

# Essays on Decarbonising Energy Supply

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## Acronyms

AR4	Fourth Assessment Report by the IPCC
CC	Climate change
CCS	Carbon capture and storage
CET	Constant elasticity of transformation
CGE (model)	Computable general equilibrium (model)
CO <sub>2</sub>	Carbon dioxide
DART model	Dynamic Applied Regional Trade model
EE	Energy efficiency
FAO	Food and Agricultural Organization of the United Nations
GAMS	Generalized Algebraic Modelling System
GDP	Gross domestic product
GHG	Greenhouse gases
GMM	Generalised method of moments
GTAP	Global trade analysis project
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental variable
kgoe	Kilogramme oil equivalent
kWh	Kilowatt hour
LDV	Lagged dependent variable
LSDV (estimator)	Least squares dummy variable (estimator)
LSDVC (estimator)	Corrected least squares dummy variable (estimator)
MPSGE	Mathematical programming system for general equilibrium analysis
MTBE	Methyl tertiary-butyl ether
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary least squares
R&D	Research and development
RD&D	Research, development and deployment
RE	Renewable energy
SET Plan	European Strategic Energy Technology Plan
UNEP SEFI	United Nations Environment Programme Sustainable Energy finance Initiative
UNFCCC	United Nations Framework Convention on Climate Change
WDI	World Development Indicators

# 1 Introduction

The scientific community with the Intergovernmental Panel on Climate Change (IPCC) at its forefront has provided compelling evidence demonstrating that the “warming of the climate system is unequivocal”, as stated in the IPCC’s Fourth Assessment Report (AR4; IPCC, 2007, p.30), and that it is anthropogenic emissions of greenhouse gases (GHG) that drive global warming. The topic of this dissertation “Decarbonising energy supply” is embedded in this wider debate on climate change and its mitigation.

## 1.1 The challenge of climate change

To set the scene for the remainder of this dissertation, this first section starts with highlighting the causes and manifold consequences of past and future climate change. Observed consequences of a warming climate include rising sea levels that potentially affect and destroy human and natural systems. More than half of the observed sea level rise since 1993 is attributed to the thermal expansion of oceans due to rising temperatures, the remaining drivers being melting glaciers, ice caps and polar ice sheets (IPCC, 2007). Another consequence are changes in precipitation levels, with the direction of change depending on the geographic region. Increased precipitation is recorded in “eastern parts of North and South America, northern Europe and northern and central Asia” while precipitation levels have decreased “in the Sahel, the Mediterranean, southern Africa and parts of southern Asia”. Furthermore, a “*likely*”<sup>1</sup> increase in drought-affected areas globally is observed (IPCC, 2007, p.30). Another important impact are changes in the occurrence of extreme weather and climate events. These impacts show complex regional variation, as evidenced in IPCC (2012) assessing the trends in occurrences of cold and warm days and nights, heavy precipitation events, tornados, droughts and floods, to name a few.<sup>2</sup> Such events cause significant economic

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<sup>1</sup>*Likely* and *very likely* denote probabilities of occurrence of greater than 66 and 90 per cent, respectively. These are derived from assessments “using expert judgement and statistical analysis of a body of evidence”. The trust in results based on more qualitative analysis is expressed in confidence levels on a scale from 0 to 10, with *high confidence* scoring about 8 out of 10 and *medium confidence* about 5 out of 10. See IPCC (2007, p.27) for a full introduction to the “Treatment of uncertainty” and the definition of different confidence levels and likelihood ranges.

<sup>2</sup>A brief summary of some of their findings: “It is likely that anthropogenic influences have led to warming of extreme daily minimum and maximum temperatures at the global scale. There is medium confidence that anthropogenic influences have contributed to intensification of extreme precipitation at the global scale. It is likely that there has been an anthropogenic influence on increasing extreme coastal high water due to an



losses and fatalities with uneven impacts across world regions, with the IPCC concluding with *high confidence* that “economic, including insured, disaster losses associated with weather, climate, and geophysical events are higher in developed countries”. However, “fatality rates and economic losses expressed as a proportion of gross domestic product (GDP) are higher in developing countries” (IPCC, 2012, p.9).

With regard to the causes of this change, the AR4 has improved the certainty about the link between anthropogenic emissions of GHG and climate change, stating that “most of the observed increase in global average temperatures since the mid-20<sup>th</sup> century is *very likely* due to the observed increases in anthropogenic GHG concentrations” (IPCC, 2007, p.39). It is highlighted that the likelihood of this causal link has increased since the Third Assessment Report dating from 2001 and calling the link *likely*. To stress the importance of human activities, global anthropogenic GHG emissions have increased from 28.7 to 49 Giga tonnes CO<sub>2</sub>-equivalents over the period 1970 to 2004 (IPCC, 2007), an increase of 93 per cent or 2.7 per cent annually on average. Carbon dioxide (CO<sub>2</sub>) is by far the most relevant GHG currently amounting to more than three quarters of all emissions when converted to CO<sub>2</sub> equivalents. The most important source of emissions is fossil fuel use, which contributed over half (56.6 per cent) to total anthropogenic GHG emissions (in CO<sub>2</sub> equivalents) in 2004. The second most important source of emissions is the category “deforestation, decay of biomass etc”. Attributing emissions across economic sectors, the most important source of emissions in 2004 were energy supply with 25.9 per cent, followed by industry and forestry with 19.4 and 17.4 per cent, respectively (IPCC, 2007; Metz et al., 2007). The growth in emissions has been much more rapid in the developing world. World Bank data display a growth in CO<sub>2</sub> emissions<sup>3</sup> between 1970 and 2008 of 38 per cent in OECD countries compared to 253 per cent in non-OECD countries. This corresponds to average annual increases of 1.0 and 6.7 per cent, respectively (World Bank, 2011).

How this growth in emissions projects into the future is the subject of continued scenario modelling. The IPCC emission scenarios<sup>4</sup> show different temperature changes, with *likely*

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increase in mean sea level” (IPCC, 2012, p.9).

<sup>3</sup>The World Bank data on CO<sub>2</sub> emissions only include emissions from the burning of fossil fuels and the manufacture of cement (World Bank, 2011).

<sup>4</sup>These so-called ‘SRES scenarios’ have been put forward originally in the IPCC Special Report on Emissions Scenarios (IPCC, 2000). The results are driven by the scenario-specific assumptions on socio-economic, demographic and technological parameters given current climate change mitigation policies are in place.

ranges between 1.1 to 2.9 and 2.4 to 6.4°C temperature change at the end of the 21<sup>st</sup> century compared to 1980-1999 (IPCC, 2007, p.45). The geographical pattern of projected climate change impacts over the 21<sup>st</sup> century resulting from current and future warming are similar to the impacts observed over recent decades (IPCC, 2007). Apart from further sea level rises, extreme weather events and other aspects mentioned before, important future impacts include ceasing resilience of ecosystems, loss of biodiversity and exacerbated water stress. One important uncertainty prevails over the impacts on agricultural crop yields and the extent to which reductions in yields will put additional pressure on agricultural markets already strained by a growing global population, changing dietary patterns and increased use of bioenergy. While some regions are expected to witness yield increases, others will see declines in yields; the net effects and exact spatial distribution of impacts are not entirely understood.<sup>5</sup> The IPCC concludes with *medium confidence* that on a global scale, “the potential for food production is projected to increase with increases in local average temperature over a range of 1 to 3°C, but above this it is projected to decrease” (2007, p.46).

## 1.2 The energy-climate nexus

Present and future climate change impacts as well as the fact that it is anthropogenic emissions that cause most of these impacts make a compelling case for mitigating climate change by reducing GHG emissions and at the same time adapting to climate change in order to cope with its consequences. The figures cited above on the sectoral origins of GHG emissions provide the main rationale for the focus on the energy sector in this dissertation. The decarbonisation of energy supply, or in other words the reduction of GHG emissions resulting from energy use while maintaining or even increasing energy services, is among the most critical components of climate change mitigation. This is recognised by the International Energy Agency (IEA) and the Organisation for Economic Cooperation and Development (OECD): the latest World Energy Outlook provides a pessimistic outlook with regard to containing climate change successfully as it sees only “few signs that the urgently needed change in

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<sup>5</sup>As part of a recent FAO report, Fischer (2011) reports the impact of climate change scenarios on future production potentials of rainfed wheat, maize and cereals on current cultivated land. While the effects in the developed and developing world are similar for cereals (slight increases in production potential), the projected climate change impacts on the production potential are much more beneficial or much less harmful in the developed to the developing world in the case of maize and wheat, respectively.

direction in global energy trends is underway. Although the recovery in the world economy since 2009 has been uneven, and future economic prospects remain uncertain, global primary energy demand rebounded by a remarkable 5 [per cent] in 2010, pushing CO<sub>2</sub> emissions to a new high”; furthermore, and “despite the priority in many countries to increase energy efficiency, global energy intensity worsened for the second straight year” (OECD/IEA, 2011, p.1).

Energy demand is projected to increase further and this makes for a particular challenge. Even the more ambitious “New Policies Scenario”<sup>6</sup> of the World Energy Outlook predicts a strong growth in energy demand of one-third over the period 2010 to 2035. Non-OECD countries are increasingly the driver behind this growth and determine the dynamics on global energy markets (OECD/IEA, 2011). In order to stop or even reverse this growing trend, it is undisputed that enhanced energy efficiency efforts are essential. At the same time, cleaner technologies need to make additional contributions to reducing emissions. In this context, the IPCC has recently published a “Special Report on Renewable Energy Sources and Climate Change Mitigation” (IPCC, 2011) underlining the importance of promoting renewable energy sources for climate change mitigation and accentuating the wider benefits of renewable energy deployment for social and economic development. The transport sector represents a particular challenge among the energy using sectors. The World Energy Outlook highlights that “all of the net increase in oil demand comes from the transport sector in emerging economies” (OECD/IEA, 2011, p.3), illustrating the global importance of the sector in climate change mitigation. Emissions in the EU transport sector have continued to grow in the light of other economic sectors showing decreasing trends over the last decade or two. The inclusion of a 10 per cent target for renewable energy in transport in the EU’s Renewable Energy Directive or the mandate of using 36 billion gallons of biofuel by 2022 stipulated in the US Energy Independence and Security Act represent policy responses to these concerns (energy security and rural development are further stated goals of biofuel policies).

Access to energy is widely seen as a prerequisite for economic growth,<sup>7</sup> which is the

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<sup>6</sup>The ‘New Policies Scenario’ assumes that “recent government policy commitments are [...] implemented in a cautious manner - even if they are not yet backed up by firm measures” (OECD/IEA, 2011, p.1).

<sup>7</sup>See for instance OECD/IEA (2011) and the fact that the United Nations General Assembly declared 2012 the “International Year of Sustainable Energy for All” (<http://www.sustainableenergyforall.org/>, last accessed June 4, 2012).

source of a dilemma: Economic growth in the developing world is essential for raising income levels and hence well-being of the poorest population groups. However, it also goes hand in hand with increases in energy demand and emissions. The impressive growth performance of a range of (large) developing and emerging economies in recent years and decades has contributed to the situation of non-OECD countries increasingly dominating global energy markets and driving global emissions (OECD/IEA, 2011; also Raupach et al., 2007). An often-cited example is the one of China having overtaken the USA as the world's largest emitter in 2005. The fact that China's per capita emissions in 2008 were still less than a third of per capita emissions in the USA (based on World Bank, 2011, data) demonstrates the large potential for further increases in global emissions from the emerging economies.

Initiatives such as the international Green Climate Fund, recently launched at the Durban conference and drawn up to raise 100 billion US dollars of private and public climate financing per year by 2020, as well as the channelling of foreign aid to the energy sector aim at contributing to decouple (or at least reduce the link between) economic and emission growth. A way to achieve this is for developing countries to 'leap-frog' polluting technologies that have led to the majority of accumulated emissions in the developed world. In the absence of fully accounting for the external costs of polluting technologies, the deployment of advanced technologies is expensive and therefore often not competitive with conventional technologies such as fossil energy sources. Measures such as the Green Climate Fund and foreign aid can help making them affordable for developing countries. Beyond their ability to affect energy use and emissions, technology transfer and related financial measures are a crucial 'carrot' for developing countries in exchange of the stick of signing up to a global climate regime. And indeed, the Durban summit has not only led to the launch of the Green Climate Fund but has also led to all Parties, both developed and developing countries, signing up to the Durban Platform for Enhanced Action, a pledge to come to a global agreement with legal force to contain temperature rise within 2°C. However, the conclusion of such an agreement remains uncertain as it is only envisaged for 2015 with the operationalization not expected to commence before 2020.<sup>8</sup>

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<sup>8</sup>Draft decision on the Durban Platform for Enhanced Action: [http://unfccc.int/files/meetings/durban\\_nov\\_2011/decisions/application/pdf/cop17\\_durbanplatform.pdf](http://unfccc.int/files/meetings/durban_nov_2011/decisions/application/pdf/cop17_durbanplatform.pdf) (last accessed June 4, 2012).

### 1.3 Research needs

The energy-climate nexus calls for research to address the challenge of providing access to energy to a growing population while embarking on a path to reduce global emissions. Key challenges include:

- Defining future energy supply scenarios that help meet ambitious climate change mitigation scenarios;
- Fostering energy efficiency by providing energy-saving technologies and putting in place the right incentives to trigger their adoption;
- Developing and bringing to market low-carbon energy technologies, including energy from renewable sources and deploying carbon capture and storage (CCS) technology;
- Ensuring that energy-saving and low-carbon energy technologies diffuse to less developed economies so as to enhance access to clean energy globally.

The listed challenges call for research from different disciplines. The development of new technologies and other technical issues such as the integration of renewable energies in existing energy distribution infrastructure, most notably the electricity grid, call for engineering expertise. Research in the field of (environmental) economics can provide answers to other important aspects. Part of the challenge to bring to market energy-saving and low-carbon energy technologies is their cost disadvantage compared to prevailing conventional technologies. Their relative costs are reduced when negative externalities of conventional technologies, e.g. the costs of emitting greenhouse gases associated with fossil fuel use, are properly accounted for and such approaches are at the heart of environmental economics.

Yet more targeted support for particular technologies is often needed. Focusing on renewable energy technologies, the IPCC Special Report confirms that “policy measures are still required to ensure rapid deployment of many RE sources” (IPCC, 2011, p.13). Such policies include regulatory schemes such as legally binding targets for renewable energy; an example is the EU Renewable Energy Directive. Implementing measures to reach renewable energy targets include feed-in tariffs to promote renewable electricity, investment subsidies to increase renewable energy installations, sectoral quotas for renewable energy use for instance in the power generation and the transport sector and many others. Likewise, investment subsidies

may be introduced to increase the use of energy-saving technologies. Research and development (R&D) spending by public and private bodies are important to invent the respective technologies in the first place. Designing promising support mechanisms and monitoring their effectiveness calls for research contributions from (environmental) economists.

Another aspect for economists to study is the macroeconomic context of supporting energy-saving and low-carbon technologies. This includes estimating the short- and long-term costs associated with the transition to low-carbon economies, including immediate investment costs (e.g. capital expenditures for new renewable energy installations), costs (and benefits) from (avoided) climate change and expenditures on energy services including the effects on trade balances of individual countries or trading blocks. Other, possibly unintended macroeconomic effects of renewable energy policy need to be considered. Biofuel support policy is a prime example for such unintended effects. Over the last years, many modelling studies have addressed the consequences of increased biofuel use on global agricultural markets, focusing in particular on the, highly publicised, effects on agricultural commodity and food prices and on land use change. Over the years, compelling evidence has accumulated that biofuel induced land use change is larger than anticipated and that the associated emissions considerably reduce if not negate the greenhouse gas mitigation potential of some biofuel pathways.

Another important dimension introduced above is the growing role of developing and emerging economies on global energy and carbon markets. Derived from this is the need to study alternative designs for an international climate agreement in order to understand the welfare implications for different countries and world regions (see for example Klepper and Peterson, 2007). This is needed to eventually conclude a post-Kyoto climate agreement that encompasses developed and developing country emitters. In a similar context, it is important to understand the effectiveness of international financial transfers to developing countries in bringing down energy use and emissions. This includes current and past flows of foreign aid and, in the future, assessing how the Green Climate Fund fares in terms of effectiveness.

## **1.4 Introducing the papers of this dissertation**

In the following, I outline in which way the four papers of this dissertation respond to some of the research needs mentioned above.

Chapters 2 and 3 focus on one source of renewable energy, biofuels produced from agri-

cultural crops, and the effects of the EU support policy for renewable energy in transport. Both chapters respond to the need to understand the macroeconomic impacts of promoting low-carbon energies, in particular of supporting the use of liquid biofuels in the transport sector. Ambitious renewable energy targets in the EU have increased the demand for biofuels and the associated agricultural commodities that biofuels are predominantly produced from, i.e. oilseeds for biodiesel and sugar crops and cereals for ethanol, the latter blended with or replacing conventional petrol. Given the magnitude of the demand increase and the anticipated reliance on imports for meeting mandatory biofuel quotas, there is a need to model the impacts on agricultural markets using global economic models. Such modelling also has to account for economy-wide effects given the increased link between agricultural and energy markets brought about by biofuel policy (Schmidhuber, 2007). In order to improve understanding of the economic modelling of biofuel policy and to provide guidance and point out research needs to modellers in the field, **Chapter 2**<sup>9</sup> surveys the most important earlier modelling studies that have addressed the consequences of biofuel use. It considers both partial and general equilibrium (CGE) models, focusing on the latter, and proposes a classification of three types of biofuel modelling approaches. These are an “implicit approach”, a “latent technology approach” and an approach consisting of disaggregating the underlying data structure of CGE models, the social accounting matrix. They differ in their complexity and the degree of integration of the new modelling components with the original modelling structure. Following the latent technology approach, biofuel production technologies were integrated into the CGE model DART.

**Chapter 3**<sup>10</sup> discusses the economic effects of EU biofuel use, addressing in particular biofuel production and trade, agricultural market impacts including commodity prices and welfare effects. Additionally, it addresses the role of biofuel support in the presence of support for renewable electricity and as such different ways of meeting the EU overall renewable energy target. The basis for the analysis in Chapter 3 is the integration of biofuel technologies into the DART model, described in Kretschmer et al. (2008). As such, the chapter presents an application of the extended model. The following components formed part of the modelling work by Kretschmer et al. (2008) to introduce the new technologies: Some of the

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<sup>9</sup>Chapter 2 is published in *Energy Economics* as Kretschmer and Peterson (2010).

<sup>10</sup>Chapter 3 is published in *Energy Economics* as Kretschmer et al. (2009)

original GTAP sectors had to be disaggregated to carve out new individual sectors (diesel and gasoline as well as corn), which required the collection of data on expenditure shares and taxes for the new sectors. Further extensive data collection was undertaken on biofuel cost structures, production and consumption shares as well as trade flows. Based on the data collection work, the new biodiesel and bioethanol sectors were included in the model, requiring programming and recalibration of the extended model. The model was calibrated so as to align biofuel consumption, modelled as a perfect substitute to fossil fuel consumption, with observed consumption shares in 2005. Subsequently, policy scenarios were formulated in order to investigate the effects of growing biofuel industries. Chapter 3 describes some of the alterations to the DART model, complemented by a description of the new production structures and their integration into DART in Appendix A. More recently, especially the agricultural and land use components of CGE models have become increasingly sophisticated and a range of other studies have addressed the impacts of biofuel use in particular with a focus on the land use change consequences of the EU and US policies as well as their combined effects (for example Edwards et al., 2010; Hertel et al., 2010; Laborde, 2011; O'Hare et al., 2011).

Another, more long-term, form of public support for renewable energy is public spending on research and development (R&D) in the energy sector. Effective R&D spending would both bring down costs of, for example, proven renewable energy technologies, demonstrate novel technologies on a commercial scale and/or develop entirely new technologies. In order to make best use of public money, it is important to understand the effectiveness of such budgetary support measures, to which **Chapter 4** contributes. It addresses public energy R&D spending in OECD countries and analyses whether spending over the period 1977 to 2006 has been successful in reducing energy use and emissions per GDP in a sample of 23 OECD economies. An important aspect of the analysis is that it controls for the presence of policies targeted at renewable energy, energy efficiency and climate change mitigation. Various theoretical papers introduced in the Chapter stress the importance of a regulatory framework stimulating the demand for renewable-energy and energy-saving technologies to make R&D expenditure effective. Likewise, the IPCC Special Report recognises that “[public] R&D investments in [renewable energy] technologies are most effective when complemented by other policy instruments, particularly deployment policies that simultaneously enhance demand for new technologies. Together, R&D and deployment policies create a positive feedback cycle,



inducing private sector investment” (IPCC, 2011, p25). The analysis yields some evidence for energy R&D spending to reduce energy intensities but not emission intensities in the 23 OECD countries considered. Concerning the effect of policies, some, though no robust empirical evidence was gained supporting the theoretical work on the interplay of technology-push and demand-pull measures, mostly in relation to renewable energy policies.

While the previous chapters have analysed the effectiveness and (international) impacts of domestic policy measures, **Chapter 5**<sup>11</sup> analyses the extent to which foreign aid has been successful in bringing down energy and carbon intensities of developing economies. In particular, it uses a panel data set covering close to 80 countries and spanning the period 1973 to 2005 to analyse the impact of foreign aid, and specifically of aid targeted at the energy sector, on the energy intensity and the carbon intensity of energy use. Using appropriate econometric techniques as discussed below, the analysis yields evidence for aid to be effective in reducing energy intensities of recipient countries, while carbon intensities are hardly affected.

The next chapters 2 to 5 contain the four studies referred to above. The final chapter 6 condenses the findings from the analyses of this dissertation by briefly summarising the main results and deriving policy conclusions.

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<sup>11</sup>Chapter 5 is published in the *Journal of International Development* as Kretschmer et al. (2013).

## 2 Integrating Bioenergy into Computable General Equilibrium Models – A Survey<sup>12</sup>

### Full citation

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**Keywords:** Biofuels; Bioenergy; CGE model; Climate policy

### Abstract

*In the past years biofuels have received increased attention since they were believed to contribute to rural development, energy security and to fight global warming. It became clear, though, that bioenergy cannot be evaluated independently of the rest of the economy and that national and international feedback effects are important. Computable general equilibrium (CGE) models have been widely employed in order to study the effects of international climate policies. The main characteristic of these models is their encompassing scope: Global models cover the whole world economy disaggregated into regions and countries as well as diverse sectors of economic activity. Such a modelling framework unveils direct and indirect feedback effects of certain policies or shocks across sectors and countries. CGE models are thus well suited for the study of bioenergy/biofuel policies. One can currently find various approaches in the literature of incorporating bioenergy into a CGE framework. This paper gives an overview of existing approaches, critically assesses their respective power and discusses the advantages of CGE models compared to partial equilibrium models. Grouping different approaches into categories and highlighting their advantages and disadvantages is important for giving a structure to this rather recent and rapidly growing research area and to provide a guidepost for future work.*

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<sup>12</sup>This Chapter has been written jointly with Sonja Peterson (Kiel Institute for the World Economy). An identical version (apart from some small edits and layout changes) has been published in *Energy Economics* as Kretschmer and Peterson (2010). We thank one anonymous referee and Tom Hertel for very helpful and extensive comments. Financial support from the German Federal Ministry of Education and Research (BMBF) within the WiN programme is gratefully acknowledged. My contribution was to develop the idea for the paper together with Sonja Peterson; to undertake a literature review in order to classify the biofuel modelling studies into three different approaches; and to identify general modelling issues arising from the literature together with Sonja Peterson.

### 3 The economic effects of the EU biofuel target<sup>13</sup>

#### Full citation

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#### Abstract

*In this paper we use the CGE model DART to assess the economic impacts and optimality of different aspects of the EU climate package. A special focus is placed on the 10% biofuel target in the EU. In particular we analyze the development in the biofuel sectors, the effects on agricultural production and prices, and finally overall welfare implications. One of the main findings is that the EU emission targets alone lead to only minor increases in biofuel production. Additional subsidies are necessary to reach the 10% biofuel target. This in turn increases European agricultural prices by up to 7%. Compared to a cost-effective scenario in which the EU 20% emission reduction target is reached, additional welfare losses occur due to separated carbon markets and the renewable quotas. The biofuel target has relatively small negative or even positive welfare effects in some scenarios.*

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<sup>13</sup>This Chapter is joint work with Daiju Narita and Sonja Peterson (both Kiel Institute for the World Economy). An identical version (apart from some small edits and layout changes) has been published in *Energy Economics* as Kretschmer, Narita and Peterson (2010). Financial support from the German Federal Ministry of Education and Research (BMBF) within the WiN programme is gratefully acknowledged. My contribution was to integrate biofuel technologies into the DART model as described in detail in Kretschmer et al. (2008) and summarised in Appendix A, including the underlying data collection, model calibration and actual programming in GAMS/MPSGE (with advice from Sonja Peterson); to contribute to the formulation and calibration of the scenarios with regard to the biofuel components; to carry out the final scenario runs; and to contribute majorly to interpreting and writing up the results.

## 4 Energy intensity and R&D spending<sup>14</sup>

### 4.1 Introduction

Uncertainties about a future international climate agreement, obliging both major historical as well as emerging emitters to emission cuts, remain after the 2011 Durban climate summit. A new ‘Durban Platform for Enhanced Action’ was the major outcome of the Conference.<sup>15</sup> This platform entails the conclusion of an agreement with legal force encompassing all major emitters, which would, however, only be drawn up by 2015 to enter into force in 2020. The uncertainties and the renewed postponement of a global deal imposing ‘top-down’ mitigation targets make the greenhouse gas mitigation strategies pursued by national governments and supranational bodies such as the European Commission all the more crucial. In the absence of top-down targets, these bottom-up strategies can ensure that countries continuously undertake efforts to decarbonise their economies. In 2009, the European Council announced to reduce emissions in the EU by 80 to 95 per cent by the year 2050 compared to 1990 levels. First steps to concretise this headline target have been taken: The European Commission published a ‘Roadmap for a Low Carbon Economy by 2050’ in March 2011.<sup>16</sup> A key challenge of mitigation strategies is to decarbonise energy supply by fostering low-carbon and carbon-free renewable energy technologies. For this sake, the Commission published an ‘Energy Roadmap 2050’, outlining different scenarios towards decarbonising energy supply.<sup>17</sup>

Various modelling exercises have recently been undertaken to demonstrate how Europe, individual Member States as well as other regions can reach renewable energy shares of up to 80, 90 per cent.<sup>18</sup> Efforts on the demand side to achieve considerable gains in energy efficiency

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<sup>15</sup>Draft decision on ‘Establishment of an Ad Hoc Working Group on the Durban Platform for Enhanced Action’: [http://unfccc.int/files/meetings/durban\\_nov\\_2011/decisions/application/pdf/cop17\\_durbanplatform.pdf](http://unfccc.int/files/meetings/durban_nov_2011/decisions/application/pdf/cop17_durbanplatform.pdf) (last accessed June 4, 2012).

<sup>16</sup>Communication COM(2011) 112 final from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions of 8 March 2011, ‘A Roadmap for moving to a competitive low carbon economy in 2050’, <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0112:FIN:EN:PDF> (last accessed June 5, 2012).

<sup>17</sup>Communication COM(2011) 885/2 from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions of 15 December 2011, ‘Energy Roadmap 2050’, [http://ec.europa.eu/energy/energy2020/roadmap/doc/com\\_2011\\_8852\\_en.pdf](http://ec.europa.eu/energy/energy2020/roadmap/doc/com_2011_8852_en.pdf) (last accessed June 5, 2012).

<sup>18</sup>See, for example, the energy[r]evolution study for the EU by EREC and Greenpeace (2010), as well as

are crucial in order to meet ambitious renewable energy targets and hence to reduce emissions. The EU therefore adopted a target to decrease primary energy consumption by 20 per cent by the year 2020 compared to projected levels by improving energy efficiency as part of its climate-energy package, reiterated in the 2011 proposal for an Energy Efficiency Directive.<sup>19</sup> In contrast to the renewable energy targets, however, this target is non-binding, meaning it is intended to persuade Member States to take measures to reduce energy consumption, but there is no legal obligation for them to do so.

Most forms of energy from renewable sources are currently not competitive with conventional energy sources and rely on various forms of public support. These can take the form of technology-specific feed-in tariffs, renewable energy standards and targets, to name a few, as well as R&D (research and development) subsidies in the earlier stages of development. In the EU, the most important legislative driver for the uptake of renewable energy sources is the Renewable Energy Directive<sup>20</sup> obliging the EU to meet 20 per cent of its gross final energy consumption from renewable sources by the year 2020. Examples for national support measures in the different energy sectors include the German Renewable Energy Sources Act, a feed-in tariff scheme to promote the use of renewable electricity; tax exemptions for biofuels introduced in a range of European countries and tax credits for biofuels in the USA; and the UK Renewable Heat Incentive, which gives tariff support to industrial heat users as well as grants to households for investment in renewable heat technology.

In addition to the renewable energy targets, the European Commission stresses the need to develop and commercialise new technologies to foster low-carbon energy sources and increase energy efficiency. The EU's key initiative in this respect is the 'European Strategic Energy Technology Plan', or SET Plan, whose ambition is to make low-carbon and efficient energy technologies affordable and competitive with conventional (e.g. fossil-based) energy technologies.<sup>21</sup> The SET Plan is not a European funding instrument; instead, it calls for the

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global studies at <http://www.energyblueprint.info/> (last accessed June 5, 2012), and the 'Energy Report' study by WWF and Ecofys (2011).

<sup>19</sup>Proposal COM(2011) 370 final of 22 June 2011 for a Directive of the European Parliament and of the Council on energy efficiency and repealing Directives 2004/8/EC and 2006/32/EC.

<sup>20</sup>Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, Official Journal L140/16 5.6.2009.

<sup>21</sup>The SET Plan was introduced by the European Commission's Communication COM(2007) 723 final of 22 November 2007, [http://ec.europa.eu/energy/res/setplan/doc/com\\_2007/com\\_2007\\_0723\\_en.pdf](http://ec.europa.eu/energy/res/setplan/doc/com_2007/com_2007_0723_en.pdf) (last accessed June 5, 2012).

bulk of investment in energy innovation to be provided by EU Member States and the private sector.

This focus on providing financial resources to achieve a successful transition to a low-carbon energy system warrants an analysis of the performance of past R&D efforts in the energy sector. The aim of this paper is therefore to take a closer look at the effectiveness of public R&D spending targeted at the energy sector in reducing energy and emission intensities or in other words the effectiveness in increasing energy efficiency and decarbonising economic activity. Theoretical work in this area highlights the need for accompanying ‘market-creation’ or ‘demand-pull’ measures for ‘technology-push’ R&D efforts to be effective (Sagar and van der Zwaan, 2006; Fischer, 2008; Fischer and Newell, 2008). These could take the form of public procurement measures or carbon pricing by means of a carbon tax or an emissions trading scheme. Any form of carbon pricing improves the competitiveness of low-carbon renewable energy sources with regard to fossil fuels, thereby creating a market for renewable technologies. In such a setting, R&D efforts are likely to be more effective in advancing new technologies to market, as they will meet an actual demand. Likewise, Grubb (2004) explains in the context of a six-step innovation chain model that technology-push measures are important in earlier stages of the innovation chain while demand-pull policies gain importance as technologies further advance towards diffusion.

Garrone and Grilli (2010) intend to enhance the understanding of innovation processes in the energy sector and specifically the role of public R&D spending. In order to do so, they empirically investigate the link between public R&D expenditures and energy and emission intensities and the carbon factor in the framework of a bivariate panel analysis covering 13 industrialised countries and the period 1980 to 2004. They propose Granger causality tests to investigate the direction of causality between R&D spending and the intensity variables. Their data reveal no effect of R&D spending on either emission intensity (i.e. emissions divided by GDP) or the carbon factor (i.e. emissions divided by energy use). They can demonstrate, however, that public R&D spending reduces energy intensity, defined as energy use divided by GDP. The long-term effect of doubling the energy R&D budget is estimated to reduce energy intensity by 16 per cent. They refine their analysis by categorising energy R&D spending into those measures targeted at energy efficiency and those targeted at decarbonising energy use. Similar to the aggregate results, only the former reduce energy intensity (the long-term

effect being twice as large compared to using total energy R&D spending) while the latter do not affect the carbon factor. They also find evidence for reverse causality: A doubling of the energy intensity leads to a long-term increase in public energy R&D budgets of 37 or 22 per cent, depending on the estimator used. Correspondingly, a doubling of the emission intensity increases public R&D budgets by 42 or 29 per cent in the long run.

Energy and emission intensities but also public energy R&D spending has declined over the last decades. This hints at the existence of further drivers taking energy and emission intensities onto a decreasing path. In Garrone and Grilli's bivariate analysis this remains hidden in the country fixed effects and/or the error term. By including further control variables, the present paper intends to make the processes at work more transparent. In addition, by relying on a bivariate analysis, Garrone and Grilli (2010) do not take into account further variables that could, for instance, control for the presence of market-creation policies. The work undertaken by Johnstone et al. (2010) does consider this dimension, though in a different context. The authors analyse the impact of renewable energy policies on the number of patent applications for different renewable electricity technologies. Next to (technology-specific) R&D expenditure, they include binary and continuous variables spanning a range of renewable energy policy instruments.<sup>22</sup> Their analysis extends over a sample of 25 OECD countries and the period 1978 to 2003. Their main results include that policies rather than prices drive innovation activity.

The approach of this paper is to take the work by Garrone and Grilli (2010) as the starting point for an extended analysis based on a broader sample and taking further control variables into account. Based on a macro panel of 23 OECD countries over the period 1977 to 2006 and using dynamic panel methods, this paper seeks to investigate the effect of R&D spending on energy and emission intensities in the presence of policies targeting energy efficiency and renewable energy sources.

Section 4.2 introduces the analytical background and formulates hypotheses. Section 4.3 presents the data employed in the analysis. Section 4.4 spells out the econometric model and introduces the GMM estimation procedure. Section 4.5 summarises estimation results and

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<sup>22</sup>Binary variables include tax measures, investment incentives, bidding systems, voluntary programs and quantity obligations. Besides R&D expenditures, other continuous variables are feed-in tariffs and renewable energy certificates.

section 4.6 concludes.

## 4.2 Analytical background and hypotheses

The following sub-sections set out the choice of dependent variables as well as of control variables and put forward hypotheses about the potential impacts of the chosen control variables on energy and emission intensities.

### 4.2.1 Explaining energy and emission intensities

The present analysis seeks to understand the main drivers of energy and emission intensities in OECD countries. An economy's energy intensity describes the efficiency at which energy inputs are used to generate economic output. The fact that (fossil) energy sources become increasingly scarce and hence expensive provides an important rationale for efforts targeted at increasing the efficiency of energy use or in other words reducing the amount of energy input needed to generate a unit of output (i.e. the energy intensity). Successful efficiency increases can boost the competitiveness of economies by, for instance, lowering production costs and decreasing the vulnerability to rising and fluctuating energy prices. More importantly from an environmental point of view are the associated reductions in greenhouse gas emissions given that the energy mix remains the same. Improving energy efficiency is a demonstrated low-cost or even negative-cost mitigation option (see e.g. Enkvist et al., 2007). The energy intensity of economies is hence an important variable to consider in environmental economic analysis.<sup>23</sup> Together with energy intensity reductions, the increased use of renewable energy will cut emissions further. All other things equal, increasing the use of energy from low carbon, renewable sources will increase their share in the energy mix, hence reducing the amount of greenhouse gas emitted per unit of GDP generated or in other words reducing the emission intensity of the economy. Both changes in the energy efficiency and the share of renewable energy shape an economy's emission intensity. I consider the emission intensity in the analysis as it is the prime indicator whether or not economies are moving towards

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<sup>23</sup>Increasing efficiency is a "crucial prerequisite for achieving a significant share of renewable energy sources in the overall energy supply system" and hence to meet greenhouse gas reduction targets (EREC and Greenpeace, 2010, p.12). The proposal for a new EU Energy Efficiency Directive recognises the need for increased efforts. While falling short of introducing binding targets for EU member states, the proposal introduces various new sectoral measures.



lower-carbon futures and it is therefore important to understand whether public funds for energy R&D have been effective in reducing it.

#### **4.2.2 Anticipated impacts of energy R&D spending on energy and emission intensities**

Reducing energy and emission intensities depends on the availability of energy-saving and low-carbon technologies. This explains why the present analysis investigates the effectiveness of energy R&D spending, which is essentially a ‘technology-push’ approach to bringing new technologies to the forefront. Grubb (2004) has developed a six-stage innovation chain model with the aim to dissolve the dichotomy between advocates of a technology-push approach to energy technology innovation and those favouring a demand-pull approach and claiming that e.g. emission trading schemes are sufficient to bring about the necessary innovations. Grubb proposes that a mix of policies and instruments is needed when moving along the innovation chain.<sup>24</sup> He argues that public R&D spending helps contribute to the initial stages of basic R&D and technology-specific RD&D (research, development & demonstration). Based on this theoretical work and in line with previous empirical work by Garrone and Grilli, the inclusion of public energy R&D spending as an explanatory variable is expected to reduce energy and emission intensities. Whether the effects turn out significant or not, is, however, expected to depend on the inclusion of policy variables. This hypothesis is derived from the theoretical work by Sagar and van der Zwaan (2006), Fischer (2008) and Fischer and Newell (2008) referred to above that point at the need for demand-pull policies for R&D spending to be effective.

Besides specifications including total public energy R&D spending, the analysis below investigates the effectiveness of disaggregated spending categories, specifically public R&D spending targeted at energy savings and at low-carbon technologies. Because of their more targeted nature, I expect these sub-categories to have a more significant and/or more pronounced effect on energy and emission intensities, respectively.<sup>25</sup> A final word on the potential

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<sup>24</sup>The six stages identified in Grubb’s innovation chain are: basic research and development, technology-specific research, development and demonstration, market demonstration, commercialisation, market accumulation and diffusion (Grubb, 2004, p.116).

<sup>25</sup>Having said this, the use of sub-categories of R&D in Garrone and Grilli (2010) has not altered their results substantially: They again only find a significant effect on energy intensity by R&D spending targeted at reducing energy intensities. However, the long-term effect of the latter spending category doubles compared

endogeneity of R&D: It can be assumed that the size of energy R&D spending is partly determined by a country's energy and/or emission intensities, in other words that R&D spending is endogenous in the analysis. Indeed, Garrone and Grilli (2010) check for reverse causality and find that both emission and energy intensity positively granger-cause public energy R&D spending. In line with Garrone and Grilli (2010), this is remedied by including R&D as a one period lag and, more importantly, by treating R&D as an endogenous variable in GMM estimations, as explained in section 4.4.

### **4.2.3 Anticipated impacts of energy and climate policies and other control variables on energy and emission intensities**

The need for parallel 'technology push' and 'demand pull' policies in order to bring about successful commercialisation of low-carbon technologies warrants the inclusion of policy variables. This set up allows for testing the hypothesis that including policy variables in the regressions increases the power of public energy R&D spending to reduce energy and emission intensities. In other words, it is expected that the statistical significance of the R&D variables and the size of their coefficients increase in regressions that include policy variables compared to regressions without policy variables.

Apart from the hypothesis that policy variables render R&D spending effective, i.e. significant in the regressions, the policy variables are expected to have a direct effect in reducing energy and emission intensities as well. Grubb (2004) with his innovation chain model attributes an important role to policies such as market engagement programmes, strategic deployment policies and barrier removal for overcoming the "technology valley of death" between demonstration and full commercialisation of new technologies. Where these policies are effective in commercialising low-carbon and energy-saving technologies, this should go along with a reducing effect on energy and emission intensities. The policy variables introduced in the next section can be linked to the types of policies that Grubb mentions. The database includes information on feed-in tariffs and renewable energy obligations, classified as strategic deployment policies by Grubb (2004) and internalisation policies such as emissions trading and taxes, all deemed important for crossing the "valley of death" and hence with the po-

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to total energy R&D.

tential to increase energy and emission efficiencies. Investment incentives including grants, tax reductions and preferential loans are deemed particularly important, too. These may include measures targeted at the buildings sector (investment aid for energy-efficient renovation and renewables deployment), but also grants for demonstration projects and for building up renewable generation capacity. The here employed investment incentives policy variable is constructed to include such measures that target the crucial middle stages of the innovation chain and is therefore expected to be associated with reduced energy and emission intensities. Section 4.3 explains in more detail the construction of the policy variables. At this stage, it is sufficient to add that policies are grouped to construct variables that have either renewable energy or energy efficiency objectives.<sup>26</sup> It is expected that the variables representing renewable energy measures turn out significant in estimations with emission intensity as the dependent variable, given that such measures intend to alter the energy mix in favour of more low-carbon sources. Likewise, variables representing energy efficiency measures are expected to be significant in estimations with the energy intensity as the dependent variable.

Regarding the hypothesised effects of other control variables: Higher GDP per capita is expected to be associated with lower energy and emission intensities in the sample of developed countries examined here.<sup>27</sup> This is the case when GDP per capita as a proxy for overall productivity of an economy goes along with the deployment of more advanced and energy- and emission-saving technologies and/or a shift towards higher-value and less energy-intensive sectors such as the services sector. Unless perfectly inelastic demand for energy services prevails (which is not expected), increases in energy prices will result in less energy consumption. At least part of this reduction is typically compensated by increases in other factors of production (e.g. capital such as energy saving investments), hence reducing energy and emission intensities.

### 4.3 Data description and trends in main variables of interest

This section presents the data used to test the hypotheses formulated in the previous section and presents major trends in energy and emission intensities as well as in R&D spending.

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<sup>26</sup> Additionally one variable represents voluntary measures for climate change mitigation.

<sup>27</sup> The rationale for including GDP per capita becomes clear when considering the considerable differences in GDP per capita levels within the present sample of countries. As an example, Turkey's GDP per capita in 2005 is 12 per cent of Norway's, the highest GDP per capita in the sample.

#### 4.3.1 Data sources and construction of the policy variables

Table 4.1 contains an overview of all variables (apart from the policy variables), their units and sources and Tables B.1 and B.2 in Appendix B present summary statistics. Data on energy use, emissions, total GDP and GDP per capita are retrieved from the World Development Indicators database (World Bank, 2010). A real energy price index (total energy) for households and industry comes from the IEA’s Energy Prices and Taxes database (IEA, 2010). It is available from 1978 onwards. Data on energy and emission intensities as well as on GDP per capita are available for all OECD countries with few missing entries from the World Development Indicators for the whole period 1977 to 2006. Data on public energy R&D spending are retrieved from the IEA Energy Technology RD&D statistics,<sup>28</sup> which contains data for the period 1974 to 2005. These contain disaggregated spending categories for a range of energy technologies. I classified them into 1) energy use and 2) carbon intensity targeted spending in order to construct the two variables ‘Energy-efficiency R&D ratio’ and ‘Low-carbon R&D ratio’, respectively (see Appendix B). The choices of categories mostly follow the classification put forward by Garrone and Grilli (2010, p.5611). The most important difference is that I classify all spending on renewable energies as targeted at the carbon intensity, given this is generally the most important stated rationale for these expenditures, whereas Garrone and Grilli classified some of the sub-categories as targeted at energy use. Furthermore, unlike in Garrone and Grilli I do not classify nuclear power as carbon intensity targeted spending; while being a low-carbon energy source by itself, the use of nuclear power is not considered to be a viable component of a low-carbon energy system given that its lack of flexible deployment represents a hindrance to the increased use of renewables. Data on R&D spending are available for most OECD countries, though there are some countries (mostly Eastern European) for which no data are available at all. Excluding those yields a sample of 23 countries.<sup>29</sup>

The IEA’s online databases on policies and measures covering all OECD countries allows for constructing the policy variables. Three databases are distinguished on ‘Global

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<sup>28</sup><http://www.iea.org/stats/rd.asp> (Edition 2008). RD&D denotes ‘Research, development and demonstration’. For simplicity and in line with the terminology chosen in other papers I use ‘R&D’ throughout.

<sup>29</sup>Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

Table 4.1: Overview of variables and data sources

Variable	Explanation	Source
Energy intensity	Total primary energy use in kilogram oil equivalent (before transformation to other end-use fuels) per 2000 US\$ of GDP	World Bank (2010)
Emission intensity	Carbon dioxide emissions (stemming from the burning of fossil fuels and the manufacture of cement) in kilogram per 2000 US\$ of GDP	World Bank (2010)
Energy R&D ratio	Total public energy R&D divided by GDP	IEA (2008) and World Bank (2010)
Energy-efficiency R&D ratio	Public energy R&D targeted energy efficiency (see App. B) divided by GDP	IEA (2008) and World Bank (2010)
Low-carbon R&D ratio	Public energy R&D targeted low-carbon technologies (see App. B) divided by GDP	IEA (2008) and World Bank (2010)
Energy price	Real energy price index for industry and households	IEA (2010b)
GDP per capita	GDP per capita in constant 2000 US\$	World Bank (2010)
Industry share	Industry value added expressed as % of GDP	World Bank (2010)
Investment ratio	Gross fixed capital formation expressed as % of GDP	World Bank (2010)

Note: See Table 4.2 for an overview of policy variables.

Renewable Energy’, ‘Energy Efficiency’ and ‘Addressing Climate Change’ that all contain detailed information per country disaggregated by support type, sector, target, status and governance level.<sup>30</sup> The database was constructed by scanning all three databases for all countries and years in the sample for relevant policy instruments that were consequently grouped into a range of categories. In the next step, this raw data was used to draw up count variables expressing the number of measures in a certain policy category and for a certain country/year point. Table 4.2 displays the policy variables selected for the estimations distinguishing between measures targeted at energy efficiency and renewable energy. Figure 4.1 shows the proliferation of measures on energy efficiency and renewable energy across the 23-country sample over the recent decades.<sup>31</sup>

<sup>30</sup><http://www.iea.org/textbase/pm/index.html>; last accessed March 2011.

<sup>31</sup>The estimations, based on five-year averages as introduced in section 4.4, do not include any dummy policy variables, as it did not seem sensible to average a dummy variable that is binary by definition. This has the consequence that the potentially important climate-policy related dummies indicating the signature of the Kyoto Protocol or the presence of a carbon tax or emissions trading are not included.

Table 4.2: Overview of energy and climate policy variables

Variable	Type of var.	Definition
<i>Renewable energy measures</i>		
RE certificate share	Continuous	Minimum percentage of renewable energy (RE) certificates as part of obligation scheme (based on Johnstone et al., 2010)
Feed-in tariff	Continuous	Mean feed-in tariff in 2000 US\$ cents/kWh (based on Johnstone et al., 2010)
Investment RE	Count	Includes investment incentives such as grants, subsidies, tax reductions etc. for renewable energy installations
Financial RE	Count	Favourable operating taxes, energy tax regimes favouring RE; excludes investment related measures (captured by Investment RE)
Voluntary RE	Count	Any kind of voluntary agreements on behalf of industries or other voluntary measures targeted at RE
Sum RE measures	Count	Sum of all renewable energy targeted policies and measures
<i>Energy efficiency measures</i>		
Investment EE	Count	Includes investment incentives such as grants, subsidies, tax reductions etc. for energy efficiency (EE) installations
Financial EE	Count	Favourable operating taxes, energy tax regimes favouring EE, smart metering; excludes investment related measures (captured by Investment EE)
Voluntary EE	Count	Any kind of voluntary agreements on behalf of industries or other voluntary measures targeted at EE
Sum EE measures	Count	Sum of all energy efficiency targeted policies and measures
<i>Climate change measures</i>		
Voluntary CC	Count	Any kind of voluntary agreements on behalf of industries or other voluntary measures supporting climate change (CC) mitigation

Note: Own compilation and categorisation based on <http://www.iea.org/textbase/pm/index.html> (last accessed June 5, 2012). The data on RE certificate shares and feed-in tariffs have been received from the authors of Johnstone et al. (2010), for which I thank them very much.

#### 4.3.2 Trends in main variables of interest

Figure 4.2 shows the development of the dependent variables, energy and emission intensities, aggregated over the 23-country sample over the time horizon considered in the analysis. The fall in the emission intensity of 44 per cent outweighs the fall in the energy intensity by 35 per cent over the period. These numbers illustrate that in addition to energy savings, low-carbon energy sources have increased their share in the energy mix.

Figure 4.3 shows total public energy R&D spending of the 23 OECD countries examined in this paper from 1975 to 2007. It shows a pattern of peaking expenditures in the late 1970s as a response to the oil crises of the decade.<sup>32</sup> Since then, spending has dropped drastically

<sup>32</sup>This issue has also been examined by Zhang et al. (2006).

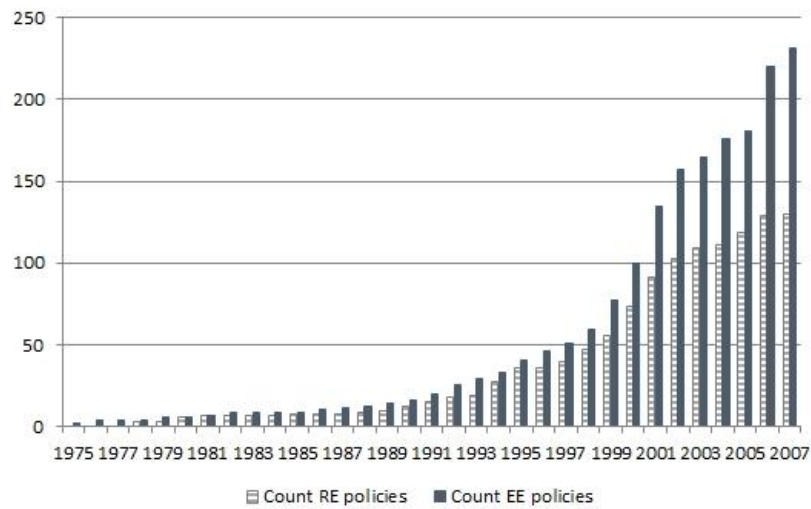


Figure 4.1: Policies and measures for renewable energy and energy efficiency in all 23 countries (Source: Based on own compilation and categorisation of policy variables from <http://www.iea.org/textbase/pm/index.html>)

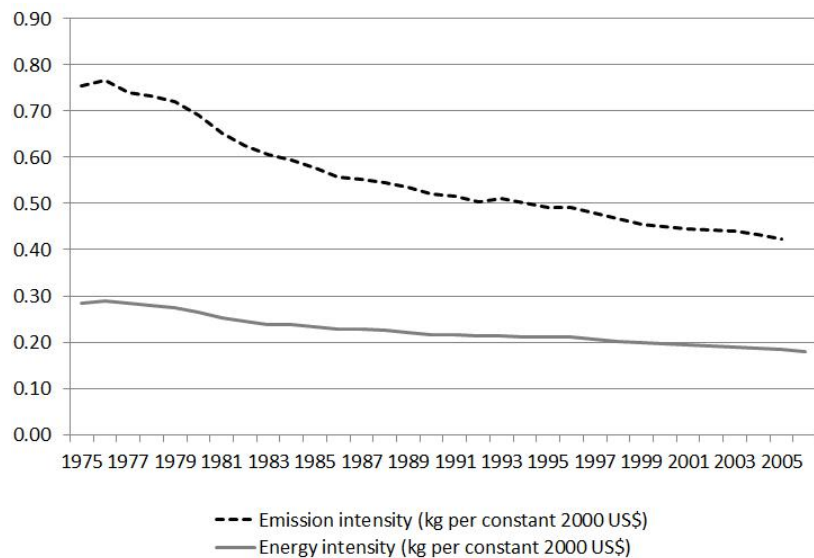


Figure 4.2: Energy and emission intensities for 23 sampled OECD countries (Source: World Bank, 2010)

and has been fairly stable since the early 1990s. In other words, while R&D investments have reacted promptly to the oil crises of the 1970s, the same cannot be said about the response to a growing concern about climate change symbolised for instance by the 1992 United Nations Earth Summit or the adoption of the Kyoto Protocol in 1997. Figure 4.3 also includes trends

in total public R&D spending (i.e. all sectors not just energy) and business R&D spending for selected categories.<sup>33</sup> Preferably, I would have included private business energy R&D spending on top of and/or as an alternative to public spending to estimate the total effect and to investigate whether the source of spending matters. A UNEP SEFI and Bloomberg New Energy Finance (2010) report shows that globally, corporate sustainable energy R&D spending has been more important than government spending over the period 2004 to 2009 covered in the report (Figure 4.4). It is, however, also seen and argued in the report that the financial crises of 2008/2009 led to a decrease in corporate spending while government spending increased substantially, leading to a small overall increase from 2008 to 2009 (years not covered in my estimation period). This is partly a result from ‘green’ stimulus packages adopted in different countries as a response to the crisis (UNEP SEFI and Bloomberg New Energy Finance, 2010).<sup>34</sup>

There are, however, no comprehensive datasets of private sector energy R&D investment, as is the case for public spending. Nemet and Kammen (2007) provide some insights for the US: Private investment did not see the sharp increase in spending as a consequence of the oil crises; it has neither seen a rising trend in recent years. During parts of the 1980s and 1990s, private and public R&D expenditures were roughly of similar size. In recent years, however, private spending is merely half of public spending. A further interesting fact the authors highlight: While US energy R&D spending represented 10 per cent out of total US R&D spending at the time of its peak around the year 1980, this share has dropped to two per cent recently. In other words, energy R&D spending goes against the trend of increasing total US R&D spending (Nemet and Kammen, 2007).

I have checked the pattern for my sample of countries for which the same holds. Looking at total sample public energy versus total public R&D spending (Figure 4.3) displays a diverging trend. Figure 4.3 also shows data on business enterprise R&D spending that represent the sum of the categories ‘Coke, refined petroleum products and nuclear fuel’ and ‘Electricity, gas and water supply’. More comprehensive data on private energy R&D spending could not be found and these data are not deemed of sufficiently high quality to be considered in the

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<sup>33</sup>These include ‘Coke, refined petroleum products and nuclear fuel’ and ‘Electricity, gas and water supply’.

<sup>34</sup>In this context, Rickels et al. (2010) show, however, that the design of worldwide stimulus packages did not live up to the UN goal of a 25 per cent spending share for measures related to climate change mitigation.



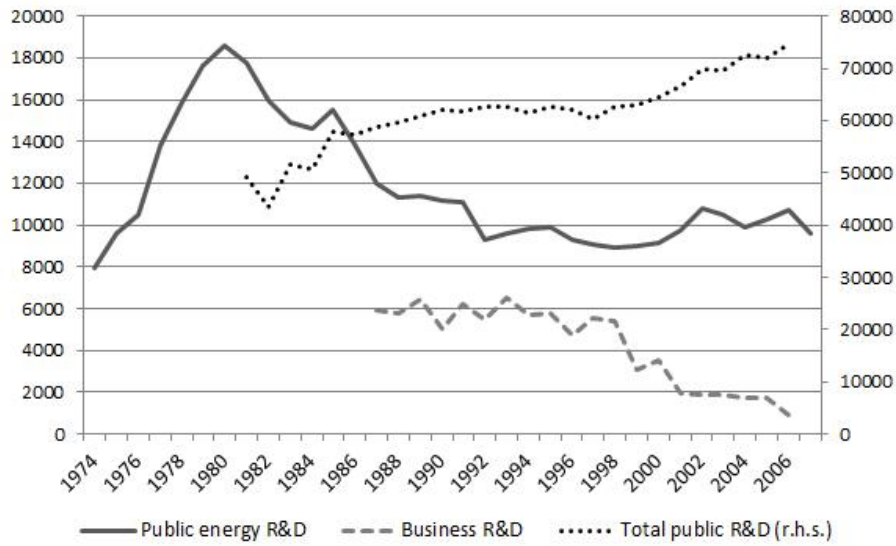


Figure 4.3: Energy and total public R&D spending for 23 sampled OECD countries, in million 2007 US\$(Source: Based on IEA, 2008, and OECD, 2010a). Note: ‘Business R&D’ is total business enterprise R&D spending on ‘Coke, refined petroleum products and nuclear fuel’ and ‘Electricity, gas and water supply’ for 23 sampled OECD countries based on OECD (2010b).

estimations for the following reasons: 1) For some countries all observations are missing while for all others data is available from 1987 onwards;<sup>35</sup> 2) for the latter countries there are considerable data gaps since 1987; and 3) the categorisation is not conform with ‘energy-sector’ R&D spending in the sense that it includes water and excludes spending targeted at renewable energies.

Figure 4.5 shows IEA total public R&D expenditure for R&D spending targeted at energy efficiency and renewable energy sources as well as at fossil sources for comparison. It is noteworthy that spending on renewable sources has recently outperformed spending on fossil sources. It is particularly interesting to see that the development of energy efficiency targeted spending deviates markedly from the other two spending categories: It has not reacted as sharply as fossil and renewable spending to the oil crises in the seventies but it has risen more steadily over time, in particular outperforming renewable spending since the beginning of the 1990s. Two targeted R&D variables are constructed as alternatives to total energy R&D spending. These are spending targeted at low-carbon technologies and spending targeted at

<sup>35</sup>Data are not available for Netherlands, New Zealand, Switzerland and only one observation is available for Belgium.

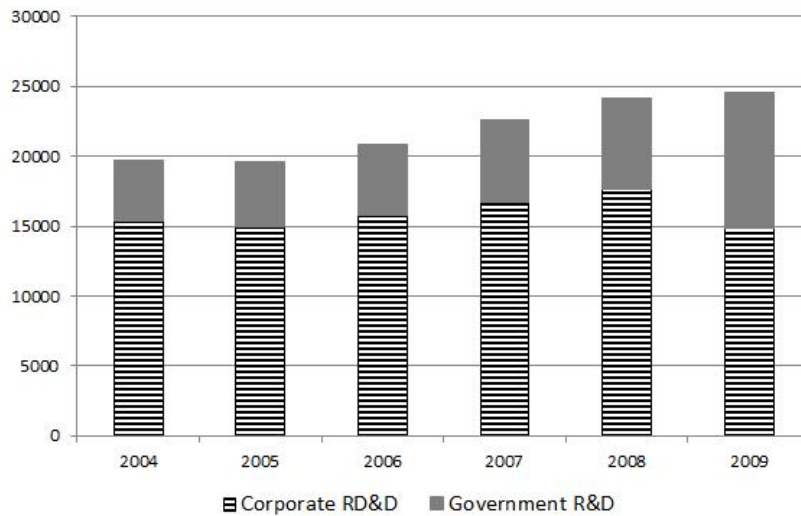


Figure 4.4: SEFI Global trends in sustainable energy investment data, in million US\$ (Source: UNEP SEFI and Bloomberg New Energy Finance, 2010)

improved energy efficiency. Appendix B (Table B.7) provides details on this categorisation.

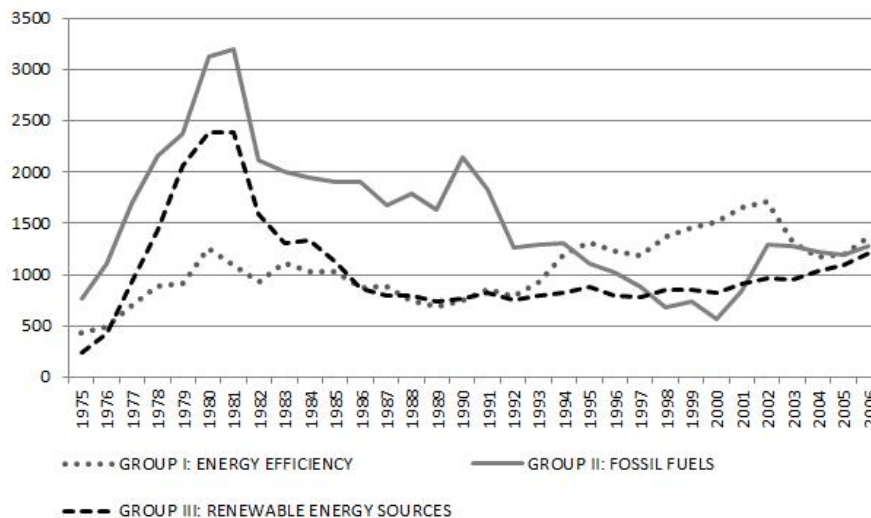


Figure 4.5: Public energy R&D spending disaggregated by groups as displayed for 23 sampled OECD countries, in million 2007 US\$ (Source: Based on IEA, 2008)

#### 4.4 Estimation procedure

Before presenting the estimation results in section 4.5, this section provides the background for the results and explains the estimations performed. The first sub-section spells out the

econometric model; the following two sub-sections discuss different econometric techniques for estimating dynamic panel models and explain in detail the chosen GMM-type estimators.

#### 4.4.1 Econometric model

Equation 1 represents the econometric model to be tested:

$$y_{it} = \beta_1 \log(y_{it-1}) + \beta_2 \log(rd_{it-1}) + \beta_3 \log(price_{it}) + \beta_4 \log(gdp_{rt}) + \beta_5 \log(pol_{it}) + \gamma_i + \epsilon_{it} \quad (1)$$

The letters  $i$  and  $t$  are the country and year index, respectively. The dependent variable is denoted by  $y_{it}$ , with  $y_{it-1}$  correspondingly being the lagged dependent variable,  $rd_{it-1}$  is the one-period lag of R&D expenditure divided by GDP,<sup>36</sup>  $price_{it}$  is the energy price index,  $gdp_{it}$  is GDP per capita,  $pol_{it}$  stands for the policy variable included and  $\gamma_i$  are country fixed effects (see also Table 4.3).<sup>37</sup> In line with Garrone and Grilli (2010), R&D spending is lagged by one period in order to investigate whether R&D spending causes energy and emission intensities. The use of five-year averages of the data in the estimations allows for a longer response time for the dependent variable to changes in R&D spending, which seems fit in the context of investigating the effect of R&D expenditure. Also, it helps smooth out fluctuations that might be of an accounting nature, such as accounting for a R&D expenditure programme in year  $X$  with actual payments being made in years  $X$  to  $X+5$ . In the case of using yearly data, one typically recurs to the use of moving averages to deal with this (as was done, for instance, in Chapter 5 of this dissertation). This smoothing out effect also explains why time dummies turned out insignificant in earlier model specifications and which I consequently did not include. All variables apart from the policy variables (and the industry and investment share variables in the robustness tests) are computed as logs.

Energy and emission intensities are variables likely to be characterised by a large degree of inertia. This means that last period's value is a likely determinant of this period's value due

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<sup>36</sup>Note that Garrone and Grilli (2010) include public energy R&D spending in absolute terms. In the absence of a control variable reflecting country size, however, this does not control for differences in absolute spending attributable to differences in country size.

<sup>37</sup>As will be discussed more thoroughly below, the estimation technique chosen is Generalised Method of Moments (GMM) instead of alternative estimators such as the corrected least squares dummy variables (LSDVC) estimator.

to structural factors in the economy and the energy sector that do not change drastically from one year to the next as a response to short term market signals. This justifies the inclusion of the lagged dependent variable, which at the same time introduces challenges for estimation as it biases OLS estimation. The next sections lay out the strategy to deal with these challenges.

Table 4.3: Overview of variable definitions

Variable	Parameter values and definitions
$Y$	Energy intensity (energy consumption / GDP) Emission intensity (emissions / GDP)
$rd$	Energy R&D ratio: Total public energy R&D spending / GDP Energy-efficiency R&D ratio: Public R&D spending targeted at energy use / GDP (see App. B) Low-carbon R&D ratio: Public R&D spending targeted at reducing emissions / GDP (see App. B)
$pol$	Various policy variables as introduced in section 4.3.1

#### 4.4.2 Estimation in the presence of endogenous regressors

The inclusion of the lagged dependent variable introduces a bias in the setting of a fixed time dimension  $T$ . This bias derives from the fact that in panel OLS estimations employing fixed or random effects, or first differencing, the lagged dependent variable exhibits contemporaneous correlation with the error term or in other words is an endogenous regressor. The following shortly introduces panel estimators focusing on the fixed effects and first difference estimator and demonstrates where the bias originates and then introduces IV and GMM techniques as the preferred way of eliminating the bias in the present setting.<sup>38</sup>

A main strength of the different panel estimators is that they deal with time-invariant unobserved heterogeneity between individuals<sup>39</sup> that are likely to be correlated with observed explanatory variables in a panel data set. A standard example for time-invariant unobserved heterogeneity is the inherent ability of individuals, for example of employees or students when trying to explain differences in wages or test results, where ability is likely to be correlated with ‘years of education’ or ‘hours studied’, respectively. In a macro panel, unobserved heterogeneity includes country-specific characteristics such as long-standing and non-changing

<sup>38</sup>The introduction to estimation in the presence of endogenous regressors and to GMM estimation in this section is primarily informed by Kennedy (2008) and Greene (2003).

<sup>39</sup>I.e. the cross section dimension of the data, ‘individuals’ in the present case being countries whereas in micro panels typically individuals or firms make up the cross section.

(at least not over the sample period) cultural traditions or characteristics including geography (e.g. land-locked) and climate conditions. Arguably, the latter can be observed and hence could be included, however, the way in which both the fixed effects and the first difference estimator deal with unobserved heterogeneity does not allow for the inclusion of such time-invariant variables, as will be seen in the following.<sup>40</sup> Equations 2 and 3 show how the fixed effects and first difference estimators, respectively, remove the unobserved heterogeneity from the data. The fixed effects estimator subtracts from all individual observations their mean value or in other words demeans the data, with the mean being the average of all observations for cross section  $i$  across time  $T$ . This transformation removes the unobserved heterogeneity, which does not change over time and therefore cancels out. The same occurs when the data is first-differenced as shown in equation 3.

$$(y_{it} - \bar{y}_i) = \beta_1(y_{it-1} - \bar{y}_i) + \beta_2(X_{it} - \bar{X}_i) + (\gamma_i - \gamma_i) + (\epsilon_{it} - \bar{\epsilon}_i) \quad (2)$$

$$(y_{it} - y_{it-1}) = \beta_1(y_{it-1} - y_{it-2}) + \beta_2(X_{it} - X_{it-1}) + (\gamma_i - \gamma_i) + (\epsilon_{it} - \epsilon_{it-1}) \quad (3)$$

Given that  $y_{it-1} = \beta_1 y_{it-2} + \beta_2 X_{it-1} + \gamma_i + \epsilon_{it-1}$ , it is easily detectable that the common element  $\epsilon_{it-1}$  present in both the differenced lagged dependent variable as well as the differenced error term (the same holds for the demeaned fixed effects model) introduces contemporaneous correlation between an explanatory variable and the error term, violating one of the standard assumptions underlying the OLS estimator and hence introducing a bias.

Instrumental variable (IV) and Generalised Method of Moments (GMM) estimators have been developed in order to deal with the bias of dynamic panel data models. An alternative way of dealing with the dynamic panel bias is the corrected least squares dummy variable estimator (LSDVC) proposed by Bruno (2005a), introduced briefly in the next section. Referring to the first-difference model in equation 3, the underlying idea of employing instrumental variables to eliminate the dynamic panel bias is to use deeper lags of the dependent variable in

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<sup>40</sup>Time-invariant variables can be included in the random effects estimator due to a different derivation of this estimator. However, an underlying assumption of the random effects estimator is that the unobserved heterogeneity is uncorrelated with other explanatory variables, an assumption difficult to meet in many contexts including the examples just mentioned.

levels as instruments for the first-differenced lagged dependent variable. This assumes that the error term  $\epsilon$  is not serially correlated. The following simple examples illustrate this: Using the model from equation 3 above, the suggested instrument  $y_{it-2} = \beta_1 y_{it-3} + \beta_2 X_{it-2} + \gamma_i + \epsilon_{it-2}$  is correlated with the variable it instruments for, i.e. the differenced lagged dependent variable,  $(y_{it-1} - y_{it-2})$ , but not correlated with the differenced error term  $(\epsilon_{it} - \epsilon_{it-1})$ . In other words, this instrument meets the standard conditions for valid instruments, relevance and exogeneity, which are expressed by equations 4 and 5, respectively:

$$E(y_{it-2} \Delta y_{it-1}) \neq 0 \tag{4}$$

$$E(y_{it-2} \Delta \epsilon_{it}) = 0 \tag{5}$$

Given it is later applied, the following paragraphs focus on introducing GMM techniques. The GMM estimator is an extension of the IV estimator that allows taking a wider set of instruments into account. This wider set of instruments may include all available lagged values of the dependent variable as instruments for  $\Delta y_{it-1}$ .<sup>41</sup> This set of instruments is organised in a GMM style matrix of instruments, as represented below following Roodman (2009a, p.138). As seen in the matrix below, separate instruments are included for each  $t$ , leading to  $(T - 2)(T - 1)/2$  instruments in total. As also mentioned in the next section, Roodman (2009a) discusses the problems associated with an instrument count that increases quadratically with  $T$  in the presence of large time dimensions as found frequently in macro panels.

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<sup>41</sup>Available instruments at time  $t$  are  $y_{it-2}$  and all previous lags, implying that one needs as a minimum three time periods of observations ( $T \geq 3$ ).

$$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ y_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & y_{i2} & y_{i1} & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & y_{i3} & y_{i2} & y_{i1} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

Including this matrix as instruments, GMM methods are employed to estimate the parameters of the model by fulfilling the moment conditions  $E(y_{i,t-l}\Delta\epsilon_{it}) = 0$  for each  $t \geq 3, l \geq 2$  (Roodman, 2009a, p.138). This illustrates the underlying mechanisms of the method of moments, of which GMM is a *generalised* form. Using the expectation of exogeneity underlying the data allows constructing a system of equations, which is solved for the unknown parameters.

A very simple example is chosen to illustrate this method of moments further (following Kennedy, 2008, p.39; also Greene, 2003, p.535). Equation 6 represents a simple linear regression model with two unknown parameters. Two moment conditions are used to estimate the parameter values: Equation 7 specifies that the error term  $\epsilon$  has an expected value of zero. Equation 8 represents the assumption that  $\epsilon$  is independently distributed and not correlated with the exogenous variable, hence their product being zero.

$$y = \beta_1 + \beta_2 x + \epsilon \tag{6}$$

$$\Sigma(y - \beta_1^* - \beta_2^* x) = 0 \tag{7}$$

$$\Sigma(y - \beta_1^* - \beta_2^* x)x = 0 \tag{8}$$

In this simple case, equations (8) and (9) turn out to be the equations of the OLS estimator. In order for the method of moments to work, one needs at least as many moment conditions as parameters to be estimated. The *generalised* method of moments has been drawn up to also deal with cases where the number of moment conditions exceeds the number of parameters.

In this case, not all moment conditions can be met and the parameter estimates are therefore chosen to minimise the extent to which the total moment conditions are violated. After this general introduction, the next section introduces different GMM estimators, focusing on the specification used in the remainder of this paper.

#### **4.4.3 Applying the GMM estimator to dynamic panels**

This sub-section traces the development of applying the GMM estimator to dynamic panels in general terms and then introduces its application in the context of the present analysis.

##### **4.4.3.1 The general approach**

A sizable body of econometric literature over the last decades has analysed the nature of the bias introduced by the lagged dependent variable and developed estimation strategies to deal with it, whose fundamentals the previous section introduced. Bruno (2005b) and Roodman (2009b) provide overviews of the seminal papers and main estimators proposed. Anderson and Hsiao (1982) introduced the IV-style estimator along the lines represented above. It first transforms the model into first differences in order to eliminate unobserved cross-sectional heterogeneity. The lagged dependent variable that is among the regressors is instrumented by the second lag of the dependent variable either in levels or differenced form. Arellano and Bond (1991) introduced the GMM estimator for the first-differenced model so as to use additional internal instruments making it more efficient than Anderson and Hsiao's estimator. Blundell and Bond (1998) introduced a system GMM estimator that consists of a system of one equation in levels containing first-differenced instruments and one equation in differences containing levels instruments; the motivation underlying system GMM is to reduce a potential small sample bias of IV and GMM estimators in the presence of highly persistent data.

With respect to the size of the bias, a seminal paper by Nickell (1981) has shown that the bias is serious for small  $T$  and becomes less severe as  $T$  grows but has been shown to still be significant with  $T$  as large as 30 (Judson and Owen, 1999). Attanasio et al. (2000), on the other hand, advocate for considering simple OLS regressions given a “big enough” time dimension. From their panel study comprising 38 to 123 countries and 24 to 34 years, they conclude that OLS estimators making use of  $T$  asymptotics are to be preferred over instrumental variables (IV) techniques that have been designed for exploiting the  $N$



asymptotics in micro panels because the higher precision of OLS outweighs the drawbacks of the bias introduced by the lagged dependent variable.

Such evidence from Monte Carlo studies that cast doubt on the use of micro-econometric methods in the context of macro panels provided a motivation for developing the LSDVC estimator, proposed by Bruno (2005a) as an alternative way of dealing with the dynamic panel bias. The LSDVC estimator is based on the standard, uncorrected least squares dummy variable (LSDV) estimator, from which bias approximation estimates are subtracted. As Bruno (2005b) explains, consistent initial estimators are needed for the calculation of these bias approximation estimates<sup>42</sup> Bruno (2005b) furthermore provides Monte Carlo evidence comparing the different LSDVC estimators to the uncorrected LSDV and different GMM estimators. According to both bias and root mean square error criteria, the LSDVC estimator outperforms the others for samples with relatively few cross sections compared to their time dimension (samples considered had cross-section to time dimensions of 20 to 20 and 10 to 40). Given that the cross-section dimension in the sample at hand is clearly larger than the time dimension and for further reasons mentioned below, the preferred estimator employed here is GMM.

#### **4.4.3.2 Application in the present paper**

Before spelling out the econometric details of the analysis, further arguments to mention in favour of using GMM techniques in the present context are inconclusive unit root test results for the main variables of interest employing the tests developed by Maddala and Wu (1999) and Im et al. (2003). This could reduce the power of LSDVC estimations based on yearly data but in the GMM estimations, the use of five-year averages erodes the basis for such time-series concerns. The most important argument for using GMM estimation is, however, the fact that R&D spending is likely to be endogenous and in fact has been demonstrated as such in the analysis by Garrone and Grilli (2010). This approach is also in line with the treatment of foreign aid as endogenous in regressions estimating the impact of aid on energy and carbon intensities of developing economies in Kretschmer et al. (2013; also Chapter 5 of this dissertation).

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<sup>42</sup>The STATA routine `xtlsdvc` developed by Bruno (2005b) to implement the LSDVC estimator includes the GMM estimators by Anderson and Hsiao (1982), Arellano and Bond (1991) and Blundell and Bond (1998) as consistent initial estimators.

One might question additionally whether policy variables are exogenous or whether the levels of energy and carbon intensities actually determine policies. It can be safely argued, however, that most renewable energy policies in advanced countries are enacted as a response to a global concern, the threat of climate change, and can thus be considered exogenous. Furthermore, measures that are a response to multilateral action (EU, UNFCCC) are unlikely to be correlated with an individual country’s energy or emission intensities.<sup>43</sup> They are hence assumed exogenous variables in GMM estimations.

Some more specific remarks on the here chosen GMM techniques: I use the two-step difference GMM estimator introduced by Arellano and Bond (1991) implemented in STATA via the *xtabond2* command written by Roodman (2009b). A main contribution of this command compared to the standard *xtabond* command is the inclusion of Windmeijer-corrected standard errors for two-step estimation. The corrected standard errors by Windmeijer are important when it comes to using two-step GMM: As explained in Roodman (2009a), a singular weighting matrix in two-step estimation is likely to occur when the number of instruments approaches the number of cross sections. In that case, STATA makes use of the generalized matrix, which leaves the consistency of the parameter estimates unaffected but leads to downward-biased standard errors. The advent of Windmeijer’s (2005) robust standard errors reduces this problem. According to Roodman (2009b), making use of Windmeijer’s robust standard errors renders two-step estimation superior to one-step estimation, with lower bias and standard errors. With a larger  $T$  dimension and small cross-sectional dimension typical for macro panels, the number of instruments included in the estimations, increasing quadratically in  $T$ , becomes a critical issue. A large instrument count is associated with weak Sargan and Hansen J-tests that are used for testing the specification and more specifically the validity of instruments, frequently producing ‘perfect’ Hansen test-statistics of one (Roodman, 2009a). Given the limited number of time periods in the present setting due to the use of five-year averages, excessive instrument counts do not arise and the full set of instruments based on all available lags can be included.

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<sup>43</sup>Rather, efforts taken by countries could be correlated with GDP per capita. However, Table B.4 in Appendix B does not reveal any serious multicollinearity between GDP per capita and policy count variables and height of feed in tariffs and renewables obligations.

## 4.5 Estimation results

The first part of this section presents results for the original model specification as set out above generated with GMM estimation techniques. The subsequent section presents results for two separate robustness tests that introduce multiple policy variables and add control variables. The final section discusses the results in light of other research.

### 4.5.1 Core GMM estimations

This section describes in detail the results from estimations with the overall energy R&D ratio and the energy-efficiency targeted R&D ratio, as summarised in Tables 4.4 and 4.5, respectively. Appendix C (Table C.1) reports results from estimations with R&D targeted at low-carbon technologies. In these specifications, policy and R&D variables remain largely insignificant and these estimations therefore do not yield many insights. Appendix C further reports additional results focusing on voluntary measures in regressions with the energy intensity on the left-hand side and including the different R&D spending variables (Table C.2). In the following, I focus on Tables 4.4 and 4.5.

Turning to the description of the results: In all results tables, the numbering of specifications (column headings) indicates whether a certain specification includes the energy intensity (E) or the emission intensity (C) as the dependent variable (the different specifications are grouped into Panels A and B, respectively). Throughout the performed estimations, instruments for the lagged differences of the dependent variable include all available lagged levels of the dependent variable (from  $y_{it-2}$  onwards). The same holds for the R&D variables. The test statistics demonstrate in most cases instrument validity as well as reasonable instrument counts.

Looking at the results for the overall energy R&D ratio in Table 4.4: Energy R&D significantly reduces energy intensity in specification E3 including the stringency of a renewable energy obligation scheme. Given the log-linear model specification, coefficients can be interpreted as elasticities: As an example, a one per cent increase in the energy R&D ratio in specification E3 reduces the energy intensity by about 0.03 per cent; or put differently, a doubling of R&D efforts (i.e. a 100 per cent increase) is needed to reduce the energy intensity by about 3.2 per cent. Taking into account the coefficient of the lagged dependent variable,

the long-run effect of doubling R&D efforts can be calculated, amounting to 5.2 per cent.<sup>44</sup> Energy R&D fails to reduce significantly energy intensity in the other specifications and neither reduces emission intensities. In some of the specifications with the energy intensity as the dependent variable, the coefficient for energy R&D is close to significance at the 10 per cent level (E1, E5 and E6). Even so, these results do not represent robust evidence for the hypothesis that energy R&D spending reduces energy and emission intensities.

A further hypothesis put forward was that the significance and size of the effect of R&D spending is conditional on the presence of demand-pull policies. There is, however, no robust increase in coefficients or t-statistics due to the inclusion of policy variables across the different specifications. The one specification where energy R&D spending is significant is E3 controlling for the stringency of a renewable energy obligation scheme, but this alone cannot be interpreted as robust evidence supporting the hypothesis. Looking at the effect of policies in their own right, Table 4.4 shows that in emission intensity specifications C4 and C6 investment incentives for renewable energy and all renewable energy measures summed together significantly reduce the emission intensity. This finding gives some support to the hypothesis of expecting a reduction of the emission intensity in the presence of renewable energy policies. However, also in the energy intensity specifications, it is renewable energy rather than energy efficiency measures that display the highest t-statistics (feed-in tariff and renewable energy investment support, i.e. specifications E2 and E4). The policy variables targeting energy efficiency (E7 to E9 and C7 to C9) neither turn out significant nor influence the effectiveness of R&D spending.

Looking at other control variables: The inertia in the lagged dependent variables is much less pronounced than in unreported LSDVC regressions based on yearly data. While the lagged energy intensity is highly significant, the lagged emission intensity is not significant. GDP per capita robustly reduces energy and emission intensities and turns out highly significant in most specifications. This confirms the hypothesis that higher GDP per capita as a proxy for productivity levels goes along with more energy efficient and cleaner technologies and hence reduced energy and emission intensities. As an example, a one per cent increase in GDP per capita leads to reductions in energy and emission intensities of up to 0.40 and

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<sup>44</sup>This is calculated as  $\beta_2/(1 - \beta_1)$ , where  $\beta_1$  and  $\beta_2$  are the coefficients of the lagged dependent variable and the R&D variable, respectively (see equation 1 above).

0.64 per cent, respectively. The energy price index generally reduces energy and emission intensities, again confirming the previously formulated hypothesis that, all else equal, higher energy prices make energy less and other factors of production more attractive hence reducing an economy's energy and (though to a less robust extent) emission intensity. The size of the coefficients of the energy price index is generally smaller than the coefficients preceding GDP per capita. Across all specifications in Table 4.4, the coefficients translate into a reduction of the respective dependent variable of between 0.11 and 0.29 per cent for a one per cent increase in the energy price index and a reduction between 0.22 and 0.64 per cent for a one per cent increase in GDP per capita. It hence appears that the state of development of an economy (as expressed by its GDP per capita level) is a more important determinant of energy and emission intensities than the development of the energy price index.

Having said this, there are some anomalies in specifications E6 as well as C4, C6 and C9, in the sense that the energy price index is no longer significant. In addition, no variables remain significant in specification E6. All of these specifications apart from C4 include policy variables representing the count of all renewable energy or energy efficiency measures. C4 includes the policy variable representing renewable energy investment incentives instead. Several observations emerge that could form part of the explanation: In C4 and C6, the respective policy variables are significant, potentially 'taking away' explanatory power of the energy price index. In other words, it could be policy measures rather than energy price signals that trigger the adoption of technologies that save energy and emissions.<sup>45</sup> The same does not hold for specifications E6 and C9, though t-statistics of the policy variables in those specifications are higher than in some of the remaining ones. This observation is also valid for Table 4.5 (and to a lesser extent for Table C.1, where the policy variable is only significant in specification C4). Furthermore, the specifications scrutinised here are characterised by rather low p-values of the Hansen J-test, a test for overall instrument validity. In particular, the p-value of the Hansen test is lowest in E6 among all energy intensity specifications and lowest for C4, C6 and C9 among all emission intensity specifications. This does not hold in an equally robust way for Table 4.5. Nevertheless, at least the Hansen test statistic for specification E6 is at the low end in Table 4.5.<sup>46</sup> Weak instruments and hence a weaker model

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<sup>45</sup>Though in a different context, this observation would be in line with the finding of Johnstone et al. (2010) that it is policies rather than prices that trigger innovation activity in the energy sector.

<sup>46</sup>This observation holds to some extent for Table C.1 as well, where the p-values for the Hansen test are

specification could form part of the explanation for the diverging results, though it is not clear how this came about in the first place.

Turning to the results from estimations including R&D spending targeted at energy efficiency: Table 4.5 confirms the hypothesis that energy efficiency targeted R&D spending is more likely to explain energy intensities than emission intensities and has greater explanatory power than overall R&D spending. The R&D variable is significant in several specifications including the baseline specification E1. However, total energy R&D spending (Table 4.4) mostly displays larger coefficients in the energy intensity specifications. This is different in the emission intensity specifications, where the coefficients of targeted R&D spending are higher compared to those of overall R&D spending (though both are insignificant at conventional levels). While energy efficiency targeted R&D spending is never significant in regressions with the emission intensity as the dependent variable, in columns C2 to C9 (with the exception of C5) both its coefficient and t-statistic increase in the presence of policies.

The largest significant effect of energy efficiency R&D spending is found in specification E3 (including the renewable energy certificate share): An increase in R&D spending of one per cent reduces the energy intensity by 0.03 per cent, or in other words a rather small reduction of 2.9 per cent results from a doubling of R&D spending. The long run effect is also highest in specification E3 and equal to a reduction of 4.7 per cent for a doubling of R&D spending. Focusing further on the left hand panel of Table 4.5, the presence and height of renewable obligations strengthens the coefficient and t-statistic of R&D spending, as it did in Table 4.4 for the overall R&D spending ratio. The same holds for financial renewable energy incentives and the sum of renewable energy measures (here the significance remains stable). In the presence of investment incentives and the sum of energy efficiency measures, on the other hand, R&D spending loses its significance. These results can be seen as some tentative, yet mixed evidence supporting the hypothesis that the effectiveness of R&D spending increases in the presence of policies. On the effect of the policy measures themselves: The results are similar to those in Table 4.4: None of the policies is significant in the energy intensity estimations but again renewable energy investment policies and the sum of all renewable energy policies reduce emission intensities.

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below or just above 0.10 in several specifications, indicating weak instruments and potentially explaining the lack of insights from these estimations.

Other control variables perform similarly as in Table 4.4. This also holds for the loss of significance in the energy price index in specifications E6, C4, C6, C7 and C9. Potential explanations have been proposed above already. Results for specification E6 are somewhat different to the same specification in Table 4.4 in the sense that the lagged dependent variable and R&D spending remain significant while GDP per capita and the energy price index turn out insignificant.

A few remarks highlighting the main findings from the estimations summarised in Tables C.1 and C.2 in Appendix C. As previously mentioned, Table C.1 shows that R&D spending targeted at low-carbon technologies fails to reduce energy and emission intensities throughout all specifications. Results for other variables are largely similar to what has been found in estimations including the other R&D spending variables as discussed above. Turning to Table C.2 in Appendix C focusing on voluntary measures: Somewhat surprisingly, while the policy variables themselves all turn out insignificant, total R&D spending enters significantly in energy-intensity estimations including voluntary measures targeted at renewable energy, energy efficiency and climate mitigation, respectively. Energy-efficiency R&D remains significant in Columns E7 and E9 (renewables and climate voluntary measures). The same does not hold for estimations with the emission intensity as the dependent variable.

Final remarks on the effect of the policy variables: Apart from what has been mentioned in the previous paragraphs, I highlight the negative relationship between investment incentives for renewable energy and the count of all renewable measures with emission intensities. While not rendering R&D spending effective, their presence does increase the respective coefficients of the R&D variables (and mostly their t-statistics as well). It is apparent that energy efficiency measures do not turn out significant. This can be explained by energy efficiency measures often being of a more soft nature without ‘hard’ and binding targets, exemplified by the situation in the EU where binding renewable energy targets exist but no equivalent for energy efficiency.

Table 4.4: Results from Difference GMM estimations – total energy R&D

<i>Dependent var.</i>	(E1)	(E2)	(E3)	(E4)	(E5)	(E6)	(E7)	(E8)	(E9)
<i>Panel A: log(energy intensity)</i>									
log(LDV)	0.516*** (4.21)	0.394*** (3.50)	0.377*** (2.97)	0.404* (1.77)	0.504*** (4.21)	0.355 (1.48)	0.530*** (4.24)	0.503*** (3.83)	0.550*** (4.80)
log(GDP per capita)	-0.286*** (-3.22)	-0.395*** (-4.34)	-0.395*** (-5.38)	-0.223* (-1.92)	-0.296*** (-3.14)	-0.235 (-1.64)	-0.268*** (-3.12)	-0.308*** (-2.85)	-0.312*** (-3.79)
log(energy price)	-0.162*** (-2.81)	-0.210*** (-3.19)	-0.207*** (-3.21)	-0.118* (-1.73)	-0.172** (-2.76)	-0.114 (-1.30)	-0.166* (-2.06)	-0.168** (-2.78)	-0.197** (-2.68)
Lagged log(energy R&D ratio)	-0.0213 (-1.70)	-0.0194 (-1.14)	-0.0323** (-2.14)	-0.0292 (-1.47)	-0.0214 (-1.61)	-0.0338 (-1.68)	-0.0163 (-1.44)	-0.0154 (-1.09)	-0.0140 (-1.46)
Feed-in tariff		0.392 (1.20)							
RE certificate share			-0.383 (-0.55)						
Investment RE				-0.0191 (-1.34)					
Financial RE					0.00975 (0.36)				
Sum RE measures						-0.0112 (-1.03)			
Investment EE							0.00113 (0.15)		
Financial EE								0.00747 (0.81)	
Sum EE measures									0.00244 (1.08)
N	82	78	79	82	82	82	82	82	82
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.73	3.71	3.76	3.73	3.73	3.73	3.73	3.73	3.73
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.192	0.646	0.779	0.908	0.222	0.808	0.160	0.341	0.134
Number of instruments	14	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.258	0.386	0.200	0.165	0.241	0.139	0.234	0.304	0.348
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.192	0.611	0.236	0.141	0.311	0.199	0.223	0.371	0.511



<i>Dependent var.</i>	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)	(C9)
	<i>Panel B: log(emission intensity)</i>								
log(LDV)	0.166 (1.61)	0.149 (0.85)	0.123 (0.73)	0.143 (0.97)	0.140 (0.98)	0.0879 (0.66)	0.143 (1.07)	0.170 (1.51)	0.101 (0.59)
log(GDP per capita)	-0.586*** (-4.11)	-0.640*** (-4.13)	-0.642*** (-3.38)	-0.488** (-2.36)	-0.612*** (-3.79)	-0.480** (-2.40)	-0.587*** (-3.84)	-0.577*** (-4.27)	-0.557*** (-3.83)
log(energy price)	-0.247*** (-3.07)	-0.287*** (-3.08)	-0.240** (-2.26)	-0.142 (-1.62)	-0.255** (-2.54)	-0.111 (-1.06)	-0.206* (-1.93)	-0.243** (-2.65)	-0.160 (-1.25)
Lagged log(energy R&D ratio)	-0.0128 (-0.41)	-0.00543 (-0.17)	-0.0164 (-0.50)	-0.0153 (-0.43)	-0.0111 (-0.35)	-0.0234 (-0.62)	-0.0227 (-0.74)	-0.0147 (-0.47)	-0.0275 (-0.81)
Feed-in tariff	0.512 (0.94)								
RE certificate share			-0.272 (-0.20)						
Investment RE				-0.0205* (-2.05)					
Financial RE					0.00115 (0.02)				
Sum RE measures						-0.0162* (-1.79)			
Investment EE							-0.00572 (-0.55)		
Financial EE								-0.00733 (-0.21)	
Sum EE measures									-0.00505 (-1.08)
N	80	76	77	80	80	80	80	80	80
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.64	3.62	3.67	3.64	3.64	3.64	3.64	3.64	3.64
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.283	0.292	0.282	0.322	0.275	0.416	0.336	0.293	0.337
Number of instruments	14	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.208	0.118	0.147	0.102	0.199	0.094	0.164	0.223	0.133
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.678	0.638	0.815	0.774	0.473	0.731	0.721	0.843	0.952

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ ; LDV denotes lagged dependent variable

Table 4.5: Results from Difference GMM estimations – energy efficiency targeted R&D

<i>Dependent var.</i>	(E1)	(E2)	(E3)	(E4)	(E5)	(E6)	(E7)	(E8)	(E9)
<i>Panel A: log(energy intensity)</i>									
log(LDV)	0.525*** (4.25)	0.397** (2.66)	0.385** (2.77)	0.409* (1.94)	0.518*** (4.94)	0.404* (1.86)	0.527*** (3.83)	0.523*** (4.23)	0.573*** (5.17)
log(GDP per capita)	-0.262*** (-4.07)	-0.380*** (-3.01)	-0.356*** (-3.60)	-0.187 (-1.67)	-0.269*** (-4.29)	-0.200 (-1.64)	-0.259*** (-3.16)	-0.285*** (-3.18)	-0.305*** (-3.76)
log(energy price)	-0.153** (-2.78)	-0.198** (-2.65)	-0.187** (-2.64)	-0.111* (-1.78)	-0.159*** (-3.08)	-0.114 (-1.54)	-0.157** (-2.11)	-0.160*** (-2.88)	-0.189** (-2.67)
Lagged log(energy-efficiency R&D ratio)	-0.0157* (-1.91)	-0.0178 (-1.30)	-0.0286** (-2.23)	-0.0233 (-1.59)	-0.0162** (-2.17)	-0.0225* (-1.84)	-0.0142 (-1.51)	-0.0112 (-1.24)	-0.0109 (-1.38)
Feed-in tariff	0.351 (1.19)								
RE certificate share			-0.393 (-0.49)						
Investment RE				-0.0198 (-1.42)					
Financial RE					0.00749 (0.27)				
Sum RE measures						-0.00980 (-1.27)			
Investment EE							0.000657 (0.09)		
Financial EE								0.00731 (0.95)	
Sum EE measures									0.00225 (0.91)
N	82	78	79	82	82	82	82	82	82
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.73	3.71	3.76	3.73	3.73	3.73	3.73	3.73	3.73
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.101	0.486	0.881	0.752	0.092	0.663	0.127	0.199	0.095
Number of instruments	14	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.322	0.288	0.230	0.154	0.320	0.164	0.300	0.370	0.395
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.472	0.407	0.421	0.125	0.654	0.307	0.605	0.386	0.835

<i>Dependent var.</i>	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)	(C9)
<i>Panel B: log(emission intensity)</i>									
log(LDV)	0.198 (1.34)	0.123 (0.56)	0.114 (0.59)	0.126 (0.92)	0.174 (0.89)	0.0708 (0.55)	0.157 (0.89)	0.201 (1.29)	0.129 (0.70)
log(GDP per capita)	-0.553*** (-3.88)	-0.654*** (-3.85)	-0.652*** (-3.02)	-0.459* (-1.74)	-0.582*** (-3.23)	-0.455* (-1.83)	-0.588*** (-3.50)	-0.547*** (-4.23)	-0.540*** (-3.03)
log(energy price)	-0.226*** (-3.97)	-0.275** (-2.67)	-0.214** (-2.41)	-0.109 (-1.25)	-0.234*** (-3.15)	-0.0785 (-0.85)	-0.189 (-1.69)	-0.229*** (-3.57)	-0.123 (-0.92)
Lagged log(energy-efficiency R&D ratio)	-0.0141 (-0.59)	-0.0185 (-0.80)	-0.0262 (-1.23)	-0.0307 (-1.19)	-0.0143 (-0.58)	-0.0353 (-1.32)	-0.0275 (-1.05)	-0.0147 (-0.63)	-0.0375 (-1.31)
Feed-in tariff	0.550 (1.07)								
RE certificate share			-0.444 (-0.32)						
Investment RE				-0.0282** (-2.30)					
Financial RE					0.00182 (0.02)				
Sum RE measures						-0.0194* (-2.02)			
Investment EE							-0.00678 (-0.51)		
Financial EE								-0.00460 (-0.15)	
Sum EE measures									-0.00618 (-1.05)
N	80	76	77	80	80	80	80	80	80
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.64	3.62	3.67	3.64	3.64	3.64	3.64	3.64	3.64
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.322	0.286	0.275	0.361	0.307	0.459	0.341	0.314	0.385
Number of instruments	14	15	15	15	15	15	15	15	15
Hausen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.219	0.120	0.206	0.146	0.209	0.175	0.175	0.229	0.160
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.810	0.355	0.398	0.358	0.697	0.635	0.642	0.918	0.828

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  \*\*\*; LDV denotes lagged dependent variable

#### 4.5.2 Robustness checks

A first robustness test includes **multiple policies**. It could be argued that this is a more realistic setting as policies targeted at different energy variables frequently coexist in the real world. Policies were included one by one in the main regressions above in order to understand better the effect of individual policies. Table C.3 in Appendix C reports the results. Results on R&D variables are robust to the inclusion of multiple policy variables. Where total R&D was significant in energy intensity estimations, it remains so with further policies accounted for (Panel A). Robust, however, also means that the performance of R&D spending in emission intensity estimations does not improve and remains insignificant throughout. The same holds for the estimations including energy efficiency targeted R&D in Panel B of Table C.3. One observation to point out is that the inclusion of multiple policy variables tends to rather increase than decrease the t-statistics of the R&D variable, comparing for instance columns (C4) and (C6) in Table C.3 to column (C3) in Table 4.5. Results are furthermore robust for estimations including R&D spending targeted at low-carbon technologies (Panel C).

Another robustness check includes **additional control variables** to the econometric model. I start out by adding industrial value added as a share of GDP. As in Kretschmer et al. (2013) this serves to capture changes in the composition of the economy acknowledging that the industrial sector is likely to be more energy intensive than activities in the agricultural and services sector. In another set of estimations, I include the investment ratio (gross fixed capital formation as a percentage of GDP). Enhanced investment activity could lead to a more rapid replacement of the capital stock and thus could imply a shift towards a more efficient production structure. This is at least an effect that would be expected for OECD countries, where industrialisation has generally started prior to the beginning of our estimation period in 1976 hence subsequent investment is likely to indeed renew the existing capital stock instead of newly introducing energy-intensive industry, which could be associated with higher energy and emission intensities. I finally include both the industry share and the investment ratio in the estimations.

It turns out that the previous results are sensitive to accounting for changes in the sectoral structure of the economies and more importantly for investment. The significance of R&D spending and of policy variables remains in some of the estimations involving the industry share, but not in all. This is even though the industry share itself remains insignificant

throughout.<sup>47</sup> R&D spending is insignificant in all emission intensity estimations as before, however, here the inclusion of the industry share increases coefficients (they mostly decrease in energy intensity regressions) as well as t-statistics, which remain low nevertheless. The inclusion of the investment ratio influences results more significantly (see Table C.4). Investment as a share of GDP displays a significant negative relationship with energy intensity while it is insignificant (but also negative) in emission intensity estimations. When accounting for investment, R&D spending is never significant anymore. Including both the investment ratio and the industry share simultaneously implies that the investment ratio is no longer significant in most cases. As before, R&D spending and most policy variables are insignificant.

### 4.5.3 The results in perspective

This section serves to put the results reported in the previous sections into the context of related studies. Similar to the results that this study arrived at, Garrone and Grilli (2010) find that energy R&D spending influences the energy efficiency but not the emission intensities of a sample of OECD economies. R&D spending targeted at energy efficiency and low-carbon technologies does not alter this pattern in either study. These results hold across the two studies despite the difference in the data set: Garrone and Grilli work with a smaller data set of 13 countries spanning 25 years compared to 23 countries and 31 years in the present analysis. They also hold despite the differences in defining the R&D variables. While the present analysis uses R&D to GDP ratios in order to control for the size of the economies, Garrone and Grilli (2010) use absolute R&D spending in their bivariate analysis, hence leaving country size uncontrolled. This latter difference implies that a comparison between sizes of coefficients in the two studies is meaningless. Garrone and Grilli (2010) offer additional results on reverse causality and point out that both the emission and energy intensities positively granger-cause energy R&D spending. They consequently interpret that “energy R&D budgeting is critically exposed to political pressure [...] and consequently deserves greater monitoring and evaluation efforts” (p.5610).

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<sup>47</sup>On the sign of the (albeit insignificant) coefficients: The industry share is largely preceded by a negative sign in energy-intensity estimations (unlike what was expected) while its sign is largely positive in emission-intensity estimations. This changes when I take into account the investment ratio simultaneously; in these estimations, the industry share, while still remaining insignificant throughout, turns positive in almost all estimations for both dependent variables.

Similar to the present results though in a different context, Kretschmer et al. (2013) find that foreign aid has some power to reduce energy intensities of developing economies but fails to reduce the carbon intensity of energy supply, i.e. the carbon factor. While the developing-country context is arguably specific and among others goes along with utterly different energy mixes, the studies offer similar explanations for this pattern of results. Garrone and Grilli (2010) point out that the inability of energy R&D to influence emission intensities is due to its inability to influence the carbon factor. Unreported regressions undertaken in the present analysis confirm this inability. Garrone and Grilli (2010) explain this with the greater uncertainty of research programmes targeted at low-carbon technologies, “a field where the design of policies complementary to public energy R&D is especially challenging” (p.5607) and “accompanying measures (i.e. policies oriented to diffusion and deployment, a sharper design of energy R&D budgets, a continuous assessment of research programmes” (p.5610) are crucial alongside R&D investment. Likewise, Kretschmer et al. note that the “incentives for emission savings could be strengthened through a carbon price, and possibly also through a better targeting of financial and technological assistance” (2013, p.86).

As mentioned earlier, some of the policy variables have been adopted from Johnstone et al. (2010). Given the different research question at hand in their study (the impact of R&D expenditure and renewable energy policies on patent applications for different low-carbon technologies), a comparison between their results and those generated here is hardly possible. An interesting result from their study is that “policy, rather than prices, appears to be the main driver of innovation” in low-carbon technologies (p.146). In other words, their market related variables electricity price and growth of electricity consumption turn out insignificant. This is different to the present results. In the context of economy-wide energy and carbon intensities, market factors such as the energy price index as well as economic development as represented by GDP per capita play a very important role. Their dominant role is likely to explain some of the failure to detect longer-term effects from energy R&D spending, a result that extends the bivariate analysis by Garrone and Grilli (2010).

As their analysis is disaggregated according to different low-carbon technologies, Johnstone et al. (2010) can furthermore identify differences in the impacts of renewable energy policies on different technologies. They find that the effectiveness of policies depends on the relative cost of a technology: As an example, renewable energy targets, a measure that usu-

ally does not distinguish between technologies, favour low-cost technologies while specifically designed feed-in tariffs allow for innovation in high-cost technologies as well. While this exact distinction is not relevant in the context at hand, the concluding section stresses the merits of a more disaggregated analysis.

## 4.6 Conclusions

This paper empirically analyses the effect of energy R&D spending on energy and emission intensities in OECD countries, accounting for the presence of policies targeted at renewable energy, energy efficiency and climate change. I find some evidence for energy R&D spending to reduce energy intensities but not emission intensities in the 23 OECD countries considered and over the years 1977 to 2006. The negative effect on energy intensities is primarily found in estimations using energy-efficiency targeted R&D spending whose effect becomes stronger and/or more significant in the presence of renewable energy policy measures. R&D spending targeted at low-carbon technologies shows negative coefficients throughout but fails to pass conventional significance levels in all estimations.

A focus of the analysis was whether the inclusion of policy measures targeted at energy and climate outcomes would improve the effectiveness of R&D spending according to theoretical work that technology-push measures such as R&D spending would need to be accompanied by market creation policies. In some instances, the introduction of policy variables does indeed render R&D spending significant (or increases t-statistics without R&D becoming significant) and/or increases the size of its coefficients. While this provides some empirical evidence supporting the theoretical work on the interplay of technology-push and demand-pull measures, this result is not robust across all estimations. Another conclusion is that it was almost exclusively policies targeted at renewable energy wielding this effect, such as the minimum percentage of renewable energy certificates as part of obligation schemes, investment and other financial incentives for renewables and the sum of all renewable energy measures. Surprisingly, while voluntary measures remained largely insignificant, their presence made the reducing effect of the total R&D spending ratio on energy intensities significant in a robust way.

Speaking of the significance of policy measures themselves, it is again renewable energy measures rather than energy efficiency measures that turn out significant, especially the al-

ready mentioned minimum percentage of renewable energy certificates as part of obligation schemes, investment incentives and the sum of all renewable energy measures. Speaking of further control variables, both GDP per capita and energy prices show a largely robust negative relationship with energy and emission intensities. The lagged dependent variable is significant in energy intensity estimations but not in estimations explaining emission intensities.

The results prove to be largely robust to including multiple policy measures in the regressions. They turned out to be sensitive, however, to the inclusion of the industry share and more so of the investment ratio. This second robustness check could be interpreted as pointing out the difficulty of using R&D spending as an explanatory variable in an econometric analysis because of its long lead times in having an effect whereas the effect of investment in capital formation is much easier to detect.

Future research could be undertaken to tackle the present failure of providing more compelling evidence for the effectiveness of R&D spending in the presence of policy measures. Given the availability of a fine disaggregation of public R&D spending data according to individual objectives and technologies, the obvious next step would be to also have sectoral data on the left hand side of the estimations. In that way, one could try, for instance, to explain the effect of energy efficiency spending targeted at the residential sector on the energy performance of buildings in the presence of policy measures supporting energy efficient renovation. Likewise, the emission intensity of the power sector would be an obvious choice for a sectoral dependent variable. The lack of precision of an aggregate, country-level analysis as the present one is all the more relevant in a context where policy variables are used, which might be very targeted in nature and only applicable to narrow sectors. While the approach of counting the number of measures under one category has been put forward as a way of at least capturing the variety of measures applied to all sectors in one policy variable, the policy variables here are unweighted sums of measures. Subsequent analysis could improve this aspect by weighting policies according to the size of the sector they are targeted at and the budgeted size of the policy, where applicable.

Another limitation concerning the construction of the policy variables database is a degree of inherent subjectivity or impreciseness associated with allocating policies to different categories. In addition, the databases used for the construction of policy variables give no indication about the effectiveness in implementing the policy measures and so aspects such as



poor management of certain policy measures cannot be captured by assigning them a lower weight.

Finally, the availability of longer time series would allow covering the most recent years, a period that was at least in EU countries characterised by the emergence of much more coherent sets of policy measures to foster renewable energy as a response to the obligations imposed by the Renewable Energy Directive.<sup>48</sup> It will hence be interesting to see whether R&D spending can be demonstrated to be more effective in the presence of a closer network of market creation policies in the future.

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<sup>48</sup>Reporting on the progress made by Member States, the Commission states that the introduction of binding targets has triggered a pronounced increase in the efforts made by Member States. Communication COM(2011) 31 final from the Commission to the European Parliament and the Council of 31 January 2011: Renewable Energy: Progressing towards the 2020 target.

## 5 Does Foreign Aid Reduce Energy and Carbon Intensities of Developing Economies?<sup>49</sup>

### Full citation

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### Abstract

*Advanced OECD countries are widely held responsible for containing global carbon emissions by providing financial and technical support to developing economies where emissions are increasing most rapidly. It is open to question, however, whether more generous official development assistance would help fight climate change effectively. Empirical evidence on the effects of foreign aid on energy and carbon emission intensities in recipient countries hardly exists. We contribute to closing this gap by considering energy use and carbon emissions as dependent climate-related variables and the volume and structure of aid as possible determinants. In particular, we assessed the impact of aid that donors classify to be specifically related to energy issues. We performed dynamic panel Generalised Method of Moments and Least Squares Dummy Variable Corrected estimations. We found that aid tends to be effective in reducing the energy intensity of GDP in recipient countries. All the same, the carbon intensity of energy use is hardly affected. Scaling up aid efforts would thus be insufficient to fight climate change beyond improving energy efficiency.*

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<sup>49</sup>This Chapter has been written jointly with Michael Hübler (now Centre for European Economic Research, ZEW) and Peter Nunnenkamp (Kiel Institute for the World Economy). An identical version (apart from some small edits and layout changes) is published in the *Journal of International Development* as Kretschmer et al. (2013). We would like to thank Michaela Rank and Stephan Baier for most helpful assistance in collecting the data. Several colleagues provided kind support and advice with respect to methods and data issues, including Axel Dreher, Holger Görg, Matthias Hartmann, Dierk Herzer and Sebastian Petrick. My contribution was to help in spelling out the econometric model; to do most of the data collection and preparation; to devise the estimation strategy, especially with regard to the choice of appropriate estimators (with advice from my co-authors); to perform all estimations; and to contribute to the interpretation and writing up of results.

## 6 Conclusions

The research conducted in the framework of this dissertation contributes to the evidence base on the effect of different policies including biofuel support mechanisms, public energy R&D spending and foreign aid on the decarbonisation of energy supply. In particular, the analyses have responded primarily to three key research questions derived from the energy-climate nexus and the twin challenges of securing energy supply while decarbonising our economies. These are 1) understanding the macroeconomic impacts of promoting energy-saving and low-carbon technologies, here the impacts of promoting EU biofuel use up to the year 2020; 2) understanding the effectiveness of public support mechanisms in decarbonising economies, here the effectiveness of past public energy R&D spending in the presence of energy and climate policies in OECD countries; and 3) understanding the way in which developed countries can contribute to decarbonising the economies of developing countries by means of foreign aid.

The analyses presented here are examples of both ex-ante (Chapters 2 and 3) and ex-post (Chapters 4 and 5) policy evaluation. Both forms of policy evaluation are important to draw lessons for designing effective policy measures and also to understand and eventually mitigate potential unintended side effects. EU policy in the field of biofuels is a good example for highlighting this need for evidence-based policy-making: ex-ante analyses were either not (well) conducted or not considered and have consequently failed to highlight the inherent risks the policy entails in terms of increased land use competition, land use emissions and higher agricultural commodity prices.

**Chapter 2** has reviewed different ways of modelling biofuel technologies in economic CGE models, aiming to contribute to the ongoing improvements in models that will in turn allow for better ex-ante modelling of the effects of policies. It distinguished three types of biofuel modelling approaches, an “implicit approach”, a “latent technology approach” and an approach consisting of disaggregating the underlying data structure of CGE models, the social accounting matrix. The studies reviewed yield a wide range of results, suggesting that crucial assumptions need to undergo continued ‘reality checks’ to narrow this range. Further improvements in modelling were expected to be made with better data availability and in fact this and considerable attention and resources devoted to the modelling of biofuel policies have advanced the research considerably over the past years since the time of writing.

Especially the land use components of economic models have improved, an improvement need that was particularly stressed by Kretschmer and Peterson (2010). Another improvement still outstanding is the modelling of second-generation biofuel technologies that make use of a broader feedstock basis (including for example forest and agricultural residues). These biofuels are hoped to reduce some of the negative impacts of first-generation biofuels, most notably (indirect) land use change and associated emissions, but in fact, their potential to do so is as of yet neither well understood nor studied. Even so, there are calls from industry and civil society for specific support measures for these fuels, which goes against the aim of gathering the evidence before adopting policy measures.

**Chapter 3** built on an extended version of the CGE model DART to analyse the economic effects of a 10 per cent biofuel blending share in the EU in different scenarios including emission mitigation targets and varying shares of renewable electricity. Given assumed technology cost parameters and the development of carbon prices (endogenous in DART), it was found that EU emission targets alone trigger only minor increases in biofuel production as biofuel technologies remain largely uncompetitive making targeted subsidies necessary to reach a 10 per cent biofuel share. One focus of the analysis were the agricultural market impacts and in particular the impacts on commodity prices. Significant price effects were found with average EU agricultural sector prices increasing by up to 7 per cent in the biofuel scenarios in 2020 compared to a reference scenario (up to 3.5 per cent for world agricultural prices). The results of the welfare analysis yield the interesting observation of lower welfare losses, compared to the reference scenario, in a scenario with a 10 per cent biofuel and a moderate renewable electricity share than in a scenario with no biofuel target but a higher (30 per cent) renewable electricity share. However, it also concluded that in the presence of biofuel targets worldwide, greater distortionary effects from biofuel promotion leading to larger welfare losses as well as larger increases in world agricultural prices would be expected. A policy implication that emerges from this paper is the need for a better understanding of the cost-effectiveness and welfare implications of the renewable energy mix especially when thinking about future, higher renewable energy targets. Such analysis needs to take into account the actual amount of emissions saved by different renewable options. This is especially relevant in the case of bioenergy and its associated land use and land use change emissions.

The analysis of the impact of energy R&D spending in OECD countries in **Chapter 4**

yields some evidence of energy R&D spending having been effective in reducing energy but not emission intensities. The further disaggregation of energy R&D spending shows that the negative effect on energy intensities is primarily found in estimations using energy-efficiency targeted R&D spending. This effect becomes stronger and/or more significant in the presence of renewable energy policy measures. R&D spending targeted at low-carbon technologies has not significantly reduced energy or carbon intensities. Some, but no robust empirical evidence was found supporting the importance of demand-pull measures for R&D spending to be effective as suggested by theoretical work. Where policies have increased the size or significance of the effect of R&D on energy intensities, these were almost exclusively renewable energy and not energy efficiency policies. Future research that would readdress the questions within a sectoral analysis would be useful for refining the results reached here. The result that renewable energy measures are found to be better suited to enhance or allow for the effectiveness of R&D spending suggests that energy efficiency considerations need to figure more prominently in energy policy making. This, for instance, could result in the adoption of energy efficiency targets along with renewable energy targets.

The analysis of foreign aid to reduce energy and carbon intensities in developing economies (**Chapter 5**) suggested a modest contribution of total aid inflows to reducing energy intensities in recipient countries. On the other hand, aid did not turn out to be effective in reducing carbon intensities. Sectoral aid data were used accounting for aid targeted at the energy and the industrial sector. The main results for total aid also hold for energy aid, while aid for the industrial sector turns out to be ineffective. The main caveat of the results relates to the fungibility of aid or in other words the potential that recipients may redirect domestic funds away from the energy sector as a consequence of donors targeting this sector, which could (partly) explain the lack of effectiveness of foreign aid to improve energy and carbon intensities. The small contribution of aid inflows to reducing energy intensities suggests that policy makers both in recipient and donor countries should conceive of aid as complementing domestic (i.e. recipient countries') policies for improving energy efficiency and preventing wasteful use of energy (as for instance triggered by fossil fuel subsidies). Policy making could strengthen the incentive for emission savings through the introduction of carbon pricing and better targeting of financial and technological assistance, for example in the framework of the Green Climate Fund. The fact that energy sector aid leaves the results qualitatively

unchanged calls for a more targeted approach of rigorously redirecting aid to renewable energy and energy efficiency funding and/or even identifying concrete projects with large and cost-effective energy and emission saving potentials.

The continued analysis of different mechanisms to foster renewable energy deployment and reduce energy and carbon intensities is important, especially given the continued failure to reach a binding international agreement to contain climate change. In the meantime and in parallel to the top-down, multilateral UNFCCC process, individual countries and regions such as the EU have imposed or are in the process of imposing decarbonisation targets. This suggests a gradual shift towards a bottom-up approach to climate change mitigation (see for instance Carraro and Egenhofer, 2007). In the time until 2020 when a global agreement is hopefully agreed and operationalised, domestic climate and energy policy, including the elements studied in this dissertation, will be crucial to avoid carbon lock-in effects due to carbon-intensive investments in emerging economies. The results of the research presented here ideally contribute to the design of effective policy measures facilitated by a better understanding of anticipated impacts as well as by monitoring their effectiveness once implemented.

## References

- Anderson, T. W. and C. Hsiao (1982). Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics* 18(1), 47–82.
- Arellano, M. and S. Bond (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58 (2), 277–297.
- Attanasio, O.P., L. Picci and A.E. Scorcio (2000). Saving, Growth, and Investment: A Macroeconomic Analysis Using a Panel of Countries. *Review of Economics and Statistics* 82(2), 182–211.
- Blundell, R. and S. Bond (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* 87(1), 115–143.
- Bruno, G.S.F. (2005a). Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models. *Economics Letters* 87(1), 361–366.
- Bruno, G.S.F. (2005b). Estimation and Inference in Dynamic Unbalanced Panel Data Models with a Small Number of Individuals. *Stata Journal* 5(4), 473–500.
- Carraro, C. and C. Egenhofer (eds.) (2007). Climate and Trade Policy: Bottom-up Approaches Towards Global Agreement. ESRI studies series on the environment. Edward Elgar, Cheltenham, USA and Northampton, USA.
- Edwards, R., Mulligan, D. and Marelli, L. (2010). Indirect Land Use Change from increased biofuels demand: Comparison of models and results for marginal biofuels production from different feedstocks. JRC Scientific and Technical Reports, European Commission Joint Research Centre, Institute for Energy, Ispra, Italy.
- Enkvist, P.A., T. Nauc ler and J. Rosander (2007). A cost curve for greenhouse gas reduction. *The McKinsey Quarterly* 1, 34–45.
- EREC and Greenpeace (2010). Energy[r]evolution: Towards a Fully Renewable Energy Supply in the EU 27. [http://www.energyblueprint.info/fileadmin/media/documents/national/2010/0910\\_gpi\\_E\\_R\\_\\_eu\\_report\\_4\\_lr.pdf](http://www.energyblueprint.info/fileadmin/media/documents/national/2010/0910_gpi_E_R__eu_report_4_lr.pdf) (last accessed January 22, 2012).
- Fischer, C. (2008). Emissions pricing, spillovers, and public investment in environmentally friendly technologies. *Energy Economics* 30, 487–502.
- Fischer, C. and R.G. Newell (2008). Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management* 55, 142–162.
- Fischer, G. (2011). How can climate change and the development of bioenergy alter the long-term outlook for food and agriculture? In: Conforti, P. (Ed.) *Looking ahead in world*

*food and agriculture: Perspectives to 2050*. Food and Agriculture Organization of the United Nations, Rome, Italy.

Garrone, P. and L. Grilli (2010). Is there a relationship between public expenditures in energy R&D and carbon emissions per GDP? An empirical investigation. *Energy Policy* 38, 5600–5613.

Greene, W. H. (2003) (5th ed.). *Econometric Analysis*. Upper Saddle River, NJ [and others]: Prentice-Hall.

Grubb, M. (2004). Technology Innovation and Climate Change Policy: An Overview of issues and Options. *Keio Economic Studies* 41(2), 103–132.

Hertel, T. W., Tyner, W. E. and Birur, D. K. (2010). Global Impacts of Biofuel Mandates. *Energy Journal* 31(1), 75-100.

IEA (2008). Energy Technology RD&D budgets database (2008 edition). International Energy Agency, Paris, France.

IEA (2010). Energy Prices and Taxes Statistics, IEA online database (3rd quarter 2010 edition). International Energy Agency, Paris, France.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115, 53–74.

IPCC (2000). Summary for Policy Makers. In: *IPCC Special Report Emissions Scenarios* [N. Nakicenovic and R. Swart (eds.)], Cambridge University Press, Cambridge, United Kingdom.

IPCC (2007). *Climate Change 2007: Synthesis Report of the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK, and New York, NY, USA.

IPCC (2011). Summary for Policymakers. In: *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation* [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds.)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC (2012). Summary for Policymakers. In: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 3-21.

Johnstone, N., I. Haščič and D. Popp (2010). Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. *Environmental and Resource Economics* 45,



133–155.

Judson, R.A. and A.L. Owen (1999). Estimating Dynamic Panel Data Models: A Guide for Macroeconomists. *Economic Letters* 65(1), 9–15.

Kennedy, P. (2008) (6th ed.). A guide to econometrics. Malden, MA [and others]: Blackwell.

Klepper, G., S. Peterson and K. Springer (2003). DART97: A Description of the Multi-regional, Multi-sectoral Trade Model for the Analysis of Climate Policies. Kiel Working Paper 1149, Kiel Institute for the World Economy, Kiel, Germany.

Klepper, G. and S. Peterson (2007). Distribution Matters - Taxes vs. Emissions Trading in Post-Kyoto Climate Regimes. Kiel Working Paper 1380, Kiel Institute for the World Economy, Kiel, Germany.

Kretschmer, B., M. Hübler and P. Nunnenkamp (2013). Does Foreign Aid Reduce Energy and Carbon Intensities of Developing Economies? *Journal of International Development* 25, 67–91.

Kretschmer, B., D. Narita and S. Peterson (2009). The economic effects of the EU biofuel target. *Energy Economics* 31, S285–S294.

Kretschmer, B. and S. Peterson (2010). Integrating Bioenergy into Computable General Equilibrium Models – A Survey. *Energy Economics* 32, 673–686.

Kretschmer, B., S. Peterson and A. Ignaciuk (2008). Integrating biofuels into the DART model. Kiel Working Paper 1472, Kiel Institute for the World Economy, Kiel, Germany.

Maddala, G.S. and S. Wu (1999). A Comparative Study of Unit Root Tests With Panel Data and A New Simple Test. *Oxford Bulletin of Economics and Statistics* 61, 631–652.

Nemet, G.F. and D.M. Kammen (2007). U.S. energy research and development: Declining investment, increasing need, and the feasibility of expansion. *Energy Policy* 35, 746–755. Data online: <https://mywebSPACE.wisc.edu/nemet/web/RandD2006.html> (last accessed June 5, 2012).

Nickell, S.J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica* 49(6), 1417–1426.

OECD (2010a). OECD.Stat Gross Domestic Expenditure on R-D by sector of performance and type of cost. Organisation for Economic Co-Operation and Development, Paris, France: [http://stats.oecd.org/OECDStat\\_Metadata/ShowMetadata.ashx?Dataset=GERD\\_COST&ShowOnWeb=true&Lang=en](http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=GERD_COST&ShowOnWeb=true&Lang=en) (last accessed May 2011).

OECD (2010b). OECD.Stat Business enterprise R-D expenditure by industry and by source of funds. Organisation for Economic Co-Operation and Development, Paris, France: [http://stats.oecd.org/OECDStat\\_Metadata/ShowMetadata.ashx?Dataset=](http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=)

BERD\_FUNDS&ShowOnWeb=true&Lang=en (last accessed May 2011).

OECD-IEA (2011). World Energy Outlook 2011 – Executive Summary. International Energy Agency, Paris, France.

O’Hare, M., M. Delucchi, R. Edwards, U. Fritsche, H. Gibbs, T. Hertel, J. Hill, D. Kammen, D. Laborde, L. Marelli, D. Mulligan, R. Plevin and W. Tyner (2011). Comment on ”Indirect land use change for biofuels: Testing predictions and improving analytical methodologies” by Kim and Dale: statistical reliability and the definition of the indirect land use change (iLUC) issue. *Biomass and Bioenergy* 35(10), 4485-4487.

Raupach, M. R., G. Marland, P. Ciais, C. Le Qur, J. G. Canadell, G. Klepper and C. B. Field (2007). Global and Regional Drivers of Accelerating CO<sub>2</sub> Emissions. *Proceedings of the National Academy of Sciences (PNAS)* 104(24), 10288–10293.

Rickels, W., L. Kleemann, G. Klepper, S. Peterson and S. Petrick (2010). Konjunktur für den Klimaschutz? Klima- und Wachstumswirkung weltweiter Konjunkturprogramme. *Aussenwirtschaft* 2010 II, Universität St. Gallen.

Roodman, D. (2009a). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics* 71(1), 135–158.

Roodman, D. (2009b). How to do xtabond2: an introduction to difference and system GMM in Stata. *Stata Journal* 9(1), 86–136.

Sagar, A.D. and B. van der Zwaan (2006). Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. *Energy Policy* 34, 2601–2608.

UNEP SEFI and Bloomberg New Energy Finance (2010). Global Trends in Sustainable Energy Investment 2010: Analysis of Trends and Issues in the Financing of Renewable Energy and Energy Efficiency, <http://sefi.unep.org/english/globaltrends2010.html> (last accessed June 5, 2012).

World Bank (2010). World Development Indicators. Washington, D.C., USA.

World Bank (2011). World Development Indicators. Washington, D.C., USA.

WWF and Ecofys (2011). The Energy Report: 100% Renewable Energy by 2050. [www.panda.org/energyreport](http://www.panda.org/energyreport) (last accessed June 5, 2012).

Zhang, J.-T. Y. Fan and Y.-M. Wei (2006). An empirical analysis for national energy R&D expenditures. *International Journal of Global Energy Issues* 25(1-2), 141–159.

# Appendices

## A The integration of biofuel technologies in the DART model

The integration of biofuel technologies in the computable general equilibrium (CGE) model DART forms the basis for the simulations in Chapter 3 of this dissertation. The way in which we integrated biofuel technologies including the disaggregation of GTAP sectors to introduce new sectors and all associated data collection and changes to the model's structure are described in detail in Kretschmer et al. (2008). General features of the DART model are not repeated here, given they are introduced in Kretschmer et al. (2009) (Chapter 3). Kretschmer et al. (2009) furthermore explain the general procedure of introducing biofuels in DART as latent technologies. Here I focus on some more detailed aspects of the integration of the new production sectors, i.e. the production structure in the new sectors compared to the production structure in the original DART sectors and the way in which biofuels are included on the consumption side of the model while at the same time presenting the choice of important parameters. The following summary is informed both by Kretschmer et al. (2008) as well as Klepper et al. (2003), the latter describing the standard DART model without biofuels, on which we built.

### *Biofuel production*

Bioethanol and biodiesel can be produced from different agricultural feedstocks (sugar cane and beet, wheat and corn for bioethanol and different oilseeds and vegetable oil for biodiesel). The shares of the respective feedstock and other inputs such as capital, labour and electricity were determined on the basis of industry data provided by meó Consulting Team (as shown in Table 2 of Kretschmer et al., 2009). The production structures in both biofuel and other sectors in the DART model are described by multi-level nested constant elasticity of substitution (CES) functions. Figure A.1 shows the production structure in the biofuel sectors which translates into a corresponding MPSGE code, the 'mathematical programming system for general equilibrium analysis' (developed by Rutherford, 1987) within the GAMS programming language in which the DART model is written. At the top level, the feedstock input, electricity and a value added composite of capital and labour are connected by a Leon-

tief function, i.e. are modelled as perfect complements with an elasticity of substitution of zero. The fact that the agricultural feedstock as the raw material is the dominant input in biofuel production justifies the lack of substitution potential. In the lower level nests, capital and labour form the value added composite described by a Cobb-Douglas function with an elasticity of substitution of one as in the standard DART model (Klepper et al., 2003) and as commonly found in CGE models. Both feedstock and electricity inputs can be either imported or domestically produced. In line with the Armington assumption commonly employed in CGE models, imported and domestic goods are considered heterogeneous goods and are hence imperfect substitutes (accounting for example for a home bias of consumers). Given the global market for the agricultural commodities wheat, corn and vegetable oils (as well as for gasoline and other refined oil products), a higher Armington elasticity of substitution of 8 as opposed to 4 for all remaining goods is chosen.

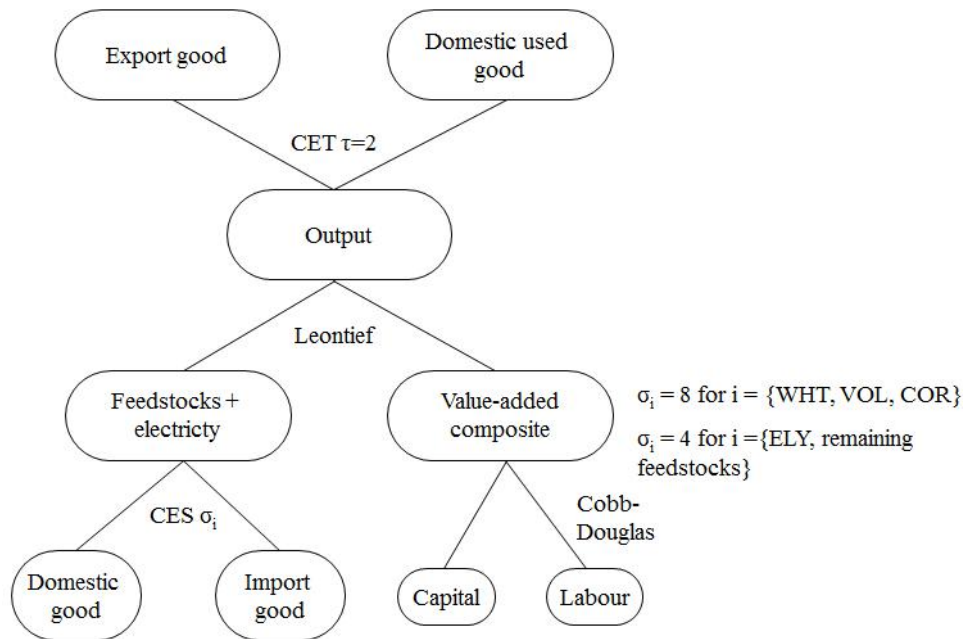


Figure A.1: Biofuel production structure in DART (Source: Adapted from Kretschmer et al., 2008)

Another important characteristic not apparent from Figure A.1 is that while the initial feedstock shares are derived from actual 2005 production, a high elasticity of substitution of 16 between the different feedstocks is assumed so that feedstock inputs can change in accordance with changes in relative crop prices. However, in a given region a certain feedstock

is only available as a biofuel raw material if some biofuel production based on this feedstock is recorded in 2005 (in line with Table 3 of Kretschmer et al., 2009). As is evident from Figure A.1, the production factor land is not part of the nesting structure; it is, however, indirectly an input to biofuel production given its use in producing biofuel feedstocks. This is seen in Figure A.2, representing the standard DART production structure in other (non fossil fuel) production sectors. Land is part of the “KLE” nest, a multi-level CES function to combine the factor inputs land, capital, labour and an energy aggregate. To represent a lower substitutability between land and other factors of production, the relatively low constant elasticity of substitution of 0.25 was chosen between land and other factors of production, the remaining elasticities within “KLE” are again in line with Klepper et al., 2003).

As seen from the upper part in Figures A.1 and A.2, both biofuel and other outputs can become either domestically consumed products or export goods. These are modelled as imperfect substitutes in line with a constant elasticity of transformation (CET) of 2.

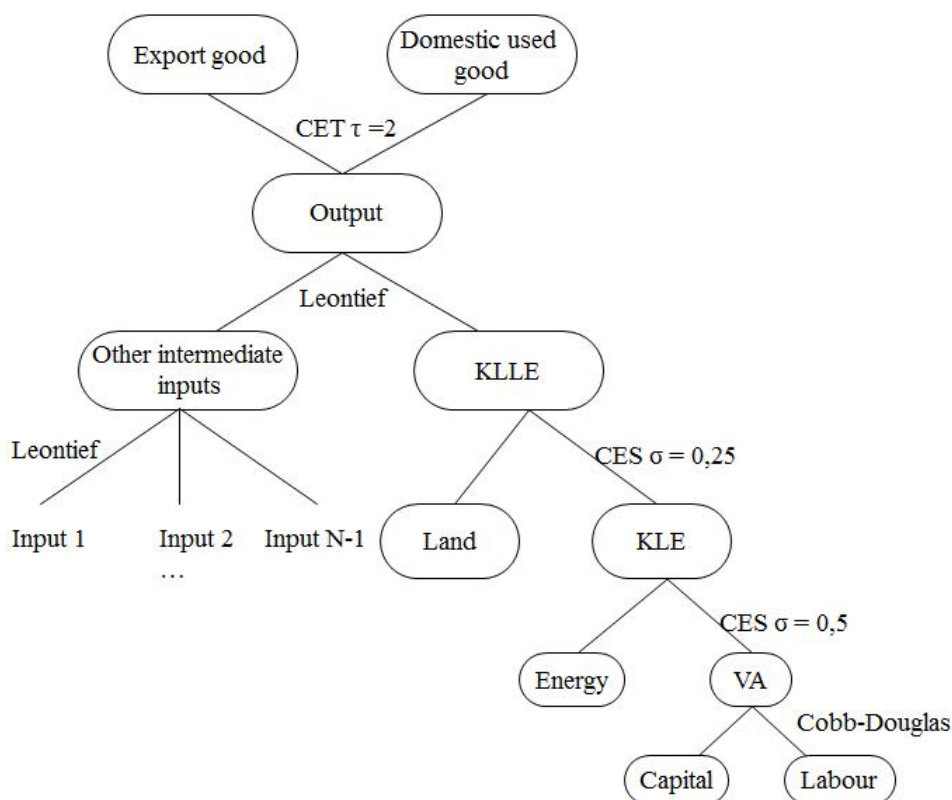


Figure A.2: Production structure in remaining (non fossil fuel) DART sectors (Source: Adapted from Klepper et al., 2003)

### *Biofuel consumption*

Having explained the structure of biofuel production in DART, I turn to the consumption side. The key modelling attribute here is that biofuels are modelled as perfect substitutes to conventional fuels, i.e. consumers have no preference between conventional diesel and gasoline as compared to biodiesel and bioethanol, respectively. This assumption is based on the fact that with moderate overall biofuel consumption targets, biofuels are predominantly consumed in low blends such as E10 (gasoline with a 10% bioethanol share) or B7 (diesel with a 10% bioethanol share), which can be handled by (most) normal engines. This assumption would not hold in the presence of higher blending shares that would involve transaction costs such as requiring the existence of so-called flex-fuel vehicles whose engines take fuels of varying blending shares. It should also be noted that the assumption of perfect substitutes disregards concerns consumers may have with regard to biofuels, for example in relation to sustainability or engine compatibility.

It is on the biofuel consumption side that we have included constraints in the model so as to replicate bioethanol and biodiesel consumption shares as observed in 2005. Endogenously determined subsidies on biofuel production force the model to replicate the 2005 shares. As explained in the main text, in the reference scenario these shares are kept constant throughout the modelling period up to 2020. When modelling the 10% biofuel consumption target, a new constraint is imposed that becomes gradually more stringent over time so as to hit a 10% overall biofuel consumption share in 2020 (in EU Member States in line with the policy scenarios modelled). As also explained in Kretschmer et al. (2009), biofuel consumption can be met by imports, particular with bioethanol from Brazil and biodiesel from Malaysia/Indonesia.

## B Data sources and descriptive statistics for Chapter 4

Table B.1: Summary statistics (based on yearly data)

Variable	No. of obs.	Mean	Std. Dev.	Min	Max
Energy intensity (kgoe/2000 US\$ of GDP)	537	0.215	0.077	0.090	0.492
Emission intensity (kg/2000 US\$ of GDP)	525	0.498	0.200	0.133	1.102
Energy R&D ratio	521	0.00050	0.00040	0.00000	0.00207
Energy-efficiency R&D ratio	505	0.00013	0.00012	0	0.00079
Low-carbon R&D ratio	505	0.00008	0.00008	0	0.00056
GDP per capita (2000 US\$)	537	20409	8730	2770	41901
Energy price index (2005=100)	537	91.04	15.30	50.26	149.33
Industry share (% of GDP)	524	0.307	0.047	0.190	0.448
Investment ratio (% of GDP)	537	0.221	0.035	0.151	0.351
Voluntary CC	537	0.071	0.278	0	2
Investment RE	537	1.009	1.560	0	7
Financial RE	537	0.209	0.564	0	3
Voluntary RE	537	0.039	0.194	0	1
Investment EE	537	1.086	1.853	0	10
Financial EE	537	0.300	0.676	0	3
Voluntary EE	537	0.490	0.989	0	8
Sum RE measures	537	2.000	2.464	0	12
Sum EE measures	537	2.957	3.887	0	20
RE certificate share (% of renewable energy certificates)	504	0.001	0.008	0	0.104
Feed-in tariff (in 2000US\$ cents/kWh)	496	0.016	0.035	0	0.216

Note: R&D ratios are all calculated by dividing the respective R&D spending by total GDP (all in 2000 US\$). All policy variables are count variables, see the description of how the policy database was constructed in section 4.3.1

Table B.2: Summary statistics (based on 5-year averages)

Variable	No. of obs.	Mean	Std. Dev.	Min	Max
Energy intensity (kgoe/2000 US\$ of GDP)	82	0.210	0.068	0.099	0.396
Emission intensity (kg/2000 US\$ of GDP)	82	0.493	0.193	0.156	0.960
Energy R&D ratio	80	0.00036	0.00024	0.00001	0.00108
Energy-efficiency R&D ratio	80	0.00010	0.00009	0	0.00054
Low-carbon R&D ratio	80	0.00006	0.00005	0	0.00021
GDP per capita (2000 US\$)	82	21496	8411	3541	39715
Energy price index (2005=100)	82	87.15	9.12	64.91	112.93
Industry share (% of GDP)	82	0.292	0.042	0.192	0.407
Investment ratio (% of GDP)	82	0.216	0.031	0.166	0.313
Voluntary CC	82	0.107	0.295	0	1
Investment RE	82	1.224	1.539	0	6
Financial RE	82	0.244	0.571	0	3
Voluntary RE	82	0.063	0.226	0	1
Investment EE	82	1.293	1.808	0	9
Financial EE	82	0.349	0.691	0	3
Voluntary EE	82	0.634	0.994	0	6
Sum RE measures	82	2.417	2.401	0	9
Sum EE measures	82	3.590	3.706	0	17
RE certificate share (% of renewable energy certificates)	79	0.002	0.009	0	0.065
Feed-in tariff (in 2000US\$ cents/kWh)	78	0.023	0.037	0	0.178

Note: The R&D ratios are all calculated by dividing the respective R&D spending (in 2000 US\$) by total GDP (in 2000 US\$). All policy variables are count variables, see the description of how the policy database was constructed in section 4.3.1

Table B.3: Correlation matrices of core variables (based on 5-year averages)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Energy intensity	1								
(2) Emission intensity	0.7888	1							
(3) Energy R&D ratio	-0.0481	-0.1765	1						
(4) Energy-efficiency R&D ratio	0.0613	-0.0948	0.7362	1					
(5) Low-carbon R&D ratio	-0.0973	-0.1345	0.5849	0.7189	1				
(6) GDP per capita	-0.3559	-0.5432	0.5091	0.4295	0.2426	1			
(7) Energy price	-0.3203	-0.0741	-0.1257	-0.262	-0.042	-0.2206	1		
(8) Investment ratio	-0.2773	-0.1316	-0.0498	-0.0562	0.0148	-0.1224	0.3113	1	
(9) Industry share	-0.0304	-0.0534	0.3433	0.3213	0.2105	0.0295	0.1367	0.2894	1



Table B.4: Correlation matrix of GDP per capita and policy variables (based on 5-year averages)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) GDP per capita	1											
(2) RE certificate share	0.1275	1										
(3) Feed-in tariff	-0.0431	0.0033	1									
(4) Investment RE	0.3644	0.3241	0.2366	1								
(5) Financial RE	0.3292	-0.0227	-0.0626	0.2618	1							
(6) Voluntary RE	0.2423	0.1144	-0.0471	0.1623	0.2575	1						
(7) Sum RE measures	0.4284	0.3453	0.2558	0.9314	0.4534	0.2961	1					
(8) Investment EE	0.3373	0.4617	0.1956	0.6739	0.3019	0.255	0.7004	1				
(9) Financial EE	0.195	0.0441	0.3687	0.4684	0.2283	0.0001	0.4622	0.3587	1			
(10) Voluntary EE	0.3478	0.2012	-0.0198	0.5137	0.1617	0.263	0.5447	0.5736	0.1409	1		
(11) Sum EE measures	0.4274	0.4224	0.2636	0.7541	0.351	0.3603	0.8107	0.9214	0.488	0.6957	1	
(12) Voluntary CC	0.1789	0.1728	0.0322	0.495	-0.0007	0.2578	0.4868	0.3803	0.1793	0.6199	0.5099	1

Table B.5: Comparison of energy and carbon intensities across countries in 1975 and 2007

Energy intensity (kgoe energy use per 2000US\$)		Emission intensity (kg per 2000 US\$)		Carbon factor (kg emissions per kgoe energy use)	
1975	2007	1975	2007	1975	2007
Switzerland	0.103	Switzerland	0.090	Switzerland	0.133
Japan	0.143	Norway	0.099	Sweden	0.165
Greece	0.155	Ireland	0.107	Norway	0.217
Portugal	0.155	Denmark	0.110	Japan	0.241
Spain	0.192	UK	0.120	France	0.246
Italy	0.196	Norway	0.136	Denmark	0.279
Austria	0.197	Austria	0.149	UK	0.306
Denmark	0.198	Italy	0.150	New Zealand	0.310
Norway	0.200	Germany	0.159	Italy	0.314
France	0.227	Sweden	0.166	Spain	0.380
Ireland	0.244	France	0.175	France	0.384
UK	0.247	Netherlands	0.183	Denmark	0.387
Sweden	0.258	Greece	0.192	Turkey	0.659
New Zealand	0.267	Spain	0.196	Finland	0.718
Turkey	0.268	Portugal	0.198	UK	0.748
Netherlands	0.300	US	0.200	Netherlands	0.478
Germany	0.302	Belgium	0.215	Ireland	0.489
Finland	0.313	Australia	0.238	Belgium	0.500
Australia	0.322	Finland	0.239	Australia	0.508
Belgium	0.324	New Zealand	0.259	US	0.585
US	0.385	Turkey	0.268	Canada	0.631
Canada	0.483	Canada	0.312	Australia	0.716
Hungary	0.699	Hungary	0.431	Turkey	0.774
				Hungary	0.910
				Norway	2.031
				Sweden	2.069
				New Zealand	2.085
				Switzerland	2.274
				Finland	2.338
				Canada	2.391
				Turkey	2.453
				Netherlands	2.591
				Austria	2.701
				US	2.705
				France	2.707
				Portugal	2.776
				Belgium	2.883
				Australia	2.911
				Italy	2.929
				Japan	3.016
				UK	3.025
				Spain	3.157
				Denmark	3.182
				Hungary	3.288
				Greece	3.307
				Ireland	3.315
				Germany	.
				Sweden	0.976
				France	1.409
				Switzerland	1.476
				Norway	1.591
				Finland	1.758
				Belgium	1.805
				New Zealand	1.946
				Canada	2.067
				Austria	2.070
				Hungary	2.111
				Netherlands	2.152
				Portugal	2.317
				Germany	2.377
				Japan	2.441
				US	2.492
				Spain	2.494
				Denmark	2.542
				UK	2.552
				Italy	2.560
				Turkey	2.884
				Ireland	2.940
				Australia	3.012
				Greece	3.047

Note: kgoe is kilogramme oil equivalent

Table B.6: Comparison of RD&D spending relative to GDP across countries in 1975 and 2007

Total Energy RD&D in 2000 US\$ per Million 2000 US\$ GDP	2006		1975		2006		1975		2006		
	Energy-intensity targeted RD&D in 2000 US\$ per Million 2000 US\$ GDP		Energy-intensity targeted RD&D in 2000 US\$ per Million 2000 US\$ GDP		Energy-intensity targeted RD&D in 2000 US\$ per Million 2000 US\$ GDP		Energy-intensity targeted RD&D in 2000 US\$ per Million 2000 US\$ GDP		Carbon-factor targeted RD&D in 2000 US\$ per Million 2000 US\$ GDP		
	1975	2006	1975	2006	1975	2006	1975	2006	1975	2006	
Belgium	2116.8	Finland	808.5	Sweden	353.56	Finland	332.83	New Zealand	117.76	Denmark	337.27
UK	1392.5	France	652.3	Belgium	341.76	Italy	198.20	Sweden	67.91	Finland	250.77
Germany	1368.7	Japan	584.0	Canada	271.52	Netherlands	140.64	Netherlands	32.04	Norway	165.79
Canada	1103.6	Canada	577.0	Germany	144.48	Switzerland	140.62	US	27.65	Netherlands	152.34
Netherlands	943.2	Denmark	533.1	New Zealand	107.47	Sweden	136.07	Canada	22.23	Canada	142.21
Sweden	783.0	Norway	518.9	Ireland	99.34	Canada	120.28	Japan	16.29	Sweden	139.52
US	748.5	Switzerland	418.1	Norway	89.70	Japan	113.17	Belgium	12.33	Switzerland	121.62
Spain	514.7	Netherlands	364.1	Netherlands	74.98	Denmark	104.34	Spain	12.26	Austria	110.85
Japan	509.8	Italy	363.5	UK	72.83	Austria	76.70	Germany	12.15	France	102.77
New Zealand	344.5	Sweden	346.5	Denmark	47.79	France	63.60	Switzerland	11.40	Hungary	81.03
Denmark	319.2	Austria	230.9	Japan	43.86	Norway	60.11	Denmark	7.65	Japan	76.88
Norway	150.1	US	228.7	US	22.51	New Zealand	58.00	UK	5.02	Germany	65.48
Ireland	147.5	Germany	227.4	Spain	21.76	US	41.11	Norway	0.95	New Zealand	61.12
Switzerland	75.0	New Zealand	169.1	Switzerland	11.40	Ireland	38.15	Ireland	0	UK	58.74
Australia	.	UK	115.7	Australia	.	Germany	21.23	Australia	.	Italy	57.11
Austria	.	Hungary	99.1	Austria	.	Spain	10.43	Austria	.	Spain	50.11
Finland	.	Spain	98.1	Finland	.	UK	10.01	Finland	.	US	38.48
France	.	Ireland	57.4	France	.	Turkey	1.27	France	.	Ireland	19.23
Greece	.	Turkey	13.5	Greece	.	Portugal	0.20	Greece	.	Turkey	9.55
Hungary	.	Portugal	12.2	Hungary	.	Hungary	0.00	Hungary	.	Portugal	3.42
Italy	.	Australia	.	Italy	.	Australia	.	Italy	.	Australia	.
Portugal	.	Belgium	.	Portugal	.	Belgium	.	Portugal	.	Belgium	.
Turkey	.	Greece	.	Turkey	.	Greece	.	Turkey	.	Greece	.

Note: . denotes data point not available

Table B.7: Classification of IEA (2008) public energy R&amp;D expenditure data

	Energy use	Carbon intensity
<b>GROUP 1: ENERGY EFFICIENCY</b>	X	
I.1 Industry		
I.2 Residential Commercial		
I.3 Transportation		
I.4 Other Conservation		
<b>GROUP II: FOSSIL FUELS</b>		
II.1 Total Oil and Gas		
II.1.1 Enhanced oil and gas production		
II.1.2 Refining transport and storage of oil and gas	X	
II.1.3 Non-conventional oil and gas production		
II.1.4 Oil and gas combustion	X	
II.1.5 Oil and gas conversion		
II.1.6 Other oil and gas		
II.2 Total Coal		
II.2.1 Coal production and preparation and transport	X	
II.2.2 Coal combustion	X	
II.2.3 Coal conversion (excluding IGCC)		
II.2.4 Other coal		
II.3 Total CO2 Capture and Storage		X
II.3.1 CO2 capture/separation		
II.3.2 CO2 transport		
II.3.3 CO2 storage		
<b>GROUP III: RENEWABLE ENERGY SOURCES</b>		X
III.1 Total Solar Energy		
III.1.1 Solar heating and cooling (including day lighting)		
III.1.2 Photovoltaics		
III.1.3 Solar thermal-power and high-temperature applications		
III.2 Wind Energy		
III.3 Ocean Energy		
III.4 Total Bio-Energy		
III.4.1 Production of transport biofuels including from wastes		
III.4.2 Production of other biomass-derived fuels including from wastes		
III.4.3 Applications for heat and electricity		
III.4.4 Other bio-energy		
III.5 Geothermal Energy		
III.6 Total Hydropower		
III.6.1 Large hydropower (capacity >10 MW)		
III.6.2 Small hydropower (capacity <10 MW)		
III.7 Other Renewables		

<b>GROUP IV: NUCLEAR FISSION and FUSION</b>		
IV.1 Total Nuclear Fission		
IV.1.1 Light-water reactors (LWRs)		
IV.1.2 Other converter reactors		
IV.1.3 Fuel cycle		
IV.1.4 Nuclear supporting technology		
IV.1.5 Nuclear breeder		
IV.1.6 Other nuclear fission		
IV.2 Nuclear Fusion		
<b>GROUP V: HYDROGEN AND FUEL CELLS</b>		X
V.1 Total Hydrogen		
V.1.1 Hydrogen production		
V.1.2 Hydrogen storage		
V.1.3 Hydrogen transport and distribution		
V.1.4 Other infrastructure and systems R&D		
V.1.5 Hydrogen end uses including combustion; excluding fuel cells		
V.2 Total Fuel Cells		
V.2.1 Stationary applications		
V.2.2 Mobile applications		
V.2.3 Other applications		
<b>GROUP VI: OTHER POWER AND STORAGE TECHS</b>	X	
VI.1 Electric Power Conversion		
VI.2 Electricity Transmission and Distribution		
VI.3 Energy Storage		
<b>GROUP VII: TOTAL OTHER TECHNOLOGIES OR RESEARCH</b>		
VII.1 Energy System Analysis		
VII.2 Other		
<b>TOTAL ENERGY RD&amp;D</b>		

The public energy R&D expenditure categories have been classified into 1) energy use and 2) carbon intensity targeted spending for the purpose of this study. The choices of categories mostly follow the classification in Garrone and Grilli (2010, p.5611), with the most important difference being that I classify all spending on renewable energies as targeted at the carbon intensity, given this is generally the most important stated rationale for these expenditures, whereas Garrone and Grilli classified some of the sub-categories as targeted at energy use. Furthermore, unlike Garrone and Grilli I do not classify nuclear power as carbon intensity targeted spending; while being a low-carbon energy source by itself, the use of nuclear power is not considered to be a viable component of a low-carbon energy system given that its lack of flexible deployment represents a hindrance to the increased use of renewables.

## C Additional regression results for Chapter 4

Table C.1: Results from Difference GMM estimations – R&D targeted at low-carbon technologies divided by GDP

<i>Dependent var.</i>	<i>Panel A: log(energy intensity)</i>								
	(E1)	(E2)	(E3)	(E4)	(E5)	(E6)	(E7)	(E8)	(E9)
log(LDV)	0.603** (2.77)	0.457*** (3.24)	0.486*** (3.34)	0.546** (2.68)	0.605*** (2.90)	0.557** (2.49)	0.598** (2.72)	0.553** (2.57)	0.654*** (3.53)
log(GDP per capita)	-0.262* (-1.89)	-0.344*** (-4.25)	-0.330*** (-3.71)	-0.210 (-1.33)	-0.275** (-2.09)	-0.230 (-1.15)	-0.258 (-1.65)	-0.328** (-2.39)	-0.288* (-2.01)
log(energy price)	-0.172** (-2.22)	-0.201*** (-2.84)	-0.193*** (-3.05)	-0.134 (-1.60)	-0.191** (-2.53)	-0.142 (-1.34)	-0.177* (-1.87)	-0.197*** (-2.97)	-0.206** (-2.41)
Lagged log(low-carbon R&D ratio)	-0.0125 (-0.81)	-0.0153 (-0.94)	-0.0191 (-1.45)	-0.0120 (-0.81)	-0.0121 (-0.76)	-0.0134 (-0.93)	-0.00914 (-0.54)	-0.00781 (-0.41)	-0.00300 (-0.21)
Feed-in tariff		0.353 (1.32)							
RE certificate share			-0.284 (-0.34)						
Investment RE				-0.0127 (-1.46)					
Financial RE					0.0227 (0.90)				
Sum RE measures						-0.00593 (-0.82)			
Investment EE							0.000821 (0.10)		
Financial EE								0.0168 (1.70)	
Sum EE measures									0.00335 (1.02)
N	82	79	80	82	82	82	82	82	82
Number of countries	23	22	22	23	23	23	23	23	23
Average time periods per country	3.57	3.59	3.64	3.57	3.57	3.57	3.57	3.57	3.57
AR(2) ( <i>prob &gt; chi<sup>2</sup></i> )	0.280	0.337	0.650	0.540	0.224	0.486	0.288	0.549	0.170
Number of instruments	14	15	15	15	15	15	15	15	15
Hansen test ( <i>prob &gt; chi<sup>2</sup></i> )	0.115	0.219	0.092	0.067	0.149	0.058	0.101	0.218	0.232
Difference-in-Hansen ( <i>prob &gt; chi<sup>2</sup></i> )	0.083	0.170	0.049	0.086	0.230	0.104	0.132	0.185	0.353

<i>Dependent var.</i>	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)	(C9)
	<i>Panel B: log(emission intensity)</i>								
log(LDV)	0.213 (1.35)	0.229 (1.34)	0.170 (1.02)	0.173 (1.13)	0.205 (1.11)	0.142 (0.95)	0.219 (1.21)	0.231 (1.40)	0.166 (0.89)
log(GDP per capita)	-0.579*** (-3.48)	-0.582*** (-3.98)	-0.602*** (-3.26)	-0.526** (-2.73)	-0.602*** (-3.44)	-0.516** (-2.70)	-0.580*** (-3.44)	-0.565*** (-3.41)	-0.559*** (-3.83)
log(energy price)	-0.230*** (-3.20)	-0.274*** (-3.12)	-0.223** (-2.41)	-0.158* (-1.90)	-0.236*** (-3.02)	-0.140 (-1.51)	-0.216** (-2.34)	-0.224*** (-3.00)	-0.178 (-1.68)
Lagged log(low-carbon R&D ratio)	-0.0148 (-0.76)	-0.0124 (-0.66)	-0.0142 (-0.79)	-0.0165 (-0.79)	-0.0172 (-0.94)	-0.0158 (-0.75)	-0.0193 (-1.09)	-0.0168 (-0.93)	-0.0175 (-0.98)
Feed-in tariff	0.427 (0.92)								
RE certificate share			-0.256 (-0.21)						
Investment RE				-0.0158** (-2.08)					
Financial RE					0.00404 (0.05)				
Sum RE measures						-0.0110 (-1.22)			
Investment EE							-0.00190 (-0.19)		
Financial EE								-0.00749 (-0.29)	
Sum EE measures									-0.00328 (-0.69)
N	80	77	78	80	80	80	80	80	80
Number of countries	23	22	22	23	23	23	23	23	23
Average time periods per country	3.48	3.50	3.55	3.48	3.48	3.48	3.48	3.48	3.48
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.347	0.398	0.313	0.355	0.358	0.399	0.402	0.376	0.359
Number of instruments	14	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.258	0.148	0.175	0.116	0.274	0.127	0.238	0.282	0.187
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.921	0.956	0.851	0.571	0.873	0.906	0.967	0.977	0.831

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  \*\*\*; LDV denotes lagged dependent variable



Table C.2: Results from GMM estimations focusing on voluntary energy and climate measures

<i>Dependent var.</i>	<i>Panel A: log(energy intensity)</i>											
	(E1)	(E2)	(E3)	(E4)	(E5)	(E6)	(E7)	(E8)	(E9)	(E10)	(E11)	(E12)
log(LDV)	0.516*** (4.21)	0.525*** (4.25)	0.603** (2.77)	0.434*** (3.25)	0.477*** (2.90)	0.518*** (4.36)	0.482*** (3.70)	0.521*** (2.89)	0.509*** (4.35)	0.571*** (2.94)	0.622*** (3.09)	0.621*** (2.79)
log(GDP per capita)	-0.286*** (-3.22)	-0.262*** (-4.07)	-0.262* (-1.89)	-0.299*** (-3.70)	-0.290*** (-3.28)	-0.293*** (-3.74)	-0.274*** (-4.54)	-0.261*** (-4.27)	-0.276*** (-3.98)	-0.266** (-2.09)	-0.268* (-1.95)	-0.263* (-1.74)
log(energy price)	-0.162** (-2.81)	-0.153** (-2.78)	-0.172** (-2.22)	-0.166*** (-2.95)	-0.157** (-2.61)	-0.170*** (-2.98)	-0.158*** (-2.94)	-0.153** (-2.66)	-0.165*** (-2.86)	-0.169* (-2.04)	-0.180** (-2.18)	-0.182*** (-2.13)
Lagged log(energy R&D ratio)	-0.0213 (-1.70)			-0.0281** (-2.10)	-0.0243* (-1.73)	-0.0213* (-2.02)						
Lagged log(energy-efficiency R&D ratio)		-0.0157* (-1.91)					-0.0197* (-2.01)	-0.0153 (-1.64)	-0.0161** (-2.32)			
Lagged log(low-carbon R&D ratio)			-0.0125 (-0.81)							-0.0143 (-0.92)	-0.0111 (-0.89)	-0.0109 (-0.68)
Voluntary RE				-0.0334 (-0.91)			-0.0279 (-0.60)			-0.0137 (-0.27)		
Voluntary EE					-0.00359 (-0.38)			-0.000199 (-0.02)			0.00344 (0.40)	
Voluntary CC						0.00851 (0.48)			0.00560 (0.30)			0.0149 (0.82)
N	82	82	82	82	82	82	82	82	82	82	82	82
Number of countries	22	22	23	22	22	22	22	22	22	23	23	23
Average time periods per country	3.73	3.73	3.57	3.73	3.73	3.73	3.73	3.73	3.73	3.57	3.57	3.57
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.192	0.101	0.280	0.690	0.352	0.232	0.261	0.155	0.153	0.280	0.262	0.307
Number of instruments	14	14	14	15	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.258	0.322	0.115	0.260	0.259	0.271	0.292	0.323	0.327	0.112	0.129	0.112
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.192	0.472	0.083	0.219	0.290	0.367	0.465	0.338	0.510	0.145	0.204	0.178

<i>Dependent var.</i>	<i>Panel B: log(emission intensity)</i>											
	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)	(C9)	(C10)	(C11)	(C12)
log(LDV)	0.166 (1.61)	0.198 (1.34)	0.213 (1.35)	0.169 (1.53)	0.143 (1.04)	0.168 (0.87)	0.179 (1.17)	0.171 (1.19)	0.200 (1.09)	0.193 (1.55)	0.210 (1.39)	0.223 (1.23)
log(GDP per capita)	-0.586*** (-4.11)	-0.553*** (-3.88)	-0.579*** (-3.48)	-0.545*** (-4.12)	-0.542*** (-3.45)	-0.543*** (-3.82)	-0.505*** (-3.17)	-0.521*** (-2.99)	-0.527*** (-3.81)	-0.561*** (-3.65)	-0.564*** (-3.23)	-0.553*** (-3.14)
log(energy price)	-0.247*** (-3.07)	-0.226*** (-3.97)	-0.230*** (-3.20)	-0.224** (-2.68)	-0.190** (-2.45)	-0.213** (-2.39)	-0.202*** (-2.89)	-0.178** (-2.31)	-0.209** (-2.47)	-0.229*** (-2.84)	-0.189** (-2.73)	-0.219** (-2.68)
Lagged log(energy R&D ratio)	-0.0128 (-0.41)			-0.0242 (-0.73)	-0.0267 (-0.81)	-0.0186 (-0.66)						
Lagged log(energy-efficiency R&D ratio)		-0.0141 (-0.59)					-0.0236 (-0.94)	-0.0280 (-0.97)	-0.0238 (-1.02)			
Lagged log(low-carbon R&D ratio)			-0.0148 (-0.76)							-0.0171 (-0.77)	-0.0167 (-0.92)	-0.0174 (-0.99)
Voluntary RE				-0.0922 (-1.14)			-0.0973 (-0.99)					
Voluntary EE					-0.0250 (-1.00)			-0.0171 (-0.84)			-0.00875 (-0.51)	
Voluntary CC						-0.0405 (-1.17)			-0.0388 (-1.20)			-0.0250 (-0.89)
N	80	80	80	80	80	80	80	80	80	80	80	80
Number of countries	22	22	23	22	22	22	22	22	22	23	23	23
Average time periods per country	3.64	3.64	3.48	3.64	3.64	3.64	3.64	3.64	3.64	3.48	3.48	3.48
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.283	0.322	0.347	0.351	0.325	0.334	0.326	0.362	0.378	0.360	0.370	0.406
Number of instruments	14	14	14	15	15	15	15	15	15	15	15	15
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.208	0.219	0.258	0.211	0.152	0.201	0.216	0.280	0.269	0.190	0.238	0.298
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.678	0.810	0.921	0.968	0.850	0.776	0.934	0.935	0.803	0.864	0.955	0.946

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ ; LDV denotes lagged dependent variable

Table C.3: Robustness check – GMM estimations including multiple policy variables

*Panel A: Including the total energy R&D ratio among the regressors*

<i>Dependent var.</i>	(E1)	(E2)	(E3)	(C1)	(C2)	(C3)
	<i>log(energy intensity)</i>			<i>log(emission intensity)</i>		
LDV	0.341** (2.08)	0.389** (2.29)	0.360** (2.11)	0.0663 (0.51)	-0.0445 (-0.22)	0.118 (0.50)
log(GDP per capita)	-0.299** (-2.32)	-0.376*** (-3.25)	-0.320*** (-4.27)	-0.613*** (-2.95)	-0.685*** (-3.59)	-0.503** (-2.18)
log(energy price)	-0.163** (-2.44)	-0.205** (-2.63)	-0.170*** (-3.23)	-0.174* (-1.73)	-0.169 (-1.25)	-0.134 (-1.26)
<b>Lagged log(total energy R&amp;D ratio)</b>	-0.0350* (-1.84)	-0.0272 (-1.62)	-0.0307** (-2.54)	-0.0254 (-0.63)	-0.0356 (-0.94)	-0.0187 (-0.49)
RE certificate share	0.260 (0.29)	-0.528 (-0.62)		0.0773 (0.07)	-1.283 (-0.78)	
Investment RE	-0.0171 (-1.26)			-0.0177* (-1.96)		-0.0194 (-1.57)
Voluntary RE			-0.0287 (-0.72)			
Investment EE		0.00263 (0.32)			-0.00364 (-0.24)	-0.00201 (-0.14)
Voluntary EE			-0.00995 (-0.71)			
Voluntary CC		-0.00458 (-0.14)	0.0199 (0.83)		-0.0589 (-1.11)	
N	79	79	82	77	77	80
Number of countries	21	21	22	21	21	22
Average time periods per country	3.76	3.76	3.73	3.67	3.67	3.64
AR(2) ( <i>prob &gt; chi<sup>2</sup></i> )	0.514	0.948	0.759	0.305	0.236	0.330
Number of instruments	16	17	17	16	17	16
Hansen test ( <i>prob &gt; chi<sup>2</sup></i> )	0.220	0.139	0.290	0.082	0.155	0.099
Difference-in-Hansen ( <i>prob &gt; chi<sup>2</sup></i> )	0.205	0.178	0.576	0.760	0.971	0.886

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ ; LDV denotes lagged dependent variable

Panel B: Including the energy-efficiency R&D ratio among the regressors

	(E4)	(E5)	(E6)	(C4)	(C5)	(C6)
	<i>log(energy intensity)</i>			<i>log(emission intensity)</i>		
LDV	0.282 (1.45)	0.362* (1.98)	0.456** (2.71)	0.0687 (0.49)	0.0267 (0.10)	0.0973 (0.46)
log(GDP per capita)	-0.241* (-1.88)	-0.361*** (-3.14)	-0.288*** (-3.98)	-0.590* (-2.05)	-0.669*** (-3.04)	-0.476* (-1.73)
log(energy price)	-0.141** (-2.29)	-0.195** (-2.62)	-0.170*** (-3.07)	-0.128 (-1.33)	-0.137 (-1.24)	-0.0997 (-0.92)
<b>Lagged log(energy-efficiency R&amp;D ratio)</b>	-0.0389** (-2.30)	-0.0295** (-2.24)	-0.0196** (-2.09)	-0.0398 (-1.48)	-0.0392 (-1.63)	-0.0319 (-1.20)
RE certificate share	0.456 (0.60)	-0.377 (-0.38)		0.365 (0.28)	-1.167 (-0.65)	
Investment RE	-0.0262* (-1.80)			-0.0255* (-2.01)		-0.0279* (-1.97)
Voluntary RE			-0.0312 (-0.62)			
Investment EE		0.00150 (0.14)			-0.00383 (-0.23)	-0.00123 (-0.09)
Voluntary EE			-0.00106 (-0.07)			
Voluntary CC		-0.00712 (-0.21)	0.00906 (0.35)		-0.0447 (-0.80)	
N	79	79	82	77	77	80
Number of countries	21	21	22	21	21	22
Average time periods per country	3.76	3.76	3.73	3.67	3.67	3.64
AR(2) ( <i>prob &gt; chi<sup>2</sup></i> )	0.580	0.953	0.492	0.345	0.283	0.362
Number of instruments	16	17	17	16	17	16
Hansen test ( <i>prob &gt; chi<sup>2</sup></i> )	0.268	0.215	0.292	0.203	0.234	0.145
Difference-in-Hansen ( <i>prob &gt; chi<sup>2</sup></i> )	0.224	0.231	0.513	0.293	0.541	0.423

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ \*\*\*; LDV denotes lagged dependent variable

Panel C: Including the low-carbon R&D ratio among the regressors

	(E7)	(E8)	(E9)	(C7)	(C8)	(C9)
	<i>log(energy intensity)</i>			<i>log(emission intensity)</i>		
LDV	0.460*** (2.96)	0.513*** (3.12)	0.580** (2.77)	0.133 (0.95)	0.142 (0.51)	0.166 (0.70)
log(GDP per capita)	-0.291** (-2.58)	-0.344*** (-3.03)	-0.271* (-1.92)	-0.572*** (-3.12)	-0.604*** (-3.12)	-0.528** (-2.36)
log(energy price)	-0.170** (-2.48)	-0.218*** (-2.87)	-0.178* (-2.05)	-0.172* (-2.01)	-0.192 (-1.53)	-0.156 (-1.55)
<b>Lagged log(low-carbon R&amp;D ratio)</b>	-0.0183 (-1.46)	-0.0139 (-1.12)	-0.0114 (-0.77)	-0.0173 (-0.88)	-0.0179 (-0.97)	-0.0160 (-0.71)
RE certificate share	0.235 (0.33)	-0.311 (-0.31)		-0.0770 (-0.08)	-0.643 (-0.38)	
Investment RE	-0.0112 (-1.21)			-0.0143* (-1.92)		-0.0156 (-1.55)
Voluntary RE			-0.0257 (-0.49)			
Investment EE		0.00277 (0.30)			-0.00104 (-0.08)	-0.000649 (-0.05)
Voluntary EE			0.000820 (0.06)			
Voluntary CC		0.0150 (0.56)	0.0183 (0.75)		-0.0256 (-0.53)	
N	80	80	82	78	78	80
Number of countries	22	22	23	22	22	23
Average time periods per country	3.64	3.64	3.57	3.55	3.55	3.48
AR(2) ( <i>prob &gt; chi<sup>2</sup></i> )	0.906	0.728	0.416	0.315	0.354	0.369
Number of instruments	16	17	17	16	17	16
Hansen test ( <i>prob &gt; chi<sup>2</sup></i> )	0.099	0.093	0.100	0.118	0.207	0.113
Difference-in-Hansen ( <i>prob &gt; chi<sup>2</sup></i> )	0.054	0.074	0.305	0.618	0.955	0.607

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ \*\*\*; LDV denotes lagged dependent variable

Table C.4: Robustness check – GMM estimations including investment as a share of GDP

<i>Dependent var.</i>	<i>Panel A: log(energy intensity)</i>								
	(E1)	(E2)	(E3)	(E4)	(E5)	(E6)	(E7)	(E8)	(E9)
log(LDV)	0.565*** (3.85)	0.446*** (3.78)	0.446*** (3.46)	0.549*** (2.90)	0.549*** (3.97)	0.483** (2.55)	0.577*** (4.02)	0.555*** (3.45)	0.617*** (4.01)
log(GDP per capita)	-0.232** (-2.61)	-0.338*** (-3.34)	-0.319*** (-4.07)	-0.187 (-1.68)	-0.234** (-2.49)	-0.187 (-1.35)	-0.225** (-2.48)	-0.241** (-2.43)	-0.258** (-2.74)
Investment ratio	-0.741** (-2.28)	-0.386* (-1.92)	-0.692** (-2.49)	-0.690** (-2.10)	-0.748** (-2.21)	-0.704** (-2.11)	-0.748** (-2.38)	-0.732** (-2.60)	-0.760** (-2.45)
log(energy price)	-0.187*** (-3.20)	-0.236*** (-3.49)	-0.225*** (-3.40)	-0.154** (-2.27)	-0.189*** (-3.19)	-0.142* (-1.80)	-0.185*** (-3.39)	-0.189*** (-3.59)	-0.212*** (-4.39)
Lagged log(energy R&D ratio)	0.00557 (0.25)	-0.00282 (-0.15)	-0.00212 (-0.09)	0.00455 (0.19)	0.00738 (0.32)	0.000392 (0.02)	0.00893 (0.40)	0.0102 (0.41)	0.0110 (0.46)
Feed-in tariff		0.235 (0.57)							
RE certificate share			0.0460 (0.08)						
Investment RE				-0.00843 (-0.72)					
Financial RE					-0.00144 (-0.05)				
Sum RE measures						-0.00756 (-0.78)			
Investment EE							0.000676 (0.12)		
Financial EE								0.00497 (0.45)	
Sum EE measures									0.00248 (1.25)
N	82	78	79	82	82	82	82	82	82
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.73	3.71	3.76	3.73	3.73	3.73	3.73	3.73	3.73
AR(2) ( <i>prob &gt; chi<sup>2</sup></i> )	0.271	0.510	0.753	0.404	0.289	0.585	0.257	0.345	0.232
Number of instruments	15	16	16	16	16	16	16	16	16
Hansen test ( <i>prob &gt; chi<sup>2</sup></i> )	0.386	0.402	0.354	0.261	0.353	0.235	0.412	0.477	0.507
Difference-in-Hansen ( <i>prob &gt; chi<sup>2</sup></i> )	0.218	0.623	0.461	0.194	0.284	0.165	0.234	0.421	0.393

<i>Dependent var.</i>	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)	(C9)
	<i>Panel B: log(emission intensity)</i>								
log(LDV)	0.288** (2.18)	0.273 (1.46)	0.253 (1.42)	0.247 (1.37)	0.249 (1.30)	0.191 (1.06)	0.252 (1.48)	0.275* (2.03)	0.174 (0.83)
log(GDP per capita)	-0.492*** (-4.40)	-0.517*** (-3.04)	-0.517*** (-2.89)	-0.442*** (-2.85)	-0.512*** (-4.44)	-0.425** (-2.25)	-0.498*** (-4.52)	-0.491*** (-4.59)	-0.469*** (-3.16)
Investment ratio	-0.861* (-1.75)	-0.647 (-1.69)	-0.659 (-1.62)	-0.614 (-0.86)	-0.981 (-1.36)	-0.606 (-0.88)	-0.785 (-1.38)	-0.867 (-1.68)	-0.716 (-1.15)
log(energy price)	-0.246*** (-3.72)	-0.267*** (-3.40)	-0.235*** (-3.12)	-0.170* (-1.80)	-0.250*** (-3.62)	-0.137 (-1.39)	-0.212** (-2.17)	-0.242*** (-3.53)	-0.145 (-1.31)
Lagged log(energy R&D ratio)	0.0188 (0.61)	0.0198 (0.64)	0.0129 (0.43)	0.00627 (0.16)	0.0199 (0.61)	-0.000806 (-0.02)	0.00843 (0.25)	0.0173 (0.53)	0.0000286 (0.00)
Feed-in tariff		0.348 (0.58)							
RE certificate share			-0.109 (-0.09)						
Investment RE				-0.0122 (-1.21)					
Financial RE					-0.0110 (-0.11)				
Sum RE measures						-0.0122 (-1.27)			
Investment EE							-0.00420 (-0.43)		
Financial EE								-0.0117 (-0.37)	
Sum EE measures									-0.00564 (-1.30)
N	80	76	77	80	80	80	80	80	80
Number of countries	22	21	21	22	22	22	22	22	22
Average time periods per country	3.64	3.62	3.67	3.64	3.64	3.64	3.64	3.64	3.64
AR(2) ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.801	0.771	0.660	0.671	0.873	0.706	0.766	0.808	0.663
Number of instruments	15	16	16	16	16	16	16	16	16
Hansen test ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.207	0.127	0.167	0.142	0.233	0.100	0.192	0.195	0.161
Difference-in-Hansen ( <i>prob</i> > <i>chi</i> <sup>2</sup> )	0.538	0.708	0.688	0.700	0.210	0.265	0.686	0.644	0.802

Note: t statistics in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  \*\*\*; LDV denotes lagged dependent variable

## Eidesstattliche Erklärung

Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit **“Essays on Decarbonising Energy Supply”** selbständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Datum

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# Curriculum vitae

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## Selected publications

Keegan, D., Kretschmer, B., Elbersen, B. and Panoutsou, C. (forthcoming). Cascading Use: A Systematic Approach to Biomass beyond the Energy Sector. *Biofuels, Bioproducts and Biorefining*.

Kretschmer, B., Hübler, M. and Nunnenkamp, P. (2013). Does Foreign Aid Reduce Energy and Carbon Intensities of Developing Economies? *Journal of International Development* 25, 67-91.

Kretschmer, B. and Peterson, S. (2010). Integrating Bioenergy into Computable General Equilibrium Models A Survey. *Energy Economics* 32, 673-686.

Kretschmer, B., Narita, D. and Peterson, S. (2009). The economic effects of the EU biofuel target. *Energy Economics* 31, S285-S294.