-price elasticity of demand of 0.185, corresponding to a large elasticity of substitution of 1.289.

The assumptions of cross-price elasticity of demand and the corresponding elasticity of substitution are summarized for each simulation in Table 6.3. It can be noted that in the Scenario 1, the value of 0.61 for the elasticity of substitution between electricity and gas reflects a degree of complementarity between the commodities. We thus expect the results of Scenario 1 to be qualitatively more similar to Scenario 2 (complements) than Scenario 3 (substitutes).

Table 6.3: Simulations and Substitution

	Base Case	Scenario 1	Scenario 2	Scenario 3
	Replicate IO	Standard Case	Complements	Substitutes
Consumption Structure	Basic CES	Nested CES	Nested CES	Nested CES
Substitution	Electricity and Non-Electricity	Electricity and Gas	Electricity and Gas	Electricity and Gas
Own-price elasticity	0.758	N/A	N/A	N/A
Cross-price elasticity	N/A	-0.250	-0.373	0.185
Elasticity of substitution	0.754	0.610	0.418	1.289

The model is solved for 40 years. In each time period, the model is solved as a set of simultaneous equations, to find a set of prices that clears all markets: the supply of each produced good equals its demand. In period 1, representing the short-run, the capital stock is fixed to the base-year value. The assumption is relaxed from period 2 onwards; the capital market can adjust through investment. Because labour supply is fixed in the national model closure, the labour market can only adjust through changes in unemployment rates. In the long-run, capital supply constraints are fully relaxed. Forward-looking consumption and investment adjust fully in the long-run.

In the Input-Output analysis, the direct rebound in household consumption was determined ex-ante from the own-price elasticity of demand for electricity. Likewise, the reduction in household electricity consumption was the same in all scenarios and calibrated using findings from the feedback literature. We imposed a 3% reduction in household electricity consumption, corresponding to a 12.40% efficiency shock and a direct rebound of 75.8. In effect the direct rebound in household electricity consumption was determined where prices in natural units were held constant. Thus, direct rebound results were the same in all scenarios, and it was only total rebound which was determined using different cross-price elasticities of demand, from different households' reaction in terms of gas demand.

In the modelling of this chapter, however, the value of households' response to the efficiency shock in terms of electricity consumption is not imposed as a constraint. In the CGE model, the rebound in household electricity consumption is determined endogenously. In this context, it is the system-wide price and income effects resulting from the efficiency shock that will influence the household rebound. Accordingly, by changing the cross-price elasticity of demand between electricity and gas, the household rebound is expected to change significantly between the simulations. In turn, the comparison of total rebound results in the four scenarios should reveal much larger differences.

4. Results

For each of the four simulations, a set of aggregate and sectoral results are obtained. In the BASE simulation, the one-level CES consumption function is used to represent household consumption, while in the other three scenarios, the other consumption function, with a multi-level CES structure is employed.

4.1. Base Case Results

In the BASE simulation, households can substitute between electricity and all other non-electricity goods with a constant elasticity of substitution of 0.754. The 12.40%

efficiency gain is applied to household electricity consumption. As a consequence, household electricity consumption falls in the short-run and households redistribute their expenditures towards non-electricity goods. Gas consumption increases, in the same proportion as consumption of other non-electricity goods. The aggregate results of the BASE simulation are presented in Table 6.4.

Table 6.4: Base Case Aggregate Results

	Short-run	Long-run
GDP	0.02	0.09
Emissions	0.01	-0.01
Consumer Price Index	0.14	0.15
Unemployment Rate	-0.25	-0.72
Total Employment	0.03	0.08
Nominal Gross Wage	0.17	0.23
Real Gross Wage	0.03	0.08
Households Consumption	0.13	0.12
Investment	0.02	0.11
Export	-0.26	-0.27
Household Electricity Use	-3.88	-4.36
Industrial Electricity Use	0.86	-0.17
Total Electricity Use	-0.92	-1.77
Household Rebound	68.69	64.86
Total Rebound	80.53	62.64

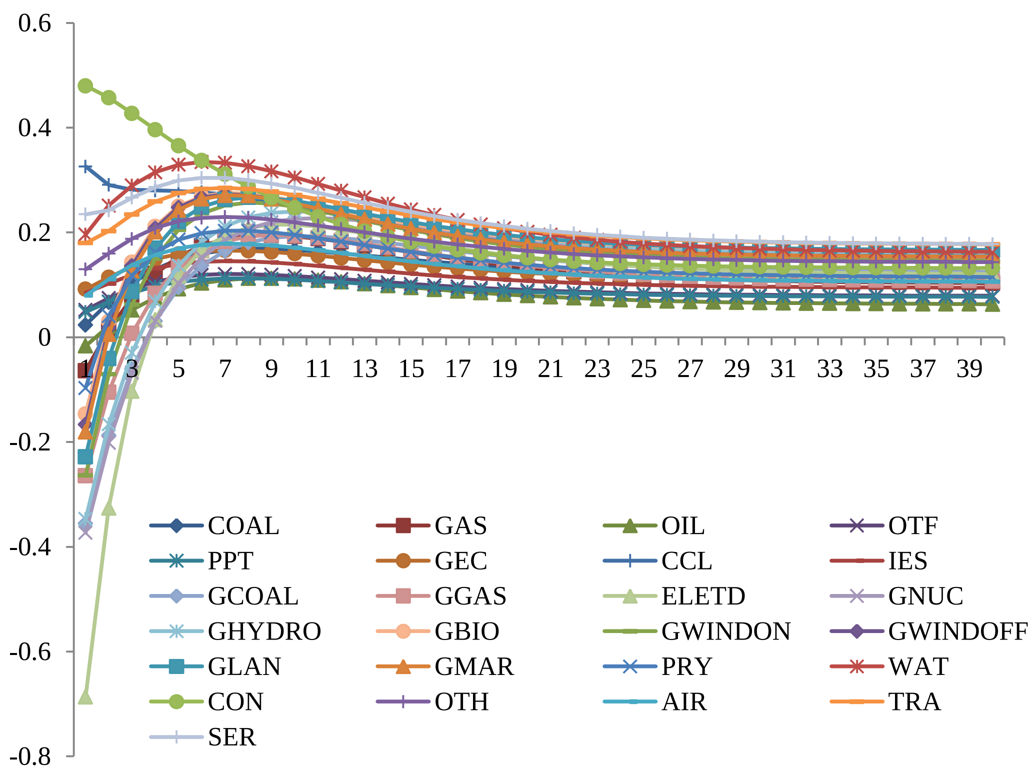
Percentage change in key macroeconomic variables

The 12.40% increase in efficiency gains lead to a 3.88% reduction in household electricity consumption in the short-run. The reallocation of expenditures to other non-electricity goods (according to the one-level CES consumption function) has a small expansionary impact on the UK economy. GDP increases by 0.02% in the short-run, stimulated by an increase in consumption (0.13%) and in investment (0.02%). There is a corresponding small increase in CO2 emissions of 0.01%. As non-electricity sectors are stimulated by the redistribution in the short-run, the demand for labour increases in those sectors. The rigidity of labour supply generates a decrease in the unemployment rate (-0.25%) and an increase in the real wage (0.03%). Overall, competitiveness is reduced as the consumer price index (cpi) increases in the short-run by 0.14%, leading to a drop in exports of 0.26%.

The reduction in household electricity consumption, and the redistribution towards other consumption activities, should in principle (and according to the I-O analysis) lead to a reduction in the industrial use of electricity, through the strong backward sectoral linkages of the electricity sector with itself. However, in the CGE model, prices are now endogenous. The fall in household demand for electricity and corresponding increase in non-electricity consumption generate short-run price drifts because of capacity constraints (in both capital and labour). Overcapacity in the electricity transmission and distribution sector, as well as sectors that are strongly linked to it (e.g. generation activities or fuel extraction sectors) leads to a fall in those sectors' output price in the short-run (See Figure 6.5). In contrast, limited capacity in sectors stimulated by the redistribution leads to a short-run increase in their output prices (e.g. Services and Transport). As a result of the drop in the electricity price, there is a substitution effect in production towards the more efficient commodity. This generates an increase in the industrial use of electricity in the short-run (0.86%), contrary to the findings of the IO analysis. The internal linkages effects are offset by this substitution effect. Overall, as a combination of the fall in household consumption and increase in industrial use, total electricity use in the UK still falls by 0.92%. The household and total rebound results are shown in the last two rows of table 6.4. In the short-run, total rebound (80.53) is larger than household rebound (68.69) due to the increase in industrial electricity use.

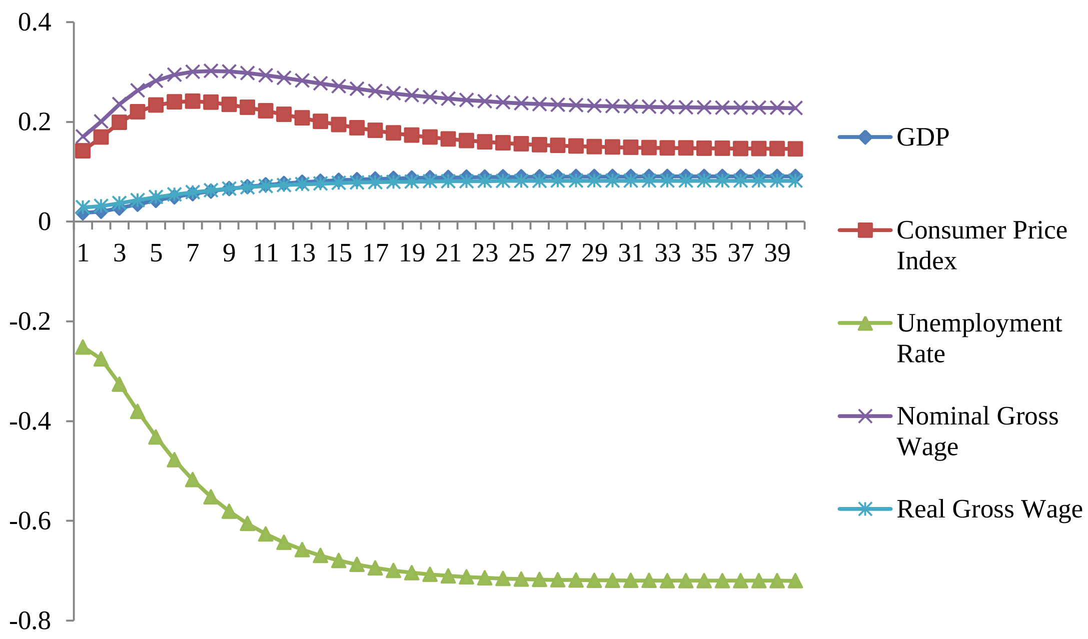
In the long-run, the capacity constraints on the capital stock have been lifted, and investment can adjust fully to the desired level of capital. Thus, the expansionary impact is greater than in the short-run, as there is a greater response to the demand stimulus from the redistributed expenditures. GDP increases by 0.09%, consumption and investment increase by 0.12% and 0.11% respectively. The net increase in investment includes both the decrease in investments in the electricity and other related sectors, as well as the increase in investments in stimulated sectors. The adjustments in capacity correct the short-run price drifts observed in electricity and non-electricity sectors, as seen in Figure 6.5.

Figure 6.5: 40-period sectoral price adjustments



Labour supply is fixed in the model through the assumption of no-endogenous migration. Thus, employment can only adjust through changes in the unemployment rate, which falls in the long-run. However, the demand stimulus still puts upward pressure on the real wage, which translates into an increase in commodity prices in the long-run, for all commodities, including electricity and electricity-related activities. This can be seen in Figure 6.5. Adjustments on the labour market in relations to GDP and price levels are shown in Figure 6.6. In the long-run, the cpi is 0.15% higher than in the base year, which reduces competitiveness and exports further. In the long-run, CO2 emissions decrease slightly, despite the larger expansionary impact, reflecting the fact that the economy is less electricity-intensive than in the base-year.

Figure 6.6: Labour Market Adjustments



In terms of electricity use in the long-run, households' electricity consumption decreased by 4.21%. This decline is greater than in the short-run, as the price of electricity has increased in natural units. Similarly, industrial use of electricity now falls in the long-run by 0.28%, due to this price increase. Overall, there is a drop in the total use of electricity in the UK by 1.78%. It is worth noting that the decreases in household and total electricity use are larger than the direct and total effects calculated in the IO analysis, due to the increase in the price of electricity in natural units in the CGE model. The falls in household and total electricity use correspond to a household rebound of 64.86 and a total rebound of 62.64, which are smaller than in the IO. However, in the long-run, the total rebound is smaller than the household, reversing the short-run findings. The reduction in total rebound effectively reflects the disinvestment effects in the electricity sector, which have reduced the industrial use of electricity in the long-run.

4.2. Substitution between gas and electricity (Scenarios 1 to 3)

In the BASE simulation, households can substitute between electricity and non-electricity goods, without distinction in the latter. If household rebound is lower than 100, households save on their electricity expenditures, and can redistribute across other consumption goods according to their initial consumption choices. However, it is likely that households have different substitution preferences for consumption goods which can provide the same or similar services. In particular, the literature on household energy expenditures shows that the substitution possibilities between fuels in household consumption are not straightforward. As discussed in the final section of Chapter 5, econometric work has shown that in the UK, gas consumption has been shown to be complementary to electricity consumption (negative cross-price elasticity), while electricity seems to be substitutable to gas consumption (positive cross-price elasticity).

These observations reveal the underlying uncertainty surrounding the cross-price elasticities of household energy demands.

This section explores to what extent the rebound from efficiency gains in household electricity consumption is sensitive to the cross-price elasticity between gas and electricity. As pointed out in Section 2, this exercise requires modifying the consumption function to disaggregate household energy consumption. A new nested CES consumption function is used where households can substitute between energy and non-energy goods. The energy composite is also made up of two composites: coal & oil and electricity & gas (the consumption structure is detailed in Section 2.2.2). The impacts of substitution possibilities on the results can be explored, by varying the elasticity of substitution in the gas and electricity composite in the CES consumption function. Three simulations are run and analysed in this section. In Scenario 1, the elasticity of substitution is set at the same value at other energy nests in the consumption function, namely ε_{ge}= 0.61. In Scenario 2, the value of the elasticity of substitution is decreased (ε_{ge}= 0.418) to reflect increased complementarity between gas and electricity. Finally in Scenario 3, the elasticity of substitution is set at ε_{ge}= 1.289, to reflect increased substitutability[84]. The aggregate economic results for each of the three scenarios are presented in Table 6.5. Each case will be discussed separately, before focusing on a comparison of rebound results across simulations.

[84] The calibration of the elasticities of substitution to the econometric findings of Baker et al. (1989) is detailed in Section 3 of this Chapter.

4.2.1. Scenario 1

In the standard case, Scenario 1, where the elasticity of substitution between electricity and gas is set at the default value, the aggregate results appear very similar to the BASE simulation. As households reduce their electricity consumption and re-distribute their expenditures to non-electricity goods there is a small expansionary impact on the economy in the short-run (GDP increases by 0.02%).

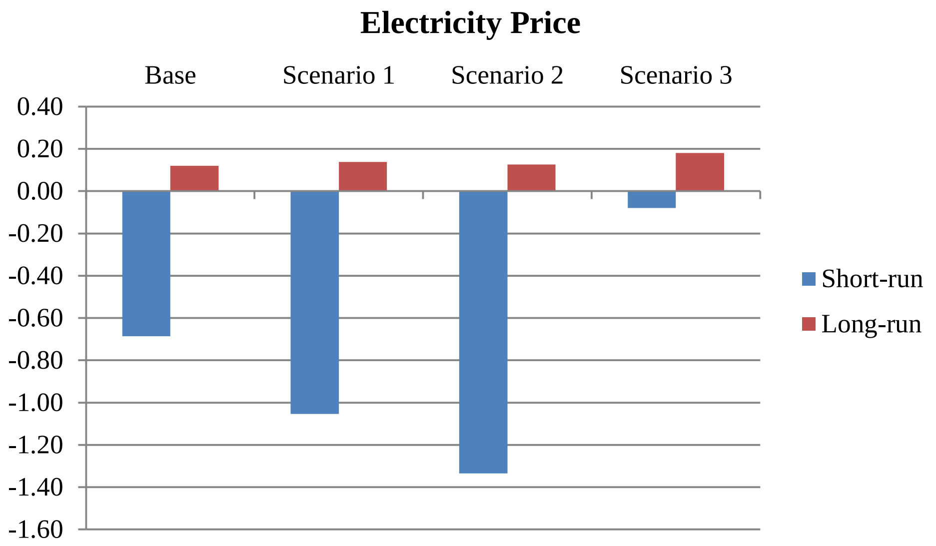
Table 6.5: Aggregate Results – Scenarios 1 to 3

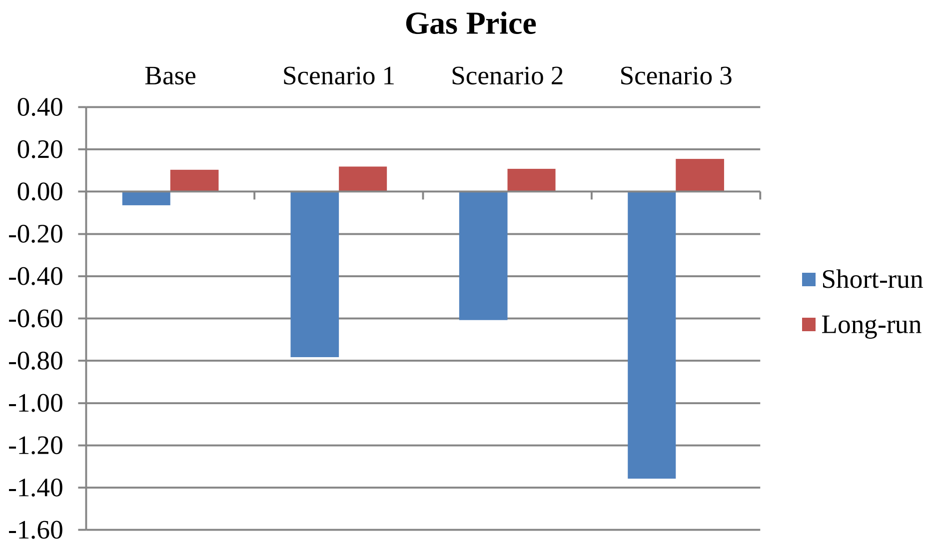
	Scenario 1		Scenario 2		Scenario 3	
	Standard		*Complements*		*Substitutes*	
	SR	LR	SR	LR	SR	LR
GDP	0.02	0.08	0.02	0.07	0.02	0.10
Emissions	-1.08	-1.26	-0.70	-0.85	-2.37	-2.75
Consumer Price Index	0.08	0.17	0.08	0.15	0.09	0.22
Unemployment Rate	-0.29	-0.83	-0.29	-0.75	-0.32	-1.08
Total Employment	0.03	0.09	0.03	0.08	0.04	0.12
Nominal Gross Wage	0.12	0.26	0.12	0.24	0.12	0.34
Real Gross Wage	0.03	0.09	0.03	0.09	0.04	0.12
Households Consumption	0.21	0.14	0.19	0.13	0.30	0.19
Investment	-0.09	0.05	-0.11	0.04	-0.04	0.07
Export	-0.10	-0.31	-0.12	-0.28	-0.03	-0.40
Household Gas Use	-10.87	-11.33	-7.22	-7.63	-23.00	-24.65
Household Electricity Use	-3.62	-4.34	-5.71	-6.50	3.32	3.56
Industrial Electricity Use	1.12	-0.40	1.46	-0.43	-0.02	-0.30
Total Electricity Use	-0.65	-1.90	-1.23	-2.74	1.26	1.16
Household Rebound	70.83	65.02	53.95	47.59	126.79	128.73
Total Rebound	86.20	59.79	73.98	42.05	126.57	124.61

However, the impact of the reallocation on the gas sector, and in turn on CO2 emissions differ significantly from the previous simulation. As electricity and gas are now directly substitutable in the consumption function, an improvement in efficiency in electricity, generates a move away from gas towards the more efficient electricity commodity.

Electricity consumption decreases by 3.62% in the short-run, which is less than in the BASE simulation, and correspondingly, gas consumption decreases by 10.87%. As different demand shocks apply to the electricity and gas sector, this will lead to different short-run price drifts. The short- and long-run price changes for electricity and gas in all simulations are show in Figure 6.7.

Figure 6.7: Electricity and Gas prices (% change from base year)





The negative demand shock on the gas sector leads to a drop in the gas price in the short run, to a much larger extent than in BASE case. In this simulation, the direct demand reduction from household for gas is combined with the indirect demand reduction from the electricity generation sectors. Because of the strong internal linkages of gas and electricity, the electricity price also drops more in Scenario 1 than in the BASE simulation, due to the indirect demand reduction in electricity inputs from the gas sector. This was also pointed out in the Input-Output chapter.

In the long-run, the expansionary impact of the shock is slightly smaller in Scenario 1 (0.08% against 0.09% in BASE), due to the decrease in demand for the gas sector. The net increase in investments is smaller (0.05%), as disinvestment effects also take place in the gas sector. The major difference in aggregate results between the two scenarios is the change in CO2 emissions. As the economy moves away from gas, both in consumption and industry, CO2 emissions are reduced by 1.26% in the long-run.

In terms of electricity, households reduce their consumption in the long-run by 4.34%, which is similar to the BASE scenario (-4.36%), corresponding to a household rebound of 65.02. Total electricity use falls by 1.90%. This is more than in the BASE scenario, from the negative indirect demand effects from the gas sector. This corresponds to a smaller total rebound of 59.79.

4.2.2. Scenario 2: Increased Complementarity

The aggregate results of Scenario 2 are shown in columns 3 and 4 of Table 6.5. Looking at the case of increased complementarity, the results show qualitatively and quantitatively similar changes in aggregate economic indicators compared to previous simulations. However, using a smaller elasticity of substitution between gas and electricity, the changes in household gas and electricity consumption following the efficiency shock are different. In this case, gas and electricity are less substitutable in household consumption. Households cannot substitute the more efficient electricity commodity for gas, as much as in Scenario 1. Thus, there is a larger decrease in household electricity consumption, and a smaller decrease in gas consumption than in Scenario 1[85].

Household electricity consumption decreases by 5.71%, and household gas consumption decreases by 7.22% in the short-run. The larger drop in electricity consumption leads to more excess capacity, and a larger drop in the price of electricity output, as shown in Figure 6.7. In Scenario 2, the electricity price falls by 1.34% in the short-run, the most of all the simulations. Accordingly, Scenario 2 also shows the largest increase in the industrial use of electricity at 1.12% in the short-run.

In the long-run, the electricity price still increases in Scenario 2 as the capacity has adjusted. Household electricity consumption decreases by 6.50% while gas consumption decreases by 7.63%. The industrial use of electricity decreases by more than in Scenario 1, because the gas distribution sector experiences a large negative shock, and as shown in the IO Chapter, it is one of the most electricity intensive sectors after electricity itself. Accordingly, total electricity use decreases by 2.74%, which is more than Scenario 1. This corresponds to the smallest total rebound at 42.05. Despite the smaller rebound in electricity use, total emissions in Scenario 2 decrease by less than in Scenario 1. This is explained by the smaller drop in household gas consumption, and in turn the smaller fall in the output of the gas sector.

[85] The lower the elasticity of substitution, the smaller the decrease in gas as a result of the efficiency shock. Essentially, if gas and electricity were perfect complements, then the efficiency gain would actually lead to an increase in gas consumption.

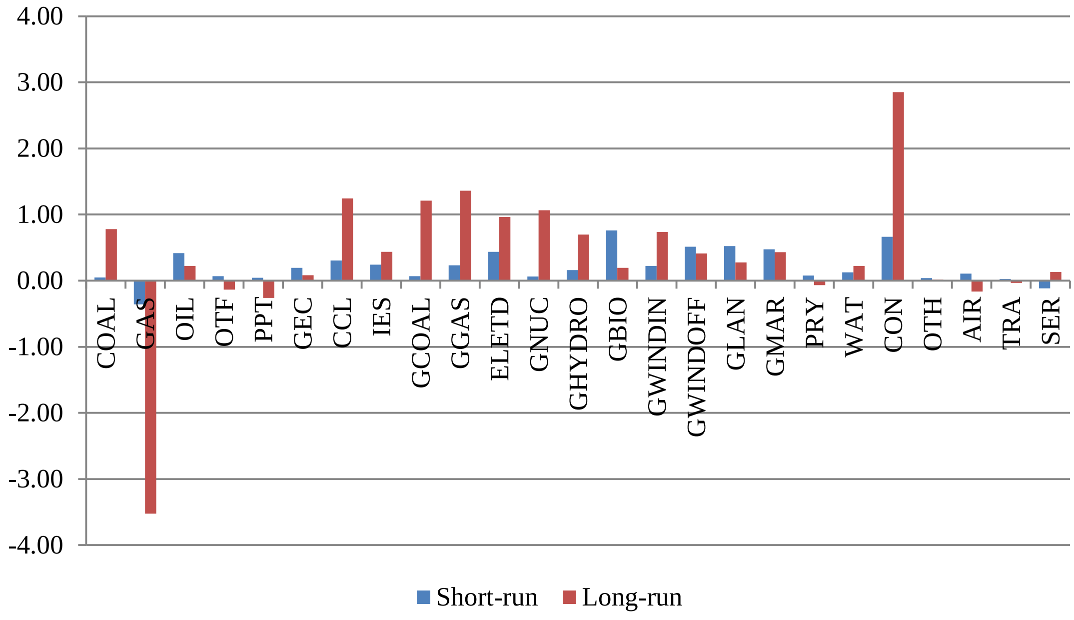
4.2.3. Scenario 3: Increased Substitution

Finally, in Scenario 3, the elasticity of substitution is increased to reflect a positive cross-price elasticity of gas demand to the electricity price. In this case, the elasticity of substitution is increased to 1.28, and this has a large impact on the results, relative to other scenarios. In this case of high substitution, as household electricity consumption becomes more efficient; households can substitute away from gas, and consume more of the efficient commodity. Accordingly, the results of the "substitutes" case show an increase in household electricity consumption of 3.32% and 3.56% in the short and long runs respectively. Calculating the household rebound, the increase in electricity consumption reflects the case of backfire. Household electricity consumption actually increases as a result of the efficiency gain. The household rebound is 126.79 in the short-run and 128.73 in the long-run.

Because household use more of the efficient fuel (electricity), their expenditures on gas decrease dramatically (by 23.00% and 24.65% in the short and long-run respectively). This has major implications for sectoral results, as shown in Figure 6.8. In contrast to the other simulations where the outputs of most sectors (particularly for electricity activities) were falling as a result of the shock, the increase in substitution boosts the demand for all electricity-supplying sectors, in addition to the previously stimulated sectors. This leads to a lasting increase in output in all but a few sectors. The gas sector is highly negatively impacted by the shock with a drop in output of 3.45%.

The increase in household electricity consumption leads to a lack of available capacity in electricity-supplying sector, but the drop in demand for the gas sector (and the strong linkages between gas and electricity) generate a drop in demand for electricity in the short-run. The combination of these conflicting effects generates a slight drop in the electricity price (shown in Figure 6.7), to a much lesser extent than the other two scenarios (0.08%).

Figure 6.8: Sectoral Output – Scenario 3



In consequence, the industrial use of electricity falls in the short run (as opposed to the increase from substitution effects in all other simulations). However, the total use of electricity in the short run is fully dominated by the increase in household consumption. We find a short-run total rebound of 126.57, which is marginally smaller than the household rebound (126.79)[86].

This is also the case in the long-run, but to a lesser extent. The electricity price has risen by 0.18%, decreasing industrial use by 0.30%. In the long run, total electricity use increases by 1.16%, mainly determined by the 3.56% increase in household electricity consumption. This results in a total long-run rebound of 124.61. Total rebound is still

[86] This is the inverse result than in Scenarios 1 and 2, where household rebound was smaller than total rebound due to increased competitiveness and industrial electricity use in the short-run.

smaller than household rebound, but the difference is mitigated by the smaller increase in electricity price in the long-run. In the long-run, the results of Scenario 3 suggest that high substitution between electricity and gas consumption leads to backfire.

Interestingly, the aggregate results of the shock in Scenario 3 are very similar to the other three scenarios, despite the large differences in sectoral results. GDP and consumption are stimulated in the long run. Employment and capital stock are also slightly stimulated, while the lasting price increase has a negative impact on exports. However, one major finding of Scenario 3 is the large drop in CO2 emissions (-2.75% in the long-run). Despite the small expansion in the economy and the increase in electricity use, the large drop in the use of gas has a very positive environmental impact. This result suggests that the 25% decrease in household gas consumption, drastically reduces emissions, while the boost to fossil-fuelled electricity-supplying sectors does not offset it.

4.3. A comparison of Rebound Results

The results of the CGE modelling confirm the observation from the IO analysis that the rebound results are sensitive to assumptions about the substitutability of fuels in household energy consumption. However, the impact on the rebound values of increasing substitution between gas and electricity is not the same in the IO and the CGE analyses. Thus, this section provides a clear comparison of all the rebound results (household and total) obtained in the Input-Output and CGE models. The rebound values for all simulations in Chapter 5 and 6 are summarized in Table 6.6.

Table 6.6: Summary of Rebound Results

			Short-Run		Long-run	
Model	**Simulation**	**Substitution**	**HH**	**Total**	**HH**	**Total**
Input-Output	BASE67	Standard	-	-	75.80	65.23
	DISAG76	Standard	-	-	75.80	73.93
	COMP76	Complements	-	-	75.80	77.44
	SUBS76	Substitutes	-	-	75.80	72.14
CGE	BASE Case	One-level CES	68.69	80.53	64.86	62.64
	Scenario 1	Standard	70.83	86.20	65.02	59.79
	Scenario 2	Complements	53.95	73.98	47.59	42.05
	Scenario 3	Substitutes	126.79	126.57	128.73	124.61

In the IO analysis, several conclusions were drawn about the rebound from efficiency gains in household electricity consumption. First, using a simple reallocation of household expenditures, the IO simulation BASE67 suggests that total rebound is lower than the household rebound. This result is mainly driven by the high internal linkages of the electricity sector. The indirect decrease in demand for the electricity sector generated a negative indirect rebound, as the sector is more electricity intensive than the non-electricity sectors stimulated by the redistribution. Additionally, the same simulation is conducted using a model calibrated with disaggregated Input-Output tables, within which the electricity sector is disaggregated between generation and network activities (nine generation sectors and one electricity transmission and distribution sector). In this DISAG76 simulation, the negative indirect rebound from backwards linkages is reduced, but the previous observation holds: total rebound is smaller than household rebound following efficiency gains in household electricity consumption. Two additional IO simulations are presented looking at the impact of treating gas differently from other non-electricity good. In COMP76 and SUBS76, the change in household gas expenditures is determined prior to the redistribution to other sectors, by multiplying an estimate of cross-price elasticity of demand for gas with regards to the electricity price and the change in the price of electricity in efficiency units. In COMP76, gas and electricity are complements (negative cross-price elasticity) and gas consumption increases as a result of the efficiency gain in electricity consumption. This leads to a positive indirect rebound effect, from the increase in the output of the gas sector. In that case, the total rebound is larger than the direct household rebound. In SUBS76, the cross-price elasticity was assumed to be positive, leading to a large decrease in household gas consumption. The results show the largest negative indirect rebound due to the mutually strong backward linkages of the electricity and gas sectors.

In order to determine the rebound in an economy-wide framework with endogenous prices and endogenous income, Chapter 6 repeats these simulations in a Computable General Equilibrium model of the UK, the UKENVI model. In this framework, the household rebound is not only determined by the direct effect (the change in household consumption resulting from the change in electricity price in efficiency units). The household rebound is also dependent on the relative price of electricity in natural units, and changes in income. Similarly, the total rebound is not only dependent on the direct and indirect changes in sectoral output determined by backwards linkages, but can also be affected by relative price changes and crowding-out effects.

Because of the dynamic nature of the CGE model, the results allow for calculating both short-run and long-run rebounds, while the IO results were static are assumed to represent long-run rebound results only, when all supply constraints are relaxed. The BASE simulation described in Section 3 in the CGE model is the closest replicate of the

DISAG76 and BASE67 simulations in the IO. Using a simple CES consumption function as a composite of electricity and non-electricity goods, this simulation estimates a smaller household rebound (both in the short and long run) than the IO analysis. The household rebound in the IO was considered equal to the direct rebound and determined by the own-price elasticity of demand (75.80 in all simulations). In the CGE, the household rebound responds to endogenous prices and income. In the BASE simulation in the short run, the smaller household rebound is explained by a smaller household income (lower real wage), whereas in the long run, it is explained by an increase in the price of electricity in natural units.

The total rebound results also reveal short-run and long-run differences between the base cases in IO and CGE models. In the short run, the total rebound is larger than household rebound, due to the temporary excess capacity in electricity-supplying sectors pushing down the electricity price. Industrial use of electricity actually increases in the short run. The positive substitution effect outweighs the negative effect from backwards linkages, resulting in different results from the IO analysis. In the long run however, total rebound is smaller than direct rebound, as disinvestment effects have taken place, and industrial use of electricity has decreased. The difference between household and total rebound is larger in the CGE than in the IO analysis (comparing long-run rebounds), due to the increase in electricity price. In the long run, in addition to the negative indirect demand shock for the electricity sector, industrial use of electricity drops due to the increase in electricity price. The reversion of the substitution effect in the long run (away from more expensive electricity) generates a larger difference between household and total rebound.

Finally, by changing the structure of the CES consumption function to introduce more flexibility in household energy substitution, we can identify the impact of increased (or decreased) substitution between electricity and gas in the CGE model as well. Comparing the three simulations with alternative values of elasticities of substitution between gas and electricity in a separate nest of the consumption function, the rebound results vary drastically. The first observation is that increasing the elasticity of substitution between electricity and gas, increases the household rebound. It is the smallest in Scenario 2 (complements), followed by Scenario 1 (middle-case) and is the largest in Scenario 3 (increased substitution). When the elasticity of substitution is larger than 1 in Scenario 3, the case of backfire occurs; and household and total rebounds are larger than 100. With higher substitution, household can substitute more in favour of the more efficient commodity. Household electricity consumption decreases by less (or even increases in Scenario 3), as substitutability increases. In all cases, the total rebound is smaller than the direct rebound in the long-run, as suggested in the IO analysis. In Scenarios 1 and 2, this observation reflects the negative indirect demand and disinvestment effects in the electricity sector. In Scenario 3, total rebound is still larger than 100, but the total backfire is smaller than the household backfire. This suggests that the negative indirect demand shock from the large decrease in household gas consumption and the increase in the electricity price decreases the industrial use of electricity, and in turn total electricity use.

Ultimately, the CGE results comparing substitution possibilities produce contrasting results with the IO comparison of Chapter 5. In the IO, complementarity suggests higher total rebound while substitutability led to lower total rebound. In the CGE, complementarity is found to decrease both household and total rebound, while high substitution is found to lead to both household and total backfire. The difference originates in the way that household consumption is structured in the CGE model, and is a crucial determinant of the rebound. By creating a gas and electricity composite in consumption, the household rebound is not only determined by the direct response to the efficiency gain, but also by the elasticity of substitution between electricity and gas; while in the IO, the household rebound is not allowed to vary with the cross-price elasticity. Since the household rebound determines the size of the redistribution of expenditures, it is the most important determinant of total rebound. When complementarity is assumed in the CGE model, the total rebound is the smallest, and the difference between household and total rebound is the largest (5.54). Indeed, households reduce their electricity use the most, which generates the largest negative demand effects and disinvestment in electricity sectors. In contrast, when substitution is increased (Scenario 3), the difference between household and total backfire is the smallest (4.12), reflecting that the negative demand shock to the gas sector does not reduce industrial use of electricity in the same proportions as other scenarios.

5. Discussion

The CGE modelling of efficiency gains in household electricity consumption in this chapter presents two advantages. First, by endogenizing prices and incomes, the model can capture the full system-wide impacts of the shock. Relative price changes particularly affect the economy's response to the efficiency gains. Households' response to the efficiency gains are determined jointly by the change in the price of electricity in efficiency units (direct rebound) but also by relative price changes in natural units and changes in incomes. Thus, the household electricity rebound in the CGE is different from the IO (where it was equivalent to the direct rebound) and also differs depending on the consumption structure chosen and the elasticity of substitution between electricity and other goods. Similarly, industrial use of electricity is not only determined by static indirect sectoral responses through backwards linkages (like in the IO), but also responds to relative price changes. If the price of electricity decreases in the short run, industrial use of electricity actually increases, and short-run rebound results show a larger total rebound than the household rebound.

Comparing the IO and CGE results in terms of the rebound results reveals that the CGE model captures a much more detailed picture of the economy-wide adjustments to an efficiency gain in household electricity consumption. In addition to the insights in relative price changes affecting sectoral and aggregate variables in the short-run, the CGE model identifies their adjustment paths to explain the long-run results. Through this analysis, the added-value from endogenizing prices and income becomes apparent. When replicating the IO simulations in the CGE analysis, the household and total rebound results are mitigated by the changes in relative prices.

The CGE simulations provide interesting insights about the economic and environmental impacts of an efficiency gain in household electricity consumption, which can be used to draw some policy conclusions. In all simulations, the efficiency gain leads to a small expansionary impact on the UK economy in the long-run. However, the different simulations reveal major differences in household and total electricity use as well as in CO2 emission reductions. With lower substitution between gas and electricity in household consumption, there are larger decreases in household and industrial electricity uses, leading to a larger decrease in total electricity use and thus a lower total rebound. In contrast, increasing substitution between gas and electricity consumptions can lead to the case of household and total backfire, where households substitute electricity (which is more efficient) for gas, leading to an increase in household and total electricity use. In the case of high substitution, the significant decrease in gas consumption generates the largest decrease in CO2 emissions, while the aggregate expansionary impact is still present, and total electricity use increases. Considering the great variation in rebound results when applying alternative elasticities of substitution between electricity and gas, there is a clear need to conduct further research on estimating substitution in household energy expenditures.

These results have strong implications for policy-makers, who have typically focused on household electricity reductions as a major benefit of a smart metering policy. Although demand reductions are considered a crucial part of achieving the goals of security of supply and carbon reductions, it is important to consider their system-wide impacts, depending on substitution possibilities. If gas and electricity are complement goods in household consumption, the efficiency gains in electricity consumption can result in large reductions in electricity and gas consumption, as well as reduction in total UK electricity use. However, if the goods are close substitutes, backfire may occur, and electricity use increase, as shown in Scenario 3. Although counterintuitively, this result might not be undesirable from the policy-makers point of view, as it is associated with a large reduction in the use of gas, leading to a decrease in CO2 emissions and a decrease in fossil-fuel dependence.

Chapter 7: Conclusions

The primary objective of this thesis is to consider the economy-wide impact of two UK policies aimed at sustainability in the energy sector, in the presence of technological change. In two separate modelling exercises, this work presents a number of original contributions to modelling innovation/technological change and its consequences in the context of sustainable energy policies for Scotland and the UK. This chapter provides a summary of the major research findings and contributions of each part of this thesis in turn, while highlighting the potential for extending this research in future work.

Part A

The production side of the energy system is the focus of Part A. The impact of a targeted production subsidy to marine electricity generation is estimated in an energy-focused CGE model for Scotland, while incorporating learning-by-doing technological change for the sector. This exercise represents the first attempt to incorporate endogenous technological change in the AMOS framework.

The targeted review of the energy-economy-environment (EEE) modelling literature reveals the range of existing assumptions to represent endogenous technological change. The literature review focuses on learning-by-doing within energy technologies, as this is identified as the most common form of endogenous technological change in EEE models. Learning-by-doing, which is defined as the costs reductions associated with cumulative experience is generally treated as one process in the literature. However, Chapter 3 identifies a clear list of alternative approaches that have been used to represent this technological change process. Methods differ in terms of the choice of the equation form, the variables chosen to embody experience and performance, and particular parameter values used to calibrate the different equation forms, and even the learning rates themselves.

In addition, Part A of this thesis represents, to my knowledge, the first modelling exercise to test these alternative specifications of learning-by-doing for an energy technology. Both the micro-simulations and the CGE modelling under the different learning-by-doing specifications reveal how crucial the modelling assumptions are in determining the paths and speed of technological improvements.

The empirically defined learning curve equation, used primarily by engineers, consistently leads to increasing efficiency improvements at a decreasing rate, which reflects the realistic observation that each doubling of experience is increasingly difficult to achieve. In contrast, the equation form inspired by economic theory and endogenous growth can lead to a range of outcomes, depending on the assumptions made about returns-to-knowledge. In the case of "fishing-out", where past accumulated experience diminishes the possibility for future learning, the results are qualitatively similar to the concave adjustments of the engineering curve. In contrast, the case of "standing-on-shoulders" leads to ever-increasing efficiency gains, and does not generate a convergence towards a new long-run equilibrium. In addition, decisions over which variable is chosen to embody experience accumulation is also shown to matter in determining the period-by-period adjustments in the economy. While using either the typical gross investment or capital stock proxies does not alter the adjustment paths, the use of output to embody experience through production generates an S-shape diffusion of marine electricity output, reflecting findings from the technological adoption curve literature.

In addition to contributions to the modelling literature, the findings of Part A of this thesis provide a number of insights which are important to consider in both policy-initiation and evaluation. First, the development of an early-stage renewable energy sector (marine in this case) is shown to be dependent not only on the targeted policy support, but also on the potential for learning-by-doing. The relative success of a subsidy policy to marine generation is contingent on costs reductions in the sector through learning effects. As the level of support to renewable technologies is determined through their relative cost-effectiveness, the long-term evolution and effectiveness of the policy itself will be affected by the potential for costs reductions. This analysis shows that policy design and evaluation should be conducted in light of these findings and attention should be given to the sensitivity of results to technological change modelling assumptions.

Future work could extend the analysis conducted in Part A in a number of ways. First, the introduction of endogenous technological change into the CGE model for Scotland has been restricted to learning-by-doing effects. This choice is motivated by the dense literature on the topic and the relative dominance of these effects in the modelling literature. However, Chapter 2 has highlighted the importance of R&D-driven technological change, particularly in economic-theory informed models. Both R&D and learning effects have been shown to influence costs reductions in new technologies depending on their level of development, calling for different policy instruments at different stages of maturity (Foxon et al., 2005). A comprehensive modelling of endogenous technological change would include both R&D-driven and learning- or experience-driven cost reductions (or efficiency improvements). Similarly, an optimal policy to encourage newer renewable technologies could include early R&D support, encouraging R&D-driven costs reductions, followed by subsidies to encourage learning in production and further costs reductions. While such a modelling exercise would be of major interest to policy-makers and to the wider academic community, it requires a step-by-step approach, to identify the additional effect from each layer of policy. Part A of this thesis represents the first step in meeting this challenge of introducing a comprehensive endogenous technological change process in the CGE model for Scotland.

One limitation of the modelling in Part A is that it considers the government intervention in subsidizing marine electricity as costless. In practice, such policy is not costless. A new government subsidy would have to be compensated through a reduction in government expenditures in other parts of the economy, or through an increase in taxes. Both of these would have further repercussions on the overall economy, and this would impact the system-wide modelling results. The reasoning for considering a costless policy in this analysis is twofold. First, from the point of view of policy evaluation, it is important to isolate the economic impact of the policy itself from the impact of consequent adjustments in government budgets. Second, due to the complex nature of adjustments when considering endogenous technological change in a CGE model, it is again important to adopt a step-by-step approach. In a context where both a policy and a new endogenous process must be modelled simultaneously, it is necessary to avoid over-complicating the interpretation of results. By considering this a costless policy, the analysis has focused on identifying the implications of endogenous technological change in the model.

Finally, as is made clear in the literature review, there is no consensus in the representation of learning-by-doing, neither in the econometric nor the EEE modelling literatures. Some of the assumptions identified in the review have already been highlighted and tested in econometric models for renewable energy technologies (e.g. the proxy for experience or for performance). However, this is not the case for the specific form of the equation. The econometric literature estimating learning rates has so far only focused on the engineering learning curve; the economic-theory-based specification has not been tested. This represents an opportunity for future research, as the estimated learning rates in such new models would likely differ from those derived from previous attempts and provide better estimates to parameterize the economic equation in EEE models. In particular, an such estimation exercise could provide estimates on the returns-to-knowledge (with regards to experience).

Part B

In Part B, the policy focus is shifted to the consumption side of the energy sector. This part considers the impact of the roll-out of smart meters on the wider-economy, through the modelling of efficiency gains in households' electricity consumption. This work represents the first attempt to model both the system-wide economic and environmental impacts of the UK smart meter roll-out and the associated expected reduction in household electricity consumption. The analysis builds on previous work on rebound effects from efficiency improvements in energy-use. This literature usually focusses on the production-side, rather than on the consumption side of the economy. Part B is the first modelling exercise to consider system-wide rebound effects from efficiency gains in *household electricity consumption*.

The Input-Output and CGE analyses show that the total rebound is consistently smaller than the household rebound, reflecting the reductions in the industrial use of electricity, through the strong internal backwards linkages within electricity sectors (i.e. the relative electricity-intensity of electricity activities). In line with previous findings in the literature on system-wide modelling of rebound effects from household energy efficiency improvements (Lecca et al., 2014), the move from the partial equilibrium Input-Output framework towards the CGE with endogenous prices and incomes put a number of upward or downward pressures on both the household and economy-wide rebounds. The household rebound is reduced in the CGE model compared to the IO analysis, due to downwards pressures from income effects in the short-run and price effects (in natural units) in the long-run. In contrast, the total rebound is increased in the short-run in the CGE model, due to the drop in electricity prices (because of short-run over capacity). In the long-run, the price effect is reversed and the total rebound is again reduced in the CGE framework.

Another major contribution of Part B is the innovation in the modelling of household energy consumption and substitution possibilities. This is the first modelling exercise formally to consider the impact of gas and electricity consumption substitution on the rebound effect from efficiency gains. Second, the econometric parameterization of substitution possibilities in household energy consumption to investigate the cases of substitutability or complementarity between gas and electricity is the first of its kind and proves to be crucial in determining the rebound effects. The successive simulations with different elasticities of substitution between fuels in household consumption reveal that the household and total rebounds increase with the elasticity of substitution.

The analysis conducted in Part B has important implications for the smart-meter roll-out, and more generally for policies aimed efficiency improvements in household electricity consumption. The analysis shows that the benefits from these improvements might be larger than the expected three percent reductions in household electricity consumption, when the economy-wide rebound is taken into account. In particular, industrial use of electricity is also expected to decrease, which would further contribute to the government's objective of demand-side management. However, this finding is crucially dependent on the size of the elasticity of substitution between electricity and gas in household energy consumption. The parameterization from the econometric literature on UK household energy demand reveals that if electricity and gas are close substitutes, the case of backfire may occur, where households actually increase their electricity use but decrease their consumption of gas. While this result appears to conflict with the policy's objectives, the case of backfire is also accompanied by a larger decrease in total CO2 emissions, driven by the move away from gas. This contributes more strongly to the overall energy policy goal of decarbonisation.

As in Part A, a number of opportunities for future research arise from the findings in Part B. First, the sensitivity of the rebound to assumptions about the consumption structure and the values of key elasticities suggests the need for further work in that area. The econometric estimates used to parameterize substitution between electricity and gas in household consumption do not give a clear picture of household energy consumption. In fact, the cross-price elasticity estimates between gas and electricity give contradictory results, indicating that these goods might be substitutes or complements in consumption. It is likely that the contradictory findings from the econometric literature are due to the nature of household energy consumption, which is fully determined by relatively long-term investments. Indeed, whether through the choice of appliance or heating system, there is a tendency to technological lock-ins in electricity or gas consumptions. The dependence of the rebound on these estimates reflects the need for more precise modelling of household energy demands, taking into consideration the longer-term "energy capital" goods.

Finally, a number of policy extensions to Part B could be considered in future research. First, in the analysis, the smart meter roll-out is again treated as a costless policy. Efficiency improvements in household consumption are modelled here without any investment costs, whereas in practice the costs of smart meters are expected to be borne by electricity suppliers. This could have a potential effect of further increasing the price of electricity and further reducing electricity use and the rebound. Second, the impacts of such a policy could be compared with other measures aimed at efficiency improvements in household consumption, where the costs of the policy could be borne directly by households. An interesting area of future research would be a comparison of rebound effects from alternative policies aimed at improving household electricity efficiency in terms of their economy-wide impacts as well as redistribution effects.

Whether focused on the production or consumption-side of the economy, this thesis has shown the importance of considering technological innovation when modelling the system-wide economic and environmental impacts of energy policies. Overall, the findings suggest that technological change in energy technologies can generate several benefits, such as costs reductions and energy and carbon savings, and thus technological change is a crucial factor contributing to bridging the gap between the conflicting energy policy goals of security of supply, decarbonisation and affordability.

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Appendix List

Appendix A: Cobb-Douglas Cost Function with Constant Returns to Scale

Total Costs of production are given in equation:

$$TC_t = rK_t * wL_t$$

Here, r and w are the prices of capital and labour inputs respectively. The Cobb-Douglas cost function for a given level of output y can be derived from the optimisation problem:

$$C = \min(rK_t + wL_t)$$

$$\text{Given that } y = AK^{\gamma_K}L^{\gamma_L}$$

This constraint can be solved for L_t, so the problem is equivalent to:

$$\min(rK_t + w\ A^{-1/\gamma_L}\ Y^{1/\gamma_L}\ K^{-\gamma_K/\gamma_L})$$

The first order condition of this optimisation problem is $\frac{\partial C}{\partial K} = 0$, which translates to:

$$r + w\ A^{-1/\gamma_L}\ Y^{1/\gamma_L}\ K^{-\gamma_K/\gamma_L} = 0$$

From this, we can derive the conditional demands for capital and labour:

$$K^d(r, w, y) = A^{-\frac{1}{\gamma_K+\gamma_L}} \left(\frac{w}{r}\,\frac{\gamma_K}{\gamma_L}\right)^{\frac{\gamma_L}{\gamma_K+\gamma_L}}\ y^{\frac{1}{\gamma_K+\gamma_L}}$$

$$L^d(r, w, y) = A^{-\frac{1}{\gamma_K+}\gamma_L} \left(\frac{w}{r}\,\frac{\gamma_K}{\gamma_L}\right)^{-\frac{\gamma_K}{\gamma_K+\gamma_L}}\ y^{\frac{1}{\gamma_K+\gamma_L}}$$

Replacing these conditional demands into the cost function, we find:

$$C(r,w,y) = rK^d + wL^d$$

$$C(r,w,y) = r\left[A^{-\frac{1}{\gamma_K+\gamma_L}}\left(\frac{w}{r}\frac{\gamma_K}{\gamma_L}\right)^{\frac{\gamma_L}{\gamma_K+\gamma_L}} y^{\frac{1}{\gamma_K+\gamma_L}}\right]$$

$$+ w\left[A^{-\frac{1}{\gamma_K+}\gamma_L}\left(\frac{w}{r}\frac{\gamma_K}{\gamma_L}\right)^{-\frac{\gamma_K}{\gamma_K+\gamma_L}} y^{\frac{1}{\gamma_K+\gamma_L}}\right]$$

Simplifying, costs become:

$$C(r,w,y) = A^{-\frac{1}{\gamma_K+\gamma_L}} y^{\frac{1}{\gamma_K+\gamma_L}}\left[\frac{\gamma_K}{\gamma_L}^{\frac{\gamma_L}{\gamma_K+\gamma_L}} + \frac{\gamma_K}{\gamma_L}^{-\frac{\gamma_K}{\gamma_K+\gamma_L}}\right] r^{\frac{\gamma_K}{\gamma_K+\gamma_L}} w^{\frac{\gamma_L}{\gamma_K+\gamma_L}}$$

With the assumption of constant returns to scale, costs become:

$$C(r,w,y) = a\,\frac{y}{A} r^{\gamma_K} w^{\gamma_L}$$

Where $a = \gamma_K^{-\gamma_K}(1-\gamma_K)^{\gamma_K - 1}$

Appendix B: 17 Sector Disaggregation of the Scottish IO Tables

	Sector Name	**abbreviation**
1	Primary	PRY
2	Manufacturing	MAN
3	Utilities and transport	UAT
4	Services	SER
5	Coal (Extraction)	COAL
6	Oil and other fuels	OIL
7	Gas	GAS
8	Electricity Transmission and Distribution	ELETD
9	Generation - Nuclear	GNUC
10	Generation - Coal	GCOAL
11	Generation - Hydro	GHYDRO
12	Generation - Gas	GGAS
13	Generation - Biomass	GBIO
14	Generation - Wind onshore	GWINDON
15	Generation - Wind offshore	GWINDOFF
16	Generation - Landfill gas	GLAN
17	Generation - Marine	GMAR

Appendix C: A Mathematical Summary of the AMOS Model Structure

The characteristics of the version of AMOS (A Micro-Macro Model of Scotland) used in this thesis are developed in the main body of text. This appendix is provided to summarize the AMOS model structure in mathematical form, where the main interactions between variables of interests are represented. The mathematical description is kept as general as possible, to reflect the possibilities of AMOS as a flexible CGE framework. It is based largely on AMOS model descriptions by Harrigan et al. (1991), McGregor et al. (1995) and Lecca et al. (2013). However, the model summarised here is adapted for Scotland, as a region of the UK, and is characterized by myopic agents. This is the model version used in Chapter 4 of this thesis[87].

The model listing summarizes the price setting equations, technology in production, trade interactions, the behaviour of households and other institutions, the government sector, production factor accumulation, the trade balance, private, foreign and public assets. Finally the short-run and steady-state conditions are outlined.

Note: the time subscript has been omitted in some equations for clarity.

Prices		
Commodity price	$PQ_i = \dfrac{PR_i.R_i + PM_i.M_i}{R_i + M_i}$	C.1

[87] Forward-looking agents are an extension of the AMOS model used here (Lecca et al., 2013). The version with forward-looking agents is used in Chapter 6 of this thesis. The main changes to the model equations for the version in Chapter 6 are listed in Appendix G.

Import price	$PM_i = \varepsilon . PWM_i . (1 + MTAX_i)$	C.2
Export price	$PE_i = \varepsilon \, . PWE_i (1 - TE_i)$	C.3
National commodity price	$PIR_j = \frac{\sum_i VR_{i,j} . PR_j + \sum_i VI_{i,j} . \overline{PI_j}}{\sum_i VIR_{i,j}}$	C.4
Value added price	$PY_j . a_j^Y = PX_j . \left(1 - btax_j - sub_j\right) - \sum_i a_{i,j}^V . PQ_j$	C.5
Consumption price	$PC_t^{1-\sigma^C} = \sum_j \delta_j^f . PQ_{j,t}^{1-\sigma^C}$	C.6
Price of government consumption	$Pgov_t^{1-\sigma^G} = \sum_j \delta_j^g . PQ_{j,t}^{1-\sigma^g}$	C.7
User cost of capital	$UCK = Pk . (ir + \delta)$	C.8
Rate of return to capital	$rk_j = PY_j . \delta_j^k . A^{\rho_j} . \left(\frac{Y_j}{K_j}\right)^{1-\rho_j}$	C.9
Capital good price	$Pk = \frac{\sum_j PQ_j \, . \sum_j KM_{i,j}}{\sum_i \sum_j KM_{i,j}}$	C.10
After tax wage	$w_t^b = \frac{w_t}{(1 + sscee + sscer) . (1 + ire)}$	C.11
Real Wage (Reg. barg.)	$\ln\left(\frac{w_t}{cpi_t}\right) = c - \mu . ln(u_t)$	C.12
Production technology		
Total output	$X_i = \min\left(\frac{Y_i}{a_i^Y} ; \frac{V_{i,j}}{a_{i,j}^V}\right)?$	C.13
Value-added	$Y_i = A . \left(B . \delta_i^k K_i^{\rho_i} + C . \delta_i^l L_i^{\rho_i}\right)^{\frac{1}{\rho_i}}$	C.14

Trade		
Total intermediate inputs	$VV_i = \gamma_{i,j}^{vv}.\left(\delta_{i,j}^{vm}VM_i^{\rho_i^A} + \delta_{i,j}^{vir}VIR_i^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$	C.15
National intermediate inputs	$VIR_{i,j} = \gamma_{i,j}^{vir}.\left(\delta_{i,j}^{vr}VR_i^{\rho_i^A} + \delta_{i,j}^{vi}VI_i^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$	C.16
Total exports	$E_i = \overline{E_i}.\left(\frac{PE_i}{PR_i}\right)^{\sigma_i^x}$	C.17
Total Regional Demand	$R_i = \sum_j VR_{i,j} + QHR_i + QVR_i + QGR_i$	C.18
Total production	$X_i = R_i + E_i$	C.19
Households and other non-government institutions		
Aggregate Household consumption	$C_t = \sum_{dngins,t} YNG_{dngins,t} - \sum_{dngins,t} SAV_{dngins,t} - HTAX_t - \sum_{dngins} TRSF_{dngins,t}$	C.20
Wealth	$W_t = NFW_t + FW_t$	C.21
Non-financial wealth	$NFW_t(1+r) = NFW_{t-1} + d_{dngins}^L.(ssce + ire).\sum_j L_{j,t}.w_t + \sum_{dngins} TRSF_{dngins,t} + TRG_{dngins,t} + REM_t$	C.22
Financial wealth	$FW_t(1+r) = FW_{t-1} + \delta_{dngins}^K.\sum_i K_i.rk_{i,t} - SAV_h$	C.33

Armington household consumption	$QH_i = \gamma_i^h \left(\delta_i^{hr} QHR_i^{\rho_i^A} + \delta_i^{hm} QHM^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$	C.34
CES Household consumption	$QH_i = (\delta_i^f)^{\rho_i^C} \left(\frac{PC_i}{PQ_i}\right)^{\rho_i^C}$	C.35
Total non-government institutional income	$YNG_{dgnins,t} = d_{dngins}^L . \sum_j L_{j,t} . w_t + d_{dngins}^K . \sum_i K_i . rk_{i,t}$ $+ d_{dngins}^h . rh_{i,t} \sum_i Hi$ $+ \sum_{dngins} TRSF_{dngins} + TRG_{dngins}$ $+ REM_{ins}$	C.36
Transfers from non-governmental institutions	$TRSF_{dngins,t} = PC_t . \overline{TRSF_{dngins}}$	C.37
Transfers from government	$TRG_{ins} = PC_t . \overline{TRG_{ins}}$	C.38
Institution Savings (non-government)	$SAV_{ins,t} = mps_{ins} . YNG_{ins,t}$	C.39
Government		

Fiscal Deficit	$$FD_t = (\overline{G_t} + I_{g,t}).P_{gov_t} + \overline{GSAV} + \sum_{dngins} TRG_{dngins_t} - \left(d_g^k.\sum_i rk_{i,t}.K_{i,t} + d_g^h \sum_i rh_{i,t}.H_{i,t} + \sum_{i,t} IMT_{i,t} + (ssce + ire).\sum_j L_{j,t}.w_t + \overline{REM_g}.\varepsilon_t\right)$$	C.40
Government expenditures	$$G_t = \sum_i QG_{i,t}.PQ_{i,t} + \overline{GSAV}$$	C.41
Armington government expenditures	$$QG_i = \gamma_i^g \left(\delta_i^{gr}.QGR_i^{\rho_i^A} + \delta_i^{gm}.QGM_i^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$$	C.42
Investment Demand		
Investment by sector of origin	$$QV_i = \sum_i KM_{i,j}.J_j$$	C.43
Total investment	$$QV_i = \gamma_i^v \left(\delta_i^{qvm}.QVM_i^{\rho_i^A} + \delta_i^{qvr}.QVIR_i^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$$	C.45
National investment	$$QVIR_i = \gamma_i^{vir} \left(\delta_i^{qvr}.QVR_i^{\rho_i^A} + \delta_i^{qvi}.QVI_i^{\rho_i^A}\right)^{\frac{1}{\rho_i^A}}$$	C.46
Investment path		
Investment by destination	$$I_{i,t} = \nu.\left(KS_{i,t}^* - KS_{i,t}\right) + \delta.KS_{i,t}$$	C.47
Desired capital stock	$$KS_{i,j}^* = \left(A_j^{\rho_i}.\delta_j^k.\frac{PY_{j,t}}{uck_t}\right)^{\frac{1}{1-\rho_j}}.Y_{j,t}$$	C.48

Factors accumulation		
Capital stock	$KS_{i,t+1} = (1-\delta)KS_{i,t} + I_{i,t}$	C.49
Labour supply	$LS_{i,t+1} = \left(1 + nim_{i,t}\right).LS_{i,t}$	C.50
Net in-migration	$nim_{i,t} = \varsigma - v^{u}\left(\ln(u_t) - \ln\left(\overline{u}^{N}\right)\right) + v^{w}\left(\ln\left(\frac{w_t}{cpi_t}\right) - \ln\left(\frac{w^{N}}{cpi^{N}}\right)\right)$	C.51
Factors market clearing		
	$K_{i,t} = KS_{i,t}$	C.52
	$LS_t(1-u_t) = \sum_j L_{j,t}$	C.53
Taxes and subsidies		
Production subsidy	$SUBSY_{i,t} = SUB_i.X_{i,t}.PX_{i,t}$	C.54
Import tax	$IMT_{j,t} = \sum_i MTAX_j.VM_{i,j,t}.PM_{i,t}$	C.55
Current Account		
Total import demand	$M_{i,t} = \sum_j VI_{i,j,t} + \sum_j VM_{i,j,t} + QHM_{i,t} + QVI_{i,t} + QVM_{i,t}$	C.56

Trade Balance	$TB_t = \sum_i M_{i,t}.PM_{i,t} - \sum_i E_{i,t}.PE_{i,t} + \varepsilon_t.(\sum_{dngins} \overline{REM_{dngins}} + \overline{FE}$	C.57
Assets		
Value of firms	$VF_{i,t} = \lambda_{i,t}.K_{i,t}$	C.58
Foreign debt	$D_{t+1} = (1 + r - \tau).D_t + TB_t$	C.59
Government debt	$GD_{t+1}.Pgov_{t+1} = \left(1 + r - \tau + \left(\frac{PC_{t+1}}{PC_t} - 1\right)\right)GD_t.Pgov_t + FD_t$	C.60
Steady-state conditions		
	$I_{i,T} = KS_{i,T}.\delta$	C.61
	$FD_T = -\left(r - \tau g + \frac{Pc_{t+1}}{Pc_t} - 1\right).Pgov_T.GD_T$	C.62
	$TB_T = (-r - \tau)D_T$	C.63
Short-run conditions		
	$KS_{i,t=1} = KS_{i,t=0}$	C.64
	$LS_{t=1} = LS_{t=0}$	C.65

Subscripts:

i, j	Sectors
t	Time
ins	Institutions
$dins$	Domestic institutions
$dngins$	Domestic non-government institutions
h	Households
g	Government

Endogenous Variables:

PQ_i	Commodity Price
PR_i	Regional Price
R_i	Regional Supply
PM_i	Import Price
PWM_i	World Import Price
M_i	Imports
$MTAX_i$	Rate of Import Tax
PE_i	Export Price
TE_i	Rate of Export Subsidy
PWE_i	World Export Price
VR_i	Regional Intermediate Inputs
VI_i	RUK Intermediate Inputs
$\overline{PI_i}$	RUK Price
PIR_i	National Price (Scotland + RUK)
VIR_i	National Intermediate Inputs (Scotland + RUK)
UCK	User Cost of Capital
Pk	Capital Good Price
A_i	Total factor productivity
K_i	Physical capital demand
L_i	Labour demand
w_t	Regional Nominal wage
w^N	National wage
w_t^b	After tax wage
X_i	Total output

Y_t	Value-added
$V_{i,j}$	Intermediate input
B_i	Capital productivity
C_i	Labour productivity
VV_i	Total intermediate inputs
VM_i	ROW intermediate inputs
E_i	Total exports
QHR_i	Regional household consumption
QVR_i	Regional investment by sector of origin
QGR_i	Regional government consumption
W	Household wealth
NFW	Household non-financial wealth
FW	Household financial wealth
$TRSF_{ins}$	Transfers from non-government institution
TRG_{ins}	Transfers from government
REM_{ins}	Institution remittance
SAV_{ins}	Institution savings
YNG_{ins}	Domestic non-government institution income
$\overline{G_t}$	Aggregate government expenditures
QG_i	Total Government expenditure on good i
$\overline{GSAV}$	Government savings
QGR_i	Regional government expenditures
QGM_i	Imported government expenditures
$KM_{i,i}$	Physical capital matrix
$HTAX$	Total household tax
J_i	Investment by destination
QV_i	Investment by origin
$QVIR_i$	National investment (Scotland +RUK)
QVM_i	ROW investment demand
QVR_i	Regional investment demand
QVI_i	RUK investment demand
I_i	Investment by destination
KS_i	Capital stock
KS_i^*	Desired capital stock

LS_i	Labour supply
nim_i	Net in-migration
u_t	Regional unemployment rate
u^N	National unemployment rate
IMT_i	Total import tax
$SUBSY_i$	Production subsidy
$M_{i,t}$	Total demand for imports
TB_t	Trade Balance (positive is trade deficit, negative is trade surplus)
VF_i	Value of firms
D_t	Foreign debt
GD_t	Government debt
λ_i	Shadow price of capital

Elasticities

ρ_i	Elasticity of substitution between labour and capital in sector j
ρ_i^A	Armington elasticity
μ	Elasticity of real wage to the unemployment rate
σ_i^x	Elasticity of exports to the regional price
σ^G	Elasticity of substitution in government consumption
ρ_i^C	Elasticity of substitution in household consumption
v^u	Elasticity of migration to the unemployment differential
v^w	Elasticity of migration to the real wage differential

Parameters

$a_{i,j}^V$	Input-Output coefficient for i used in j
a_i^Y	Share of value added in production
$btax_i$	Business tax
sub_i	Production subsidy
r	Interest rate
δ	Depreciation rate

$\delta_j^{k,l}$	Shares of capital and labour in the value-added function
$ssce$	Rate of social security paid by employees
$sscer$	Rate of social security paid by employers
ire	Rate of income tax
$\gamma_{i,j}^{vv,vir}$	Shift parameters in intermediate goods CES functions
γ_i^h	Shift parameter in household consumption
γ_i^g	Shift parameter in government consumption
$\delta_j^{vm,vir,vr,vi}$	Share parameters in intermediate goods
$\delta_i^{hr,hm}$	Share parameters in household consumption
d_{ins}^K	Share of capital in institution income
d_{ins}^L	Share of labour in institution income
δ_i^f	Share of good i in household consumption
$\delta_i^{gr,gm}$	Share parameters in government consumption
mps_{ins}	Institution rate of savings
v	Investment path accelerator mechanism
ς	Calibrated migration parameter
$MTAX$	Import tax rate
SUB_i	Production subsidy rate
τ	Proportion of subsidised debt (region)

Appendix D: 67 Sector Disaggregation of the UK IO Tables

67 Sectors aggregation		123 Sector IO	93 Sector Environmental Accounts
1	Agriculture	1	1
2	Forestry	2	2
3	Fishing	3	3
4	Coal Extraction etc.	4	4
5	Oil & Gas Extraction	5	5
6	Metal Ores Extraction, Other Mining And Quarrying	6 & 7	6 & 7
7	Food & Drinks	8-19	8
8	Tobacco	20	9
9	Clothing	21-27	10
10	Wearing Apparel & Fur Products	28	11
11	Leather Goods	29 & 30	12
12	Wood & Wood Products	31	13
13	Paper Manufacturing	32-34	14 & 15
14	Coke, Refined Petroleum & Nuclear Fuel	35	16-18
15	Industrial Gases & Dyes	36	19
16	Organic & Inorganic Chemicals	37 & 38	20 & 21
17	Fertilizers, Pesticides, etc.	39-41	22-24
18	Paints, Varnishes, Printing Ink, etc.	42	25
19	Pharmaceuticals	43	26
20	Soap & Toilet Preparations	44	27
21	Other Chemicals & Manmade Fibres	45 & 46	28 & 29
22	Rubber Products	47	30
23	Plastic Products	48	31
24	Glass & Glass Products	49	32
25	Ceramic Goods	50	33
26	Cement & Clay	51 & 52	34 & 35
27	Articles Of Concrete, etc.	53	36
28	Iron & Steel	54 - 56	37-40
29	Metal Products	57-61	41
30	Machinery & Munitions	62-68	42
31	Office Machinery & Computers	69	43
32	Elec. Equip.	70-72	44
33	TV Equip., etc.	73-75	45
34	Medical & Precision Instruments	76	46
35	Motor Vehicles	77	47
36	Earth & Space Transportation	78-80	48
37	Misc. Products	81-84	49

38	Electricity Production & Distribution	85	51-55
39	Gas Distribution	86	56
40	Water Supply	87	57
41	Construction	88	58
42	Motor Vehicle Distribution & Repair, etc.	89	59
43	Wholesale Distribution	90	60
44	Retail Distribution	91	61
45	Hotels, Catering & Pubs, etc.	92	62
46	Railway Transport	93	63
47	Other Land Transport	94	64-68
48	Water Transport	95	69
49	Air Transport	96	70
50	Ancillary Transport Services	97	71
51	Communications	98 & 99	72
52	Banking & Finance	100	73
53	Insurance And Pension Funds	101	74
54	Auxiliary Financial Services	102	75
55	Property	103-105	76
56	Renting Of Machinery	106	77
57	Computing Services	107	78
58	Research & Development	108	79
59	Professional Services	109-114	80
60	Public Administration	115	81 & 82
61	Education	116	83
62	Health Services	117 & 118	84
63	Sewage & Sanitary Services	119	85-87
64	Membership Organisations	120	88
65	Recreational Services	121	89
66	Other Service Activities	122	90
67	Private Households With Employed Persons	123	91

Appendix E: Input-Output Result Tables for Chapter 5

Table E1: BASE67 Sectoral Output Results

Change in Output (£ms)	Direct	Type I	Type II
Agriculture	4.85	8.77	10.27
Forestry	0.08	0.15	0.18
Fishing	0.03	0.29	0.33
Coal Extraction etc.	0.11	-9.61	-9.55
Oil & Gas Extraction	0.02	-68.07	-67.30
Metal Ores Extraction, Other Mining And Quarrying	0.01	0.08	0.12
Food & Drinks	16.59	28.16	33.06
Tobacco	1.25	1.25	1.46
Clothing	2.44	3.36	3.94
Wearing Apparel & Fur Products	4.67	4.70	5.49
Leather Goods	1.15	1.19	1.39
Wood & Wood Products	0.46	0.96	1.19
Paper Manufacturing	3.90	6.70	8.55
Coke, Refined Petroleum & Nuclear Fuel	2.80	1.75	2.57
Industrial Gases & Dyes	0.04	-0.28	-0.23
Organic & Inorganic Chemicals	0.03	-0.15	-0.06
Fertilizers, Pesticides, etc.	0.06	0.90	1.08
Paints, Varnishes, Printing Ink, etc.	0.13	0.40	0.49
Pharmaceuticals	0.64	0.90	1.07
Soap & Toilet Preparations	1.64	1.89	2.22
Other Chemicals & Manmade Fibres	0.68	0.75	0.89
Rubber Products	0.49	0.70	0.83
Plastic Products	0.76	2.85	3.46
Glass & Glass Products	0.16	0.56	0.67
Ceramic Goods	0.36	0.41	0.49
Cement & Clay	0.02	0.05	0.08
Articles Of Concrete, etc.	0.07	0.16	0.26
Iron & Steel	0.01	0.47	0.70
Metal Products	0.68	-2.21	-1.53
Machinery & Munitions	2.13	0.24	0.85
Office Machinery & Computers	0.32	0.35	0.43
Elec. Equip.	0.57	-0.12	0.12
TV Equip., etc.	2.18	2.40	2.83
Medical & Precision Instruments	0.80	0.98	1.20
Motor Vehicles	9.84	11.21	13.14
Earth & Space Transportation	1.00	1.00	1.25

Misc. Products	4.36	5.00	5.97
Electricity Production & Distribution	-286.87	-407.68	-405.94
Gas Distribution	2.25	-27.91	-27.19
Water Supply	1.22	1.06	1.33
Construction	2.12	1.10	3.17
Motor Vehicle Distribution & Repair, etc.	9.68	11.49	13.79
Wholesale Distribution	13.12	11.62	15.71
Retail Distribution	41.36	41.43	48.43
Hotels, Catering & Pubs, etc.	29.66	30.44	35.58
Railway Transport	1.92	1.99	2.42
Other Land Transport	3.60	8.19	9.93
Water Transport	1.17	0.94	1.19
Air Transport	5.13	5.88	7.01
Ancillary Transport Services	0.82	7.40	9.51
Communications	6.31	9.46	11.87
Banking & Finance	5.16	-2.03	1.32
Insurance And Pension Funds	10.87	12.53	15.52
Auxiliary Financial Services	0.59	1.47	1.81
Property	41.51	47.99	56.43
Renting Of Machinery	2.00	2.41	3.21
Computing Services	0.03	3.53	4.90
Research & Development	0.12	-0.13	0.00
Professional Services	0.52	15.57	20.80
Public Administration	1.06	2.07	2.53
Education	11.80	13.30	15.75
Health Services	8.04	9.57	11.30
Sewage & Sanitary Services	1.27	2.11	2.56
Membership Organisations	2.05	2.82	3.33
Recreational Services	12.32	14.77	17.50
Other Service Activities	3.69	4.28	5.07
Private Households With Employed Persons	2.18	2.19	2.55
Total	**0.00**	**-163.99**	**-80.73**

Table E2: BASE67 Sectoral CO2 Results

Change in CO2 Emissions (000tns)	Direct	Type I	Type II
Agriculture	1.38	2.50	2.93
Forestry	0.01	0.01	0.01
Fishing	0.01	0.12	0.14
Coal Extraction etc.	0.02	-2.06	-2.05
Oil & Gas Extraction	0.02	-59.22	-58.55
Metal Ores Extraction, Other Mining And Quarrying	0.00	0.02	0.03
Food & Drinks	2.51	4.26	4.99
Tobacco	0.03	0.03	0.03
Clothing	0.83	1.14	1.33
Wearing Apparel & Fur Products	0.23	0.23	0.27
Leather Goods	0.10	0.10	0.12
Wood & Wood Products	0.15	0.32	0.40
Paper Manufacturing	0.54	0.92	1.18
Coke, Refined Petroleum & Nuclear Fuel	2.87	1.80	2.65
Industrial Gases & Dyes	0.02	-0.18	-0.15
Organic & Inorganic Chemicals	0.02	-0.08	-0.04
Fertilizers, Pesticides, etc.	0.04	0.52	0.62
Paints, Varnishes, Printing Ink, etc.	0.01	0.03	0.03
Pharmaceuticals	0.08	0.11	0.13
Soap & Toilet Preparations	0.17	0.19	0.22
Other Chemicals & Manmade Fibres	0.13	0.14	0.17
Rubber Products	0.14	0.20	0.24
Plastic Products	0.14	0.51	0.62
Glass & Glass Products	0.08	0.30	0.35
Ceramic Goods	0.10	0.11	0.14
Cement & Clay	0.12	0.37	0.57
Articles Of Concrete, etc.	0.01	0.02	0.03
Iron & Steel	0.02	0.84	1.25
Metal Products	0.06	-0.18	-0.13
Machinery & Munitions	0.11	0.01	0.05
Office Machinery & Computers	0.01	0.01	0.01
Elec. Equip.	0.04	-0.01	0.01
TV Equip., etc.	0.08	0.08	0.10
Medical & Precision Instruments	0.03	0.03	0.04
Motor Vehicles	0.49	0.56	0.66
Earth & Space Transportation	0.06	0.06	0.07
Misc. Products	0.73	0.84	1.01
Electricity Production & Distribution	-1557.57	-2213.54	-2204.09

Gas Distribution	0.38	-4.70	-4.58
Water Supply	0.29	0.25	0.32
Construction	0.12	0.06	0.18
Motor Vehicle Distribution & Repair, etc.	0.59	0.70	0.84
Wholesale Distribution	0.73	0.64	0.87
Retail Distribution	2.24	2.24	2.62
Hotels, Catering & Pubs, etc.	1.18	1.21	1.41
Railway Transport	0.54	0.56	0.67
Other Land Transport	2.38	5.42	6.57
Water Transport	3.60	2.91	3.67
Air Transport	13.68	15.69	18.71
Ancillary Transport Services	0.02	0.15	0.20
Communications	0.21	0.32	0.40
Banking & Finance	0.02	-0.01	0.01
Insurance And Pension Funds	0.07	0.08	0.10
Auxiliary Financial Services	0.01	0.02	0.03
Property	0.32	0.37	0.44
Renting Of Machinery	0.11	0.14	0.18
Computing Services	0.00	0.02	0.03
Research & Development	0.00	-0.01	0.00
Professional Services	0.01	0.23	0.31
Public Administration	0.08	0.16	0.20
Education	0.47	0.53	0.63
Health Services	0.31	0.37	0.43
Sewage & Sanitary Services	0.21	0.35	0.42
Membership Organisations	0.10	0.13	0.16
Recreational Services	0.31	0.37	0.44
Other Service Activities	0.22	0.25	0.30
Private Households With Employed Persons	0.09	0.09	0.11
Total	**-1517.93**	**-2230.34**	**-2208.95**

Table E3: DISAG76 Output Results

Change in output (£ms)	**Direct**	**Type I**	**Type II**
Agriculture	4.85	8.77	9.94
Forestry	0.08	0.15	0.17
Fishing	0.03	0.29	0.32
Coal Extraction etc.	0.11	-9.61	-9.57
Oil & Gas Extraction	0.02	-68.08	-67.55
Metal Ores Extraction, Other Mining And Quarrying	0.01	0.08	0.11
Food & Drinks	16.59	28.16	31.49
Tobacco	1.25	1.25	1.34
Clothing	2.44	3.36	3.55
Wearing Apparel & Fur Products	4.67	4.70	4.79
Leather Goods	1.15	1.19	1.20
Wood & Wood Products	0.46	0.95	1.12
Paper Manufacturing	3.90	6.71	8.20
Coke, Refined Petroleum & Nuclear Fuel	2.80	1.75	2.16
Industrial Gases & Dyes	0.04	-0.28	-0.25
Organic & Inorganic Chemicals	0.03	-0.16	-0.09
Fertilizers, Pesticides, etc.	0.06	0.90	1.02
Paints, Varnishes, Printing Ink, etc	0.13	0.40	0.46
Pharmaceuticals	0.64	0.90	0.97
Soap & Toilet Preparations	1.64	1.89	2.05
Other Chemicals & Manmade Fibres	0.68	0.73	0.78
Rubber Products	0.49	0.70	0.78
Plastic Products	0.76	2.87	3.31
Glass & Glass Products	0.16	0.56	0.63
Ceramic Goods	0.36	0.41	0.45
Cement & Clay	0.02	0.05	0.08
Articles Of Concrete etc.	0.07	0.16	0.25
Iron & Steel	0.00	0.11	0.17
Metal Products	0.69	-1.76	-1.27
Machinery & Munitions	2.13	0.25	0.59
Office Machinery & Computers	0.32	0.35	0.41
Elec. Equip.	0.57	-0.05	0.10
TV Equip., etc.	2.18	2.27	2.38
Medical & Precision Instruments	0.80	0.99	1.07
Motor Vehicles	9.84	11.21	12.35
Earth & Space Transportation	1.00	1.00	1.16
Misc. Products	4.36	4.95	5.45
Electricity Transmission And Distribution	-286.87	-305.79	-304.66

Generation - Nuclear	0.00	-20.84	-20.77
Generation - Coal	0.00	-34.34	-34.21
Generation -Gas + Oil	0.00	-42.13	-41.98
Generation - Hydro	0.00	-1.26	-1.26
Generation - Biomass	0.00	-1.99	-1.98
Generation - Wind	0.00	-0.45	-0.45
Generation - Wind Offshore	0.00	-0.05	-0.05
Generation - Other	0.00	-0.80	-0.79
Generation - Marine/Solar	0.00	-0.06	-0.06
Gas Distribution	2.25	-27.92	-27.29
Water Supply	1.22	1.06	1.30
Construction	2.12	1.10	2.95
Motor Vehicle Distribution & Repair, etc.	9.68	11.49	13.57
Wholesale Distribution	13.12	11.57	14.93
Retail Distribution	41.36	41.43	48.04
Hotels, Catering & Pubs, etc.	29.66	30.44	34.66
Railway Transport	1.92	1.99	2.35
Other Land Transport	3.60	8.19	9.61
Water Transport	1.17	0.94	1.06
Air Transport	5.13	5.88	6.45
Ancillary Transport Services	0.82	7.39	9.13
Communications	6.31	9.46	11.59
Banking & Finance	5.16	-2.00	0.68
Insurance And Pension Funds	10.87	12.52	15.23
Auxiliary Financial Services	0.59	1.47	1.77
Property	41.51	47.99	55.83
Renting Of Machinery	2.00	2.42	3.10
Computing Services	0.03	3.54	4.68
Research & Development	0.12	-0.13	-0.03
Professional Services	0.52	15.58	19.96
Public Administration	1.06	2.07	2.48
Education	11.80	13.30	15.57
Health Services	8.04	9.57	11.11
Sewage & Sanitary Services	1.27	2.11	2.51
Membership Organisations	2.05	2.82	3.29
Recreational Services	12.32	14.77	17.06
Other Service Activities	3.69	4.28	5.01
Private Households With Employed Persons	2.18	2.19	2.53
Total	**0.00**	**-164.04**	**-96.87**

Table E4: DISAG76 Sectoral CO2 emission results

Change in CO2 Emissions (000tons)	Direct	Type I	Type II
Agriculture	1.38	2.50	2.83
Forestry	0.01	0.01	0.01
Fishing	0.01	0.12	0.13
Coal Extraction etc.	0.02	-2.06	-2.06
Oil & Gas Extraction	0.02	-59.23	-58.77
Metal Ores Extraction, Other Mining And Quarrying	0.00	0.02	0.03
Food & Drinks	2.51	4.26	4.76
Tobacco	0.03	0.03	0.03
Clothing	0.83	1.14	1.20
Wearing Apparel & Fur Products	0.23	0.23	0.23
Leather Goods	0.10	0.10	0.10
Wood & Wood Products	0.15	0.32	0.37
Paper Manufacturing	0.54	0.93	1.13
Coke, Refined Petroleum & Nuclear Fuel	2.87	1.80	2.23
Industrial Gases & Dyes	0.02	-0.18	-0.16
Organic & Inorganic Chemicals	0.02	-0.09	-0.05
Fertilizers, Pesticides, etc.	0.04	0.52	0.59
Paints, Varnishes, Printing Ink, etc	0.01	0.03	0.03
Pharmaceuticals	0.08	0.11	0.12
Soap & Toilet Preparations	0.17	0.19	0.21
Other Chemicals & Manmade Fibres	0.13	0.14	0.15
Rubber Products	0.14	0.20	0.22
Plastic Products	0.14	0.52	0.60
Glass & Glass Products	0.08	0.30	0.33
Ceramic Goods	0.10	0.11	0.13
Cement & Clay	0.12	0.36	0.54
Articles Of Concrete etc.	0.01	0.02	0.03
Iron & Steel	0.01	0.33	0.53
Metal Products	0.05	-0.12	-0.08
Machinery & Munitions	0.11	0.01	0.03
Office Machinery & Computers	0.01	0.01	0.01
Elec. Equip.	0.03	0.00	0.00
TV Equip., etc.	0.12	0.13	0.13
Medical & Precision Instruments	0.03	0.03	0.04
Motor Vehicles	0.49	0.56	0.62
Earth & Space Transportation	0.06	0.06	0.07
Misc. Products	0.73	0.83	0.92
Electricity Transmission And	-91.56	-97.60	-97.24

Distribution			
Generation - Nuclear	0.00	-0.56	-0.55
Generation - Coal	0.00	-1415.37	-1410.14
Generation -Gas + Oil	0.00	-700.21	-697.63
Generation - Hydro	0.00	0.00	0.00
Generation - Biomass	0.00	0.00	0.00
Generation - Wind	0.00	0.00	0.00
Generation - Wind Offshore	0.00	0.00	0.00
Generation - Other	0.00	0.00	0.00
Generation - Marine/Solar	0.00	0.00	0.00
Gas Distribution	0.38	-4.70	-4.60
Water Supply	0.29	0.25	0.31
Construction	0.12	0.06	0.17
Motor Vehicle Distribution & Repair, etc.	0.59	0.70	0.83
Wholesale Distribution	0.73	0.64	0.83
Retail Distribution	2.24	2.24	2.60
Hotels, Catering & Pubs, etc.	1.18	1.21	1.38
Railway Transport	0.54	0.56	0.65
Other Land Transport	2.38	5.42	6.35
Water Transport	3.60	2.91	3.26
Air Transport	13.68	15.69	17.20
Ancillary Transport Services	0.02	0.15	0.19
Communications	0.21	0.32	0.39
Banking & Finance	0.02	-0.01	0.00
Insurance And Pension Funds	0.07	0.08	0.10
Auxiliary Financial Services	0.01	0.02	0.03
Property	0.32	0.37	0.43
Renting Of Machinery	0.11	0.14	0.18
Computing Services	0.00	0.02	0.03
Research & Development	0.00	-0.01	0.00
Professional Services	0.01	0.23	0.30
Public Administration	0.08	0.16	0.19
Education	0.47	0.53	0.62
Health Services	0.31	0.37	0.42
Sewage & Sanitary Services	0.21	0.35	0.41
Membership Organisations	0.10	0.13	0.15
Recreational Services	0.31	0.37	0.43
Other Service Activities	0.22	0.25	0.30
Private Households With Employed Persons	0.09	0.09	0.10
Total	**-51.90**	**-2230.96**	**-2215.08**

Table E5: SUBS76 Sectoral output results

Change in output (£ms)	Direct	Type I	Type II
Agriculture	6.93	12.54	14.23
Forestry	0.12	0.20	0.24
Fishing	0.04	0.41	0.46
Coal Extraction etc.	0.16	-10.24	-10.18
Oil & Gas Extraction	0.03	-87.61	-86.84
Metal Ores Extraction, Other Mining And Quarrying	0.01	0.12	0.16
Food & Drinks	23.72	40.33	45.14
Tobacco	1.78	1.79	1.92
Clothing	3.49	4.81	5.09
Wearing Apparel & Fur Products	6.68	6.71	6.86
Leather Goods	1.64	1.71	1.72
Wood & Wood Products	0.65	1.40	1.64
Paper Manufacturing	5.58	8.65	10.80
Coke, Refined Petroleum & Nuclear Fuel	4.00	2.76	3.36
Industrial Gases & Dyes	0.05	-0.30	-0.25
Organic & Inorganic Chemicals	0.05	-0.10	-0.01
Fertilizers, Pesticides, etc.	0.09	1.29	1.46
Paints, Varnishes, Printing Ink, etc	0.19	0.57	0.66
Pharmaceuticals	0.91	1.30	1.40
Soap & Toilet Preparations	2.35	2.71	2.94
Other Chemicals & Manmade Fibres	0.97	1.06	1.13
Rubber Products	0.69	1.01	1.12
Plastic Products	1.08	4.03	4.66
Glass & Glass Products	0.23	0.80	0.91
Ceramic Goods	0.52	0.59	0.64
Cement & Clay	0.02	0.08	0.12
Articles Of Concrete etc.	0.10	0.24	0.37
Iron & Steel	0.00	0.23	0.33
Metal Products	0.99	-0.97	-0.27
Machinery & Munitions	3.04	1.07	1.56
Office Machinery & Computers	0.45	0.49	0.57
Elec. Equip.	0.82	0.11	0.33
TV Equip., etc.	3.12	3.26	3.41
Medical & Precision Instruments	1.14	1.49	1.60
Motor Vehicles	14.07	16.07	17.72
Earth & Space Transportation	1.43	1.49	1.72
Misc. Products	6.23	7.23	7.95
Electricity Transmission And Distribution	-286.87	-327.21	-325.58

Generation - Nuclear	0.00	-22.30	-22.19
Generation - Coal	0.00	-36.74	-36.56
Generation -Gas + Oil	0.00	-45.08	-44.86
Generation - Hydro	0.00	-1.35	-1.34
Generation - Biomass	0.00	-2.13	-2.12
Generation - Wind	0.00	-0.48	-0.48
Generation - Wind Offshore	0.00	-0.06	-0.06
Generation - Other	0.00	-0.85	-0.85
Generation - Marine/Solar	0.00	-0.07	-0.07
Gas Distribution	-120.11	-164.39	-163.48
Water Supply	1.74	1.49	1.84
Construction	3.02	1.02	3.70
Motor Vehicle Distribution & Repair, etc.	13.85	16.64	19.64
Wholesale Distribution	18.77	20.05	24.90
Retail Distribution	59.15	59.26	68.80
Hotels, Catering & Pubs, etc.	42.41	43.54	49.63
Railway Transport	2.75	2.92	3.43
Other Land Transport	5.15	12.11	14.15
Water Transport	1.67	1.41	1.58
Air Transport	7.33	8.49	9.31
Ancillary Transport Services	1.18	11.27	13.77
Communications	9.02	14.09	17.17
Banking & Finance	7.37	-2.83	1.04
Insurance And Pension Funds	15.54	18.70	22.60
Auxiliary Financial Services	0.84	2.15	2.59
Property	59.36	67.26	78.59
Renting Of Machinery	2.86	3.75	4.73
Computing Services	0.04	5.60	7.24
Research & Development	0.17	-0.14	0.01
Professional Services	0.74	23.17	29.50
Public Administration	1.52	2.99	3.58
Education	16.88	19.08	22.35
Health Services	11.50	13.71	15.94
Sewage & Sanitary Services	1.82	3.13	3.70
Membership Organisations	2.93	4.04	4.73
Recreational Services	17.61	21.32	24.64
Other Service Activities	5.27	6.17	7.21
Private Households With Employed Persons	3.12	3.12	3.62
Total	**0.00**	**-189.79**	**-92.95**

Table E6: SUBS76 Sectoral CO2 Emissions Results

Change in CO2 Emissions (000tons)	Direct	Type I	Type II
Agriculture	1.98	3.57	4.05
Forestry	0.01	0.01	0.02
Fishing	0.02	0.17	0.19
Coal Extraction etc.	0.03	-2.20	-2.19
Oil & Gas Extraction	0.03	-76.22	-75.56
Metal Ores Extraction, Other Mining And Quarrying	0.00	0.03	0.04
Food & Drinks	3.58	6.09	6.82
Tobacco	0.04	0.04	0.04
Clothing	1.18	1.63	1.72
Wearing Apparel & Fur Products	0.33	0.33	0.33
Leather Goods	0.14	0.14	0.14
Wood & Wood Products	0.22	0.47	0.55
Paper Manufacturing	0.77	1.19	1.49
Coke, Refined Petroleum & Nuclear Fuel	4.11	2.84	3.46
Industrial Gases & Dyes	0.03	-0.19	-0.16
Organic & Inorganic Chemicals	0.03	-0.06	-0.01
Fertilizers, Pesticides, etc.	0.05	0.75	0.85
Paints, Varnishes, Printing Ink, etc	0.01	0.04	0.04
Pharmaceuticals	0.11	0.16	0.17
Soap & Toilet Preparations	0.24	0.27	0.30
Other Chemicals & Manmade Fibres	0.18	0.20	0.21
Rubber Products	0.20	0.29	0.32
Plastic Products	0.19	0.72	0.84
Glass & Glass Products	0.12	0.43	0.48
Ceramic Goods	0.15	0.16	0.18
Cement & Clay	0.17	0.60	0.85
Articles Of Concrete etc.	0.01	0.03	0.05
Iron & Steel	0.01	0.71	1.00
Metal Products	0.07	-0.06	-0.02
Machinery & Munitions	0.16	0.06	0.08
Office Machinery & Computers	0.01	0.01	0.01
Elec. Equip.	0.04	0.01	0.02
TV Equip., etc.	0.17	0.18	0.19
Medical & Precision Instruments	0.04	0.05	0.06
Motor Vehicles	0.70	0.80	0.89
Earth & Space Transportation	0.09	0.09	0.10
Misc. Products	1.05	1.22	1.34
Electricity Transmission And Distribution	-91.56	-104.44	-103.92

Generation - Nuclear	0.00	-0.60	-0.59
Generation - Coal	0.00	-1514.53	-1506.99
Generation -Gas + Oil	0.00	-749.27	-745.54
Generation - Hydro	0.00	0.00	0.00
Generation - Biomass	0.00	0.00	0.00
Generation - Wind	0.00	0.00	0.00
Generation - Wind Offshore	0.00	0.00	0.00
Generation - Other	0.00	0.00	0.00
Generation - Marine/Solar	0.00	0.00	0.00
Gas Distribution	-20.23	-27.68	-27.53
Water Supply	0.41	0.36	0.44
Construction	0.17	0.06	0.21
Motor Vehicle Distribution & Repair, etc.	0.85	1.02	1.20
Wholesale Distribution	1.04	1.11	1.38
Retail Distribution	3.20	3.21	3.73
Hotels, Catering & Pubs, etc.	1.68	1.73	1.97
Railway Transport	0.77	0.81	0.96
Other Land Transport	3.41	8.01	9.36
Water Transport	5.15	4.36	4.87
Air Transport	19.56	22.66	24.84
Ancillary Transport Services	0.02	0.23	0.29
Communications	0.31	0.48	0.58
Banking & Finance	0.03	-0.01	0.00
Insurance And Pension Funds	0.10	0.12	0.15
Auxiliary Financial Services	0.01	0.04	0.04
Property	0.46	0.52	0.61
Renting Of Machinery	0.16	0.21	0.27
Computing Services	0.00	0.04	0.05
Research & Development	0.01	-0.01	0.00
Professional Services	0.01	0.35	0.44
Public Administration	0.12	0.23	0.28
Education	0.67	0.76	0.89
Health Services	0.44	0.52	0.61
Sewage & Sanitary Services	0.30	0.51	0.61
Membership Organisations	0.14	0.19	0.22
Recreational Services	0.44	0.54	0.62
Other Service Activities	0.31	0.36	0.43
Private Households With Employed Persons	0.13	0.13	0.15
Total	**-55.62**	**-2403.43**	**-2380.51**

Table E7: COMP76 Sectoral Output Results

Change in Output (£ms)	**Direct**	**Type I**	**Type II**
Agriculture	0.76	1.38	1.53
Forestry	0.01	0.03	0.03
Fishing	0.00	0.04	0.05
Coal Extraction etc.	0.02	-8.37	-8.37
Oil & Gas Extraction	0.00	-29.79	-29.73
Metal Ores Extraction, Other Mining And Quarrying	0.00	-0.01	0.00
Food & Drinks	2.60	4.30	4.73
Tobacco	0.20	0.20	0.21
Clothing	0.38	0.52	0.54
Wearing Apparel & Fur Products	0.73	0.74	0.75
Leather Goods	0.18	0.18	0.19
Wood & Wood Products	0.07	0.07	0.09
Paper Manufacturing	0.61	2.91	3.10
Coke, Refined Petroleum & Nuclear Fuel	0.44	-0.24	-0.19
Industrial Gases & Dyes	0.01	-0.24	-0.24
Organic & Inorganic Chemicals	0.01	-0.26	-0.25
Fertilizers, Pesticides, etc.	0.01	0.14	0.16
Paints, Varnishes, Printing Ink, etc	0.02	0.06	0.07
Pharmaceuticals	0.10	0.13	0.14
Soap & Toilet Preparations	0.26	0.29	0.31
Other Chemicals & Manmade Fibres	0.11	0.10	0.10
Rubber Products	0.08	0.10	0.11
Plastic Products	0.12	0.61	0.67
Glass & Glass Products	0.02	0.08	0.09
Ceramic Goods	0.06	0.05	0.06
Cement & Clay	0.00	-0.01	-0.01
Articles Of Concrete etc.	0.01	-0.01	0.00
Iron & Steel	0.00	-0.14	-0.13
Metal Products	0.11	-3.29	-3.23
Machinery & Munitions	0.33	-1.36	-1.32
Office Machinery & Computers	0.05	0.08	0.09
Elec. Equip.	0.09	-0.38	-0.36
TV Equip., etc.	0.34	0.35	0.36
Medical & Precision Instruments	0.13	0.01	0.02
Motor Vehicles	1.55	1.68	1.83
Earth & Space Transportation	0.16	0.05	0.07
Misc. Products	0.68	0.50	0.56
Electricity Transmission And Distribution	-286.87	-263.78	-263.63

Generation - Nuclear	0.00	-17.98	-17.97
Generation - Coal	0.00	-29.62	-29.60
Generation -Gas + Oil	0.00	-36.34	-36.32
Generation - Hydro	0.00	-1.09	-1.09
Generation - Biomass	0.00	-1.72	-1.72
Generation - Wind	0.00	-0.39	-0.39
Generation - Wind Offshore	0.00	-0.04	-0.04
Generation - Other	0.00	-0.69	-0.69
Generation - Marine/Solar	0.00	-0.05	-0.05
Gas Distribution	242.18	239.66	239.74
Water Supply	0.19	0.20	0.23
Construction	0.33	1.25	1.49
Motor Vehicle Distribution & Repair, etc.	1.52	1.39	1.66
Wholesale Distribution	2.06	-5.07	-4.63
Retail Distribution	6.50	6.48	7.33
Hotels, Catering & Pubs, etc.	4.66	4.76	5.31
Railway Transport	0.30	0.17	0.22
Other Land Transport	0.57	0.50	0.68
Water Transport	0.18	0.02	0.03
Air Transport	0.80	0.76	0.83
Ancillary Transport Services	0.13	-0.21	0.01
Communications	0.99	0.38	0.66
Banking & Finance	0.81	-0.37	-0.02
Insurance And Pension Funds	1.71	0.41	0.76
Auxiliary Financial Services	0.09	0.13	0.17
Property	6.52	10.20	11.22
Renting Of Machinery	0.31	-0.18	-0.09
Computing Services	0.00	-0.49	-0.35
Research & Development	0.02	-0.11	-0.10
Professional Services	0.08	0.69	1.26
Public Administration	0.17	0.27	0.33
Education	1.85	1.97	2.27
Health Services	1.26	1.44	1.65
Sewage & Sanitary Services	0.20	0.12	0.18
Membership Organisations	0.32	0.41	0.47
Recreational Services	1.93	1.91	2.21
Other Service Activities	0.58	0.59	0.69
Private Households With Employed Persons	0.34	0.34	0.39
Total	**0.00**	**-113.55**	**-104.85**

Table E8: COMP76 CO2 Emissions results

Change in CO2 Emissions (000tons)	Direct	Type I	Type II
Agriculture	0.22	0.39	0.44
Forestry	0.00	0.00	0.00
Fishing	0.00	0.02	0.02
Coal Extraction etc.	0.00	-1.80	-1.80
Oil & Gas Extraction	0.00	-25.92	-25.86
Metal Ores Extraction, Other Mining And Quarrying	0.00	0.00	0.00
Food & Drinks	0.39	0.65	0.72
Tobacco	0.00	0.00	0.00
Clothing	0.13	0.18	0.18
Wearing Apparel & Fur Products	0.04	0.04	0.04
Leather Goods	0.01	0.02	0.02
Wood & Wood Products	0.02	0.02	0.03
Paper Manufacturing	0.08	0.40	0.43
Coke, Refined Petroleum & Nuclear Fuel	0.45	-0.25	-0.19
Industrial Gases & Dyes	0.00	-0.15	-0.15
Organic & Inorganic Chemicals	0.00	-0.14	-0.14
Fertilizers, Pesticides, etc.	0.01	0.08	0.09
Paints, Varnishes, Printing Ink, etc	0.00	0.00	0.00
Pharmaceuticals	0.01	0.02	0.02
Soap & Toilet Preparations	0.03	0.03	0.03
Other Chemicals & Manmade Fibres	0.02	0.02	0.02
Rubber Products	0.02	0.03	0.03
Plastic Products	0.02	0.11	0.12
Glass & Glass Products	0.01	0.04	0.05
Ceramic Goods	0.02	0.02	0.02
Cement & Clay	0.02	-0.09	-0.07
Articles Of Concrete etc.	0.00	0.00	0.00
Iron & Steel	0.00	-0.41	-0.39
Metal Products	0.01	-0.22	-0.21
Machinery & Munitions	0.02	-0.07	-0.07
Office Machinery & Computers	0.00	0.00	0.00
Elec. Equip.	0.00	-0.02	-0.02
TV Equip., etc.	0.02	0.02	0.02
Medical & Precision Instruments	0.00	0.00	0.00
Motor Vehicles	0.08	0.08	0.09
Earth & Space Transportation	0.01	0.00	0.00
Misc. Products	0.12	0.08	0.09
Electricity Transmission And Distribution	-91.56	-84.19	-84.14

Generation - Nuclear	0.00	-0.48	-0.48
Generation - Coal	0.00	-1220.93	-1220.26
Generation -Gas + Oil	0.00	-604.02	-603.69
Generation - Hydro	0.00	0.00	0.00
Generation - Biomass	0.00	0.00	0.00
Generation - Wind	0.00	0.00	0.00
Generation - Wind Offshore	0.00	0.00	0.00
Generation - Other	0.00	0.00	0.00
Generation - Marine/Solar	0.00	0.00	0.00
Gas Distribution	40.78	40.36	40.37
Water Supply	0.05	0.05	0.06
Construction	0.02	0.07	0.08
Motor Vehicle Distribution & Repair, etc.	0.09	0.09	0.10
Wholesale Distribution	0.11	-0.28	-0.26
Retail Distribution	0.35	0.35	0.40
Hotels, Catering & Pubs, etc.	0.18	0.19	0.21
Railway Transport	0.08	0.05	0.06
Other Land Transport	0.37	0.33	0.45
Water Transport	0.57	0.06	0.11
Air Transport	2.15	2.01	2.21
Ancillary Transport Services	0.00	0.00	0.00
Communications	0.03	0.01	0.02
Banking & Finance	0.00	0.00	0.00
Insurance And Pension Funds	0.01	0.00	0.00
Auxiliary Financial Services	0.00	0.00	0.00
Property	0.05	0.08	0.09
Renting Of Machinery	0.02	-0.01	-0.01
Computing Services	0.00	0.00	0.00
Research & Development	0.00	0.00	0.00
Professional Services	0.00	0.01	0.02
Public Administration	0.01	0.02	0.03
Education	0.07	0.08	0.09
Health Services	0.05	0.06	0.06
Sewage & Sanitary Services	0.03	0.02	0.03
Membership Organisations	0.02	0.02	0.02
Recreational Services	0.05	0.05	0.06
Other Service Activities	0.03	0.03	0.04
Private Households With Employed Persons	0.01	0.01	0.02
Total	-44.61	-1892.80	-1890.74

Appendix F: Sectoral and CO2-intensities in the UK IO Tables

Table F1: 67 Sectors CO2 Intensities

Sector		CO2-Output Coefficient	Rank
1	Agriculture	0.285	17
2	Forestry	0.071	36
3	Fishing	0.407	13
4	Coal Extraction etc.	0.215	22
5	Oil & Gas Extraction	0.870	7
6	Metal Ores Extrac., Other Mining & Quarrying	0.235	21
7	Food & Drinks	0.151	28
8	Tobacco	0.022	59
9	Clothing	0.338	14
10	Wearing Apparel & Fur Products	0.049	48
11	Leather Goods	0.083	33
12	Wood & Wood Products	0.334	15
13	Paper Manufacturing	0.138	29
14	Coke, Refined Petroleum & Nuclear Fuel	1.028	6
15	Industrial Gases & Dyes	0.637	9
16	Organic & Inorganic Chemicals	0.559	11
17	Fertilizers, Pesticides, etc.	0.578	10
18	Paints, Varnishes, Printing Ink, etc.	0.065	37
19	Pharmaceuticals	0.122	31
20	Soap & Toilet Preparations	0.101	32
21	Other Chemicals & Manmade Fibres	0.189	23
22	Rubber Products	0.285	16
23	Plastic Products	0.180	24
24	Glass & Glass Products	0.531	12
25	Ceramic Goods	0.281	18
26	Cement & Clay	7.070	1
27	Articles Of Concrete, etc.	0.127	30
28	Iron & Steel	1.774	5
29	Metal Products	0.082	34
30	Machinery & Munitions	0.054	46
31	Office Machinery & Computers	0.018	61
32	Elec. Equip.	0.064	38
33	TV Equip., etc.	0.035	55
34	Medical & Precision Instruments	0.035	56
35	Motor Vehicles	0.050	47
36	Earth & Space Transportation	0.060	40
37	Misc. Products	0.169	25
38	Electricity Production & Distribution	5.430	2

39	Gas Distribution	0.168	26
40	Water Supply	0.238	20
41	Construction	0.056	43
42	Motor Vehicle Distribution & Repair, etc.	0.061	39
43	Wholesale Distribution	0.055	44
44	Retail Distribution	0.054	45
45	Hotels, Catering & Pubs, etc.	0.040	53
46	Railway Transport	0.279	19
47	Other Land Transport	0.661	8
48	Water Transport	3.089	3
49	Air Transport	2.668	4
50	Ancillary Transport Services	0.021	60
51	Communications	0.034	57
52	Banking & Finance	0.004	67
53	Insurance And Pension Funds	0.006	66
54	Auxiliary Financial Services	0.017	62
55	Property	0.008	64
56	Renting Of Machinery	0.057	42
57	Computing Services	0.007	65
58	Research & Development	0.041	51
59	Professional Services	0.015	63
60	Public Administration	0.077	35
61	Education	0.040	52
62	Health Services	0.038	54
63	Sewage & Sanitary Services	0.164	27
64	Membership Organisations	0.047	49
65	Recreational Services	0.025	58
66	Other Service Activities	0.059	41
67	Private Households With Employed Persons	0.041	50

Table F2: 67 Sectors Electricity Intensities

Sector		Elec-Output Coefficient	Rank
1	Agriculture	0.022	31
2	Forestry	0.037	15
3	Fishing	0.068	7
4	Coal Extraction etc.	0.061	8
5	Oil & Gas Extraction	0.013	47
6	Metal Ores Extrac., Other Mining & Quarrying	0.047	11
7	Food & Drinks	0.026	26
8	Tobacco	0.015	44
9	Clothing	0.029	20
10	Wearing Apparel & Fur Products	0.017	37
11	Leather Goods	0.011	57
12	Wood & Wood Products	0.028	23
13	Paper Manufacturing	0.026	25
14	Coke, Refined Petroleum & Nuclear Fuel	0.019	32
15	Industrial Gases & Dyes	0.088	4
16	Organic & Inorganic Chemicals	0.060	9
17	Fertilizers, Pesticides, etc.	0.054	10
18	Paints, Varnishes, Printing Ink, etc.	0.024	29
19	Pharmaceuticals	0.017	35
20	Soap & Toilet Preparations	0.019	33
21	Other Chemicals & Manmade Fibres	0.034	17
22	Rubber Products	0.034	18
23	Plastic Products	0.043	12
24	Glass & Glass Products	0.070	5
25	Ceramic Goods	0.043	13
26	Cement & Clay	0.095	3
27	Articles Of Concrete, etc.	0.035	16
28	Iron & Steel	0.069	6
29	Metal Products	0.038	14
30	Machinery & Munitions	0.028	22
31	Office Machinery & Computers	0.012	51
32	Elec. Equip.	0.024	28
33	TV Equip., etc.	0.018	34
34	Medical & Precision Instruments	0.017	36
35	Motor Vehicles	0.024	27
36	Earth & Space Transportation	0.023	30
37	Misc. Products	0.027	24
38	Electricity Production & Distribution	1.437	1
39	Gas Distribution	0.248	2
40	Water Supply	0.029	19

41	Construction	0.012	53
42	Motor Vehicle Distribution & Repair, etc.	0.013	46
43	Wholesale Distribution	0.013	50
44	Retail Distribution	0.016	42
45	Hotels, Catering & Pubs, etc.	0.017	39
46	Railway Transport	0.029	21
47	Other Land Transport	0.013	49
48	Water Transport	0.008	62
49	Air Transport	0.010	58
50	Ancillary Transport Services	0.011	56
51	Communications	0.012	52
52	Banking & Finance	0.006	64
53	Insurance And Pension Funds	0.013	48
54	Auxiliary Financial Services	0.016	40
55	Property	0.002	66
56	Renting Of Machinery	0.016	41
57	Computing Services	0.010	59
58	Research & Development	0.014	45
59	Professional Services	0.007	63
60	Public Administration	0.015	43
61	Education	0.011	54
62	Health Services	0.011	55
63	Sewage & Sanitary Services	0.017	38
64	Membership Organisations	0.005	65
65	Recreational Services	0.009	61
66	Other Service Activities	0.010	60
67	Private Households With Employed Persons	0.000	67

Table F3: 76 Sectors CO2-Output coefficients

Sectors		CO2-Output Coefficient	Rank
1	Agriculture	0.285	19
2	Forestry	0.071	37
3	Fishing	0.407	14
4	Coal Extraction etc.	0.215	24
5	Oil & Gas Extraction	0.870	8
6	Metal Ores Extrac., Other Mining & Quarrying	0.235	23
7	Food & Drinks	0.151	30
8	Tobacco	0.022	62
9	Clothing	0.338	15
10	Wearing Apparel & Fur Products	0.049	51
11	Leather Goods	0.083	35
12	Wood & Wood Products	0.334	16
13	Paper Manufacturing	0.138	31
14	Coke, Refined Petroleum & Nuclear Fuel	1.028	7
15	Industrial Gases & Dyes	0.637	10
16	Organic & Inorganic Chemicals	0.559	12
17	Fertilizers, Pesticides, etc.	0.578	11
18	Paints, Varnishes, Printing Ink, etc	0.065	39
19	Pharmaceuticals	0.122	33
20	Soap & Toilet Preparations	0.101	34
21	Other Chemicals & Manmade Fibres	0.189	25
22	Rubber Products	0.285	18
23	Plastic Products	0.180	26
24	Glass & Glass Products	0.531	13
25	Ceramic Goods	0.281	20
26	Cement & Clay	7.070	3
27	Articles Of Concrete etc.	0.127	32
28	Iron & Steel	3.029	5
29	Metal Products	0.066	38
30	Machinery & Munitions	0.054	48
31	Office Machinery & Computers	0.018	64
32	Elec. Equip.	0.049	50
33	TV Equip., etc.	0.055	46
34	Medical & Precision Instruments	0.035	58
35	Motor Vehicles	0.050	49
36	Earth & Space Transportation	0.060	41
37	Misc. Products	0.169	27
38	Electricity Transmission And Distribution	0.319	17
39	Generation - Nuclear	0.027	60
40	Generation - Coal	41.220	1
41	Generation -Gas + Oil	16.619	2
42	Generation - Hydro	0.000	71
43	Generation - Biomass	0.000	71
44	Generation - Wind	0.000	71

45	Generation - Wind Offshore	0.000	71
46	Generation - Other	0.000	71
47	Generation - Marine/Solar	0.000	71
48	Gas Distribution	0.168	28
49	Water Supply	0.238	22
50	Construction	0.056	44
51	Motor Vehicle Distribution & Repair, etc.	0.061	40
52	Wholesale Distribution	0.055	45
53	Retail Distribution	0.054	47
54	Hotels, Catering & Pubs, etc.	0.040	56
55	Railway Transport	0.279	21
56	Other Land Transport	0.661	9
57	Water Transport	3.089	4
58	Air Transport	2.668	6
59	Ancillary Transport Services	0.021	63
60	Communications	0.034	59
61	Banking & Finance	0.004	70
62	Insurance And Pension Funds	0.006	69
63	Auxiliary Financial Services	0.017	65
64	Property	0.008	67
65	Renting Of Machinery	0.057	43
66	Computing Services	0.007	68
67	Research & Development	0.041	54
68	Professional Services	0.015	66
69	Public Administration	0.077	36
70	Education	0.040	55
71	Health Services	0.038	57
72	Sewage & Sanitary Services	0.164	29
73	Membership Organisations	0.047	52
74	Recreational Services	0.025	61
75	Other Service Activities	0.059	42
76	Private Households With Employed Persons	0.041	53

Appendix G: The UKENVI Model

This appendix summarises the new equations of the UKENVI model used in Chapter 6. The equation listed represent the changes made to the AMOS model in Appendix C in order to reflect the national closure for the UK economy, and the adoption of forward-looking agents' behaviour. For additional details on this model closure see Lecca et al. (2013, 2014).

Households and other institutions	Replace C.20 with	
Forward-looking agents	$U = \sum_t (1+\rho)^{-t} \frac{C_t^{1-\sigma} - 1}{1-\sigma}$	G.1
	$\frac{C_t}{C_{t+1}} = \left(\frac{PC_t.(1+\rho)}{PC_{t+1}.(1+r)}\right)^{-\left(\frac{1}{\sigma}\right)}$	G.2
Time path of investment	Replace C.47 and C.48 with	
	$J_{i,t} = I_{i,t}\left(1 - bb - tk + \frac{\beta}{2}\frac{\left(\frac{I_{i,t}}{K_{i,t}} - \alpha\right)^2}{\frac{I_{i,t}}{K_{i,t}}}\right)$	G.3
Investment demand	$\frac{I_t}{K_t} = \alpha + \frac{1}{\beta}.\left(\frac{\lambda_{i,t}}{Pk_t} - (1 - bb - tk)\right)$	G.4
	$\dot{\lambda}_{i,t}{=}\lambda_{i,t}.(r+\delta) - R_{i,t}^k$	G.5
Adjustment costs	$\theta(x_t) = \frac{\beta}{2}\frac{(x_t-\alpha)^2}{x_t}$ with $x_t = \frac{I_t}{K_t}$	G.6
	$R_{i,t}^k = rk_t - Pk_t\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 \theta_t'\left(\frac{I}{K}\right)$	G.7

Labour Market	Replace C.50 and C.51 with	
Fixed Labour supply	$LS_{t+1} = LS_t = LS_0$	G.8
No migration	$nim_t = 0$	G.9

U	Utility
ρ	Pure rate of marginal time preference
α, β	Parameters in the adjustment cost function
bb	Rate of distortion or incentive to investment
θ	Adjustment cost function
$\lambda_{i,t}$	Shadow price of capital
rk_t	Rate of return to capital
σ	Constant elasticity of marginal utility
tk	Corporation tax
I_i	Investment by sector of origin
J_i	Investment by sector of destination wit adjustment costs
LS_t	Labour supply
nim_t	Net migration

Appendix H: 25 Sector Disaggregation of the UK IO Tables

25 sectors	Sector Title	123 sectors
1	Coal Mining and quarrying	4
2	Gas Mining and quarrying	5, 86
3	Coke ovens, refined petroleum and nuclear fuel	35
4	Other traded e.g. Food and drink	6-19, 21-31, 34, 36-38, 77-80
5	Pulp and Paper	32-33
6	Glass and Ceramics	49-50
7	Clay, cement, lime and plaster	51-52
8	Iron and Steel; non-ferrous metals	53-56
9	Generation - Coal	85
10	Generation -Gas + Oil	85
11	Electricity distribution and supply	85
12	Generation - Nuclear	85
13	Generation - Hydro	85
14	Generation - Biomass	85
15	Generation - Wind	85
16	Generation - Wind Offshore	85
17	Generation - Other	85
18	Generation - Marine/solar	85
19	Agriculture; Forestry and fishing	1-3
20	Water	87
21	Construction	88
22	Other Manufacturing and wholesale retail trade	20, 39-48, 57-76, 81-84, 89-92
23	Air Transport	96
24	Other Transport	93-95, 97-99
25	Services	100-123