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Vincent Bertrand

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Vincent Bertrand. The european union emission trading scheme and energy markets : economic and financial analysis. Economics and Finance. Université de Franche-Comté, 2012. English. NNT : 2012BESA0003 . tel-00930886

HAL Id: tel-00930886

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UNIVERSITÉ DE FRANCHE-COMTÉ
UFR des Sciences Juridiques, Économiques, Politiques et de Gestion

**THE EUROPEAN UNION EMISSION TRADING SCHEME
AND ENERGY MARKETS:
ECONOMIC AND FINANCIAL ANALYSIS**

THÈSE

pour le grade de
Docteur ès Sciences Économiques

Soutenue publiquement par

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le 5 Juillet 2012

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L'Université de Franche-Comté n'entend donner aucune approbation ou improbation aux opinions émises dans cette thèse. Ces opinions doivent être considérées comme propres à leur auteur.

Remerciements

Je tiens tout d'abord à remercier Michel Mougeot, mon directeur de thèse, pour avoir accepté d'encadrer ce travail. Son aide et ses précieux conseils m'ont été d'une grande utilité au cours de ces années. En me faisant partager son expérience, il m'a permis de mener à bien cette thèse. Pour les mêmes raisons, je remercie Florence Naegelen, ma co-directrice de thèse. Je souhaite également exprimer toute ma reconnaissance à Zaka Ratsimalahelo, pour son aide précieuse sur les questions économétriques et sa grande disponibilité.

Mes remerciements s'adressent aussi tout particulièrement à Anna Creti et Jacques Percebois, qui m'ont fait l'honneur d'accepter d'être les rapporteurs de cette thèse. Leurs commentaires ont été très enrichissant et ont contribué à améliorer la qualité de ce travail. Je remercie Florence Naegelen, Christian de Perthuis et Zaka Ratsimalahelo pour avoir accepté de faire partie du Jury.

Cette thèse a bénéficié du concours du Centre de Recherche sur les Stratégies Économiques (CRESE) et de l'UFR SJEPG de Besançon. J'exprime ma gratitude envers ces deux institutions pour avoir mis à ma disposition des moyens matériels qui furent nécessaires à l'élaboration de ce travail. En particulier, je remercie Lionel Thomas, qui dirige actuellement le CRESE, et Christian At, qui fut son prédécesseur. À ce titre, je souhaite aussi remercier May Armstrong pour m'avoir permis d'accéder à la base de données Tendances Carbone de la Caisse des Dépôts et Consignations. Je tiens aussi à remercier le personnel administratif de l'UFR SJEPG, de l'IUT-BM GACo et des bibliothèques universitaires de Besançon.

Mes remerciements vont aussi à Joanne et Laura, qui ont relu attentivement cette thèse. Leur regard m'a permis d'améliorer la qualité du manuscrit et d'affiner mon propos. Je remercie également mes collègues doctorants du CRESE, pour leur amitié et leurs encouragements. Merci en particulier à Mamadou, pour nos discussions très fructueuses autour des techniques économétriques.

Enfin, je voudrais adresser une pensée particulière à mes parents, qui m'ont permis de poursuivre mes études et qui m'ont toujours encouragé et soutenu. Je remercie également Stéphanie et Louis, pour leur patience.

Abstract

This thesis investigates relationships between the European Union Emission Trading Scheme (EU ETS) and energy markets. A special focus is given to fuel switching, the main short-term abatement measure within the EU ETS. This consists in substituting Combined Cycle Gas Turbines (CCGTs) for hard-coal plants in off-peak power generation. Thereby coal plants run for shorter periods, which allows power producers to reduce their CO₂ emissions.

In Chapter 1, we outline different approaches explaining relationships between carbon and energy markets. We also review the literature relating to these issues. Next, we further describe the fuel switching process and, in particular, we analyze the influence of energy and environmental efficiency of thermal power plants (coal and gas) on fuel switching.

In Chapter 2, we provide a theoretical analysis that shows how differences in the efficiency of CCGTs can rule interactions between gas and carbon prices. The main result shows that the allowance price becomes more sensitive to the gas price when the level of CO₂ emissions increases.

In Chapter 3, we examine interactions between carbon, coal, gas and electricity prices in an empirical study. Among the main results, we find that there is a significant link between carbon and gas prices in the long-run equilibrium.

In Chapter 4, we analyze the cross-market price discovery process between gas and CO₂ markets. We identified in previous chapters that there is a robust significant link between gas and CO₂ markets. They are linked commodities, and their prices are affected by the same information. In an empirical analysis, we find that the carbon market is the leader in cross-market price discovery process.

Keywords: Carbon Finance, Climate change economics, Energy economics, EU ETS, Fuel switching, Partial equilibrium analysis, Financial econometrics, Cross-market price discovery.

Le Marché Européen du CO₂ et les marchés de l'énergie :

Analyse économique et financière

Résumé

Cette thèse porte sur les relations entre le Système Communautaire d'Échange de Quotas d'Émission (SCEQE) et les marchés de l'énergie. Une attention particulière est donnée au changement de combustible, le principal moyen de réduire les émissions de CO₂ à court-terme dans le SCEQE. Cela consiste à substituer des centrales gaz aux centrales charbon dans la production d'électricité en dehors des heures de pointes. Ainsi, les centrales charbon fonctionnent sur de plus courtes périodes, ce qui permet de réduire les émissions de CO₂.

Le Chapitre 1 décrit différentes approches expliquant les relations entre les marchés de l'énergie et du CO₂. Une revue de littérature est ensuite présentée. Nous donnons une description détaillée du processus de changement de combustible. En particulier, l'influence de l'efficacité des centrales est analysée.

Le Chapitre 2 fournit une étude théorique de l'impact des différences d'efficacité parmi les centrales gaz pour le changement de combustible. Le principal résultat montre que la sensibilité du prix du CO₂ vis-à-vis du prix du gaz dépend du niveau des émissions de CO₂.

Le Chapitre 3 examine les interactions entre les prix de l'électricité, du charbon, du gaz et du CO₂ dans une étude empirique. Les résultats montrent une qu'il existe une relation significative entre le gaz et le CO₂ à l'équilibre de long-terme.

Le Chapitre 4 étudie le processus de découverte des informations qui influencent la formation des prix du gaz et du CO₂. La forte relation entre le gaz et le CO₂ indique que leurs prix sont affectés par les mêmes informations. Nous montrons dans une étude empirique que le marché du CO₂ domine le processus de découverte de ces informations.

Mots clés : Finance carbone, Économie du changement climatique, Économie de l'énergie, SCEQE, Fuel switching, Équilibre partiel, Économétrie financière, Processus de découverte de l'information.

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À mes parents

Introduction

In ratifying the Kyoto Protocol, the European Union committed itself to reducing its greenhouse gas (GHG) emissions by 8% relative to the 1990 level in the first Kyoto commitment period (2008-2012). In January 2005, to meet this target in a cost-effective way, the European Union established the European Union Emission Trading Scheme (EU ETS), a cap-and-trade system for carbon emissions in the energy and industrial sectors. It is the world's largest emissions trading system to date. According to the 2003/87/EC directive, the EU ETS covers about 11,000 installations,¹ which represent almost 50% of CO₂ emissions and 40% of total GHG emissions in the European Union.

The EU ETS is nowadays the central piece of the European climate policy which was initiated in 1991, with the first Community strategy to limit CO₂ emissions and increase energy efficiency. At the end of the 1980s, the observation of an average temperature increase near the Earth's surface² of about +7°C since the pre-industrial period has raised the question of the impact of human activities. This has been further suggested by the intriguing concomitance of recorded sharp increases in temperatures and GHG concentrations since 1850 (see Figures 1 and 2).

1 Covered installations are those defined in Annex 1 of the 2003/87/EC directive. Combustion installations of the energy sector with installed capacities superior to the threshold of 20 thermal MW are notably concerned. Other installations are those of sectors such as cement, refineries, pulp and paper, iron and steel.

2 The scientific reliability of calculation of a globally averaged surface temperature is disputed by some scientists. However, most of the scientists agree that regional climate variations can modify climatic conditions in other regions of the world. Accordingly, “climate change” is a more accurate terminology than “climate warming” in describing this phenomenon.

Figure 1: Northern hemisphere temperature variations from IPCC [2001] and Guesnerie [2003]

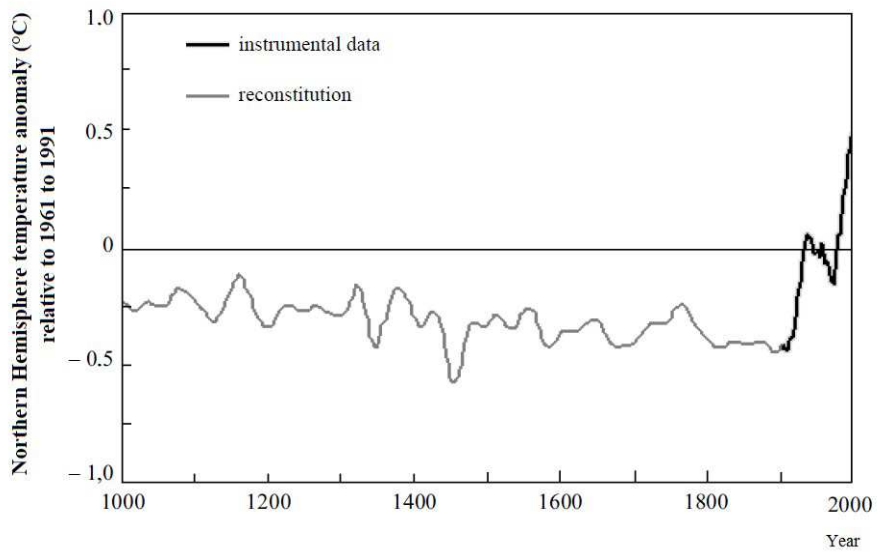
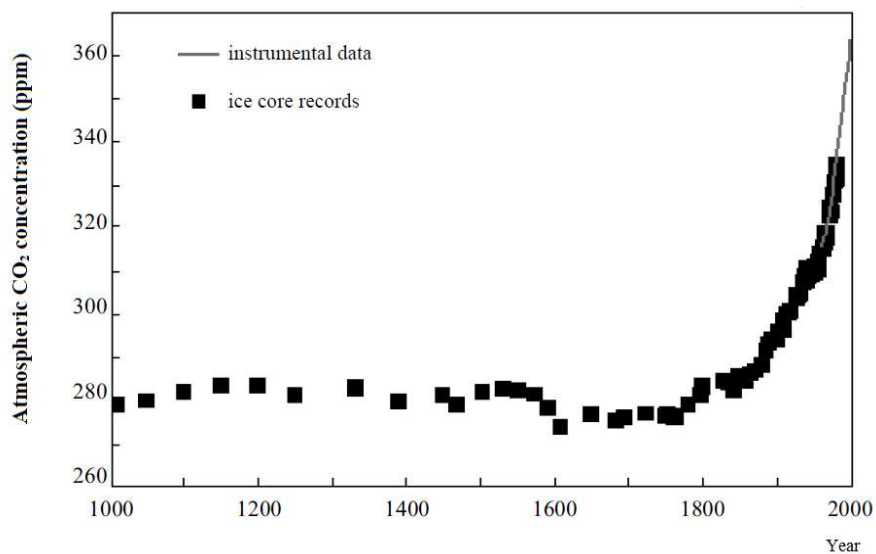


Figure 2: Atmospheric CO₂ concentrations from IPCC [2001] and Guesnerie [2003]



Following conclusions of the Intergovernmental Panel on Climate Change (IPCC), there was a wide consensus among scientists and policymakers in the early 1990s to recognize that the influence of anthropogenic GHG emissions (i.e. human-made GHG emissions) on the observed increase in globally averaged temperatures is very likely. However, human activities are not the only source of GHG emissions. Natural phenomena such as solar activity or volcanic eruptions also contribute to temperature variations and GHG concentration. Moreover, no formal proof of human influence on temperatures and climate has been given yet. Accordingly, there are a few scientists who dispute the

idea of a human-caused climate change. Nevertheless, while there do remain scientific uncertainties about the human influence, the correlation between high increases in temperature variations (and possible global warming) and anthropogenic GHG emissions give strong presumptions. From an economic point of view, those uncertainties do not justify delaying immediate actions to reduce human-made GHG emissions. The nature and scale of potential risks (as well as the fact that some effects could be irreversible and could accelerate processes) are so huge that inaction, if unfavorable events occur, may be more costly than action, even though occurrence is uncertain.³ After all, should we refuse to insure our house because we cannot be sure that it will burn? As pointed out in the Stern Review on the economics of climate change (Stern [2006a]), stabilization of atmospheric CO₂ concentrations at 550 ppm⁴ would be five to twenty times less costly than the cost of inaction.⁵

Such considerations have brought policymakers to develop an international response to the problem of climate change. Following the precautionary principle,⁶ many countries have committed to implementing climate policies, i.e. policies established to address the problem of climate change by reducing GHG emissions and financing a low-emission development. Most of those initiatives have been decided at an international level. They are reviewed in what follows.

Review on international climate policies

The EU ETS is closely related to the Kyoto Protocol Flexibility Mechanisms: the Joint Implementation mechanism (JI, article 6 of the Protocol), the Clean Development Mechanism (CDM, article 12), and the Emissions Trading mechanism (article 17). The Kyoto Protocol has extended the United Nations framework originated from the United Nations Framework Convention on Climate Change (UNFCCC) of 1992. The UNFCCC was the first step in international treaties dealing with reducing temperature increases and anthropogenic climate change (i.e. climate change with presumption of human influence). With the Kyoto Protocol, adopted in the United Nations

3 Due to irreversibility and acceleration in the increase of the greenhouse effect with higher GHG concentrations, inaction may create more and more damage and increase the cost of delayed actions. See Guesnerie [2003] and Stern [2006b].

4 Ppm (parts per million) is the measure of the number of GHG molecules in the total number of molecules of dry air. For example, 550 ppm means 550 molecules of a GHG per million molecules of dry air. See IPCC [2007].

5 Note that the Stern Review's methodology is subject to numerous discussions that we do not report here.

6 While the precautionary principle is sometimes criticized as an absurd call for “zero risks” required by anxious people, the extraordinary nature of potential consequences of climate change makes it probably much more relevant in this case.

summit of Kyoto in December 1997,⁷ an international GHG emissions reduction commitment was set for the first time. Developed countries listed in Annex B of the Protocol have committed to reduce collectively their CO₂ emissions by 5.2% compared with the 1990 level, between 2008 and 2012 (i.e. taking as reference the year 1990 for each year). Among these countries, individual contributions to the global effort span from -8% (the European Union-15) to +10% (Iceland), depending on historical contributions to concentration of CO₂ in the atmosphere (see Table 1).

Table 1: Annex B countries emission reduction targets (in the period 2008-2012) compared to the 1990 levels, based on Brohé [2008]

Country	Target (in %)
Iceland	10
Australia	8
Norway	1
New Zealand, Russian Federation, Ukraine	0
Croatia	-5
Canada, Hungary, Japan, Poland	-6
United States	-7
Bulgaria, Czech Republic, Estonia, Latvia, Liechtenstein, Lithuania, Monaco, Romania, Slovakia, Slovenia, Switzerland	-8
European Union - 15	-8

Countries' targets are converted into Assigned Amount Units (AAU)⁸ which are received by governments of Annex B countries (“Annex B Parties”). In order to facilitate the achievement of emission reduction objectives and to minimize the overall cost, an international emissions trading system offers the possibility to trade AAUs among Annex B Parties. The Emissions Trading mechanism allows countries that have AAUs in excess – due to higher emission reductions than their targets – to sell these spare units to countries that are over their targets. Other emissions units can be traded (and used for compliance) under the Kyoto Protocol's emissions trading system. These units are the Emission Reduction Units (ERUs) and the Certificates of Emission Reduction (CERs). The ERUs are units issued from the JI mechanism. The JI mechanism allows an Annex 1

7 While adopted in 1997, the Kyoto Protocol did not come into force before February 2005 due to late ratification of Russia. Australia is the latest Annex B country (i.e. countries with binding emission reduction targets in the Kyoto Protocol) to have ratified the Protocol on December 2007. So far, the United States is the only signatory (Annex B) country which has not ratified the Protocol.

8 Each unit gives the right to emit one tonne of CO₂.

country (i.e. a country listed in Annex 1 of the UNFCCC)⁹ to earn ERUs from an emission reduction project in another Annex 1 country. The CERs are units generated through the CDMs. The CDMs encourage emission reduction projects by Annex 1 countries in non-Annex 1 countries. The aim is to assist developing countries (i.e. non-Annex 1 countries) in achieving a sustainable low-carbon development. There are also units that can be used for compliance although they cannot be traded. These are the Removal Units (RMUs, articles 3.3 and 3.4 of the Kyoto Protocol) which are issued on the basis of emission reduction projects through the Land Use, Land Use Change and Forestry (LULUCF) activities.¹⁰ In each case, the CERs, ERUs and RMUs are delivered after a validation and certification process that warrants effective emission reductions. Those certification are guaranteed by the CDM Executive Board (CDM EB), for the CDMs, and by the JI Supervisory Committee (JISC), for the JI and JI-LULUCF.¹¹ It has to be noted that there is a major difference between the JI mechanism and the CDMs regarding accounting of emission credits. While CERs are additional credits, issued in addition to AAUs, ERUs are converted AAUs (i.e. a volume of AAUs equivalent to the volume of emission reductions is converted into ERUs). This was decided in order to avoid “double accounting” of emission reductions. Indeed, if the host country of the project is an Annex B country, and if the ERUs were created in addition to the host country's AAUs, emission reductions would be counted twice: as ERUs for the investing country and as unused AAUs (due to emission reductions from the project) for the host country.

Negotiations for a post-Kyoto agreement began with the Conference of the Parties (COP) of Bali in December 2007. It introduced a new negotiation process with the aim to reach an agreement for the post-2012 period at the COP of Copenhagen in December 2009. In the meanwhile, the European Union has adopted the “Climate and Energy Package”, in December 2008, which extends the EU's climate policy after 2012. The package includes three “20 targets” to reach by 2020: reducing GHG emissions by 20%, reaching 20% of renewable energy in the total energy

9 The UNFCCC distinguishes between Annex 1 and non-Annex 1 countries. Annex 1 countries are developed countries with high past emissions, whereas non-Annex 1 countries are developing countries. Annex 1 countries had committed themselves to reducing their GHG emissions under the UNFCCC. They agreed to maintain their emissions to the 1990 levels by 2000, even though these targets were not legally binding (as opposed to targets of Annex B countries under the Kyoto Protocol, which are legally binding). Annex 1 and Annex B countries are often assimilated in practice, since most of Annex 1 countries are also Annex B countries (and vice versa). Turkey is the only country included in Annex I but not in Annex B, while Croatia, Liechtenstein and Monaco are included in Annex B but not in Annex 1 (see Brohé [2008] and the UNFCCC website).

10 Note that only afforestation and reforestation are eligible as project-based emission reductions in non-Annex 1 countries, whereas all kind of LULUCF activities are eligible in Annex 1 countries (afforestation, reforestation, revegetation, forest management, cropland management, grazing land management). Accordingly, projects in LULUCF are sometimes referred to as JI-LULUCF. See JMOE and GECF [2006].

11 There is another type of project-based units outside the Kyoto Protocol regime. These are the Verified Emissions Reductions (VERs) which are issued from projects that do not follow all the JI and CDM requirements, and are not subject to certification of the CDM EB or JISC. They are traded in the voluntary markets.

consumption and increasing energy efficiency to save 20% of energy consumption. Besides, the EU ETS has been confirmed for a Phase 3 (2013-2020).

Despite the great hope in the Copenhagen Summit, it did not achieve the global binding agreement that was expected to prolong the Kyoto Protocol. The Copenhagen Accord was notable in that it referred to a collective commitment to allocate new resources to finance climate policies in developing countries: 30 billion USD for the period 2010-2012. It also stated that actions should be taken to stabilize an average temperature increase at +2°C, as recommended by the IPCC. However, no explicit binding emission targets were specified in the Accord. By contrast, the signatory countries stated what actions they are willing to take if a binding agreement is achieved in the future (see Table 2).¹²

Table 2: “Variable geometry” commitments of some of the main signatory countries to the Copenhagen Accord, from de Perthuis et al. [2010]

Country	2020 emission reduction target	Benchmark year
Annex 1 countries		
Australia	between 5% and 15% (if there is an international agreement that includes the developing countries), or even 25% (if there is a target not to exceed 450 ppm of GHG in the atmosphere)	2000
Canada	17%	2005
EU - 27	20% or 30% (if there are equivalent commitments from the other developed countries and an adequate contribution from developing countries)	1990
Japan	25% (if there is a fair and ambitious international agreement that includes the main economies)	1990
New Zealand	between 10% to 20%, if there is a full international agreement (aiming not to exceed a 2°C rise in temperature, comparable efforts from the other developed countries, adequate measures from developing countries, rules on LULUCF, access to an efficient international carbon market)	1990
Russia	15% to 25%, depending on the recognition of forests and the main emitter's commitment to reducing their emissions	1990
United States	around 17% (subject to Congress voting on the international legislation)	2005
non-Annex 1 countries (developing countries)		
Brazil	between 36% and 39% compared with the “business-as-usual” assumption	2020
China	40% to 45% reducing in GDP CO ₂ intensity	2005
India	20% to 25% reducing in GDP GHG intensity (excluding agricultural emissions)	2005

12 The Copenhagen Accord has specified a “variable geometry” commitment system, with different targets from one country to another. This is a different approach with respect to the Kyoto Protocol which provided a collective emission target for Annex B countries. For a detailed analysis of the Copenhagen Accord, see de Perthuis et al. [2010].

At the same time, no economic mechanism has been provided in the Accord, as it was the case in the Kyoto Protocol with the Flexible Mechanisms.

One year after the Copenhagen Summit, the next COP was held in Cancun in December 2010. While the Cancun Agreements reaffirmed the principles of the Copenhagen Accord, no precise decision was adopted on the legal form of countries' binding emission targets, financial resources and economic mechanisms for the post-Kyoto period. Nevertheless, Cancun has yielded some success. Notably, the enshrining of the main elements of the Copenhagen Accord into the UNFCCC framework (e.g. stabilization of average temperature increase at +2°C, calling on developed countries to reduce their GHG emissions, helping developing countries to implement a low-emissions development) and the reassurance of the intention to continue with market-based mechanisms (CDMs, Emissions Trading, etc) even in the absence of a post-Kyoto commitment. Moreover, a “Green Climate Fund” was mentioned with the goal for developed countries to mobilize jointly 100 billion USD per year by 2020 to assist developing countries in financing emission reductions and adaptation. However, there was no agreement on how money will be raised to feed that fund.

Many important decisions were agreed on during the COPs of Copenhagen and Cancun, even though Parties were often very vague regarding concrete enforcements. Among those decisions, the recognizing of the +2°C global target and the creation of a fund to finance the clean development of developing countries, are particularly important. However, there was no agreement on how to extend the Kyoto Protocol beyond 2012. Besides, although a majority of signatory countries have confirmed their support for the Copenhagen Accord, emission reduction targets remain unbinding and often undefined precisely.¹³ Thus, the primary concern of the next rounds of negotiations will be to adopt a new global agreement that prolongs the Kyoto Protocol, with legally binding emission targets, new economic mechanisms and institutions. Recently, the COP of 2011 was held in Durban in December 2011. Once again no legally binding agreement was achieved. However, the outcomes include a decision by Parties to adopt a universal legal agreement no later than 2015 (Durban Platform for Enhanced Action). The Green Climate Fund has also been confirmed. The next COP will be held in Qatar in December 2012.

So far we have reviewed how the problem of climate change has been tackled at the international level in climate policies. We have also reported the negotiations which are currently under way to

¹³ Note that reaching unanimity among Parties is a very important task since unanimity is required to enforce legally binding agreements under the UNFCCC's rules (de Perthuis et al. [2010]). In that respect, the Kyoto Protocol was an exception since the condition for the Protocol to be enforced was the ratification of at least 55 Parties of the Convention representing 55% of the global emissions of the Parties in 1990.

prolong international climate policies beyond 2012. Let us now discuss origins of the concept of emission trading and give a presentation of first experiences that were implemented before the EU ETS.

Emission trading: theory and previous experiences

An externality exists when an agent takes decisions that are not accounted for in a market price even though they affect other agents' well-being. Accordingly, producers of externalities do not have any incentives to take into account the effects of their decisions on others. Pollution is generally considered as a negative externality. A negative externality causes divergence between social and private costs. The private cost of polluting activities is under-estimated with respect to the social cost, since it neglects the “external” cost of damages created by pollution. As a result, the chosen level of pollution is higher than the socially optimal level (i.e. the level which equalizes the social marginal cost to the social marginal benefit of pollution).

The problems of excessive pollution are sometimes also tackled in terms of “public good” or “common asset”. A public good is a good that exhibits properties of non-excludability (i.e. no one can be excluded from using the good) and non-rivalry (i.e. the consumption of the good by one individual does not reduce the availability of the good for others). The open access to public goods leads to a problem which is well known by economists: free-riding, that induces over-exploitation and potential destruction of “common assets” (“the tragedy of the commons”, as defined by Hardin [1968]). Environmental goods and services are particularly exposed to that kind of inefficiency. Ecosystem services such as waste absorption capacities are typical examples of public goods which are subject to over-exploitation and this results in excessive pollution.¹⁴ The problem of climate change is unusual in that respect, since it concerns a global public good: climate stability.

However pollution is referred to – negative externality or deterioration of a public good – it leads to a market failure that results in inefficient outcomes. For economists, the solution consists in putting a price on pollution in order to “internalize” the cost of pollution in private decisions. Basically, there are two categories of economic instruments to internalize pollution: Pigouvian tax and emissions trading scheme (“cap-and-trade”). Both have been advocated by economists because they minimize the overall cost of environmental regulation compared to rigid “command-and-

¹⁴ Pollution is sometimes referred to as a “public bad” to point it out as a negative externality deteriorating an environmental public good.

control” approaches. Command-and-control regulations generally apply uniform emissions limits on regulated firms, regardless of the fact that firms are not equally efficient in reducing emissions. By contrast, with economic instruments, individual firms are free to choose how much they will reduce their emissions by comparing their abatement costs with the price of pollution. As a consequence, firms with lower costs make higher share of the overall effort of emissions reduction, and vice versa. This leads to the “least-cost solution” in which each firm equalizes its marginal abatement cost to the price of pollution.

Pigouvian tax was introduced by Pigou [1920] as a way to restore market efficiency in presence of negative externalities. In his famous example, Pigou explains that social benefits of railway services in the England of the 19th century was over-estimated due to negligence of damages caused by sparks from engines. To correct the negative externality, Pigou proposed to place a tax on railway companies varying with the amount of smoke produced and equivalent to the monetary value of the externality (i.e. equivalent to the difference between the social cost and the private cost). Hence, by making companies financially liable for the damages created by sparks, the Pigouvian tax gives an incentive to reduce the output to the socially optimal level.

The concept of the emission trading scheme was introduced by Dales [1968],¹⁵ based on the Coase theorem. Coase [1960] proposed a solution that consists in establishing property rights on emission of externalities. If transaction costs are negligible, Coase shows that parties – i.e. “disrupters” and “victims” – can achieve a socially optimal level of externality by bargaining, regardless of who initially received the property rights. The socially optimal level of externality is attained when the marginal benefit of the externality (i.e. profits arising from the activity which generates the externality) is equal to the marginal cost of the externality.¹⁶ Moreover, a market price emerges for the externality. Based on the Coasian approach, market-based instruments (MBIs) have been popularized as an efficient way to reduce pollution. They work with a central authority which sets a cap on the total amount of pollutant that can be emitted. The cap is converted into allowances that give the right to emit a certain amount of pollutant. Allowances are allocated to polluters, and they can be traded on a secondary market. A market price emerges¹⁷ and buyers pay that price to increase their emissions, while sellers can earn money by selling unused allowances. Thus, polluters

15 First references to emission trading can be found in Crocker [1966].

16 In his 1960 paper, Coase argued that the traditional Pigouvian approach may lead to results “which are not necessarily” the true social optimum, because it neglects the “reciprocal nature” of externalities: inducing disrupters to reduce harm on victims also inflicts harm on disrupters. He proposed his solution as a way to overcome this problem.

17 Emission trading schemes are sometimes referred to as “quantity instruments” because they fix the overall emission level (quantity) and allow the price to vary according to supply and demand conditions (i.e. according to scarcity of allowances, which is set by volume of emissions). By contrast, a Pigouvian tax on emissions is a “price instrument” because it fixes the price and allows quantities (i.e. emissions) to vary.

with low abatement costs have an incentive to reduce their emissions by more than needed, and those with high abatement costs can buy more allowances rather than engage in costly emission reductions. Accordingly, MBIs theoretically achieve emission reduction targets at the lowest cost to society. Such a “least-cost” solution implies equalization of marginal cost of abatement among polluters. Montgomery [1972] formalized this result and showed that it is verified in the equilibrium of the market for allowances.¹⁸

Before the EU ETS and the Kyoto Protocol, MBIs were used in many previous programs to reduce different kinds of pollution. The first experiences appeared in the United States in the 1970s and 1980s. The US Environmental Protection Agency (EPA) started in 1976 with the adoption of the “offset” mechanisms that became part of US legislation with the 1977 Clean Air Act Amendments (CAAA) to the Clean Air Act of 1970. The 1977 CAAAs allowed emission trading among facilities subject to emission restrictions regarding six air pollutants (ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen oxide and lead), under the National Ambient Air Quality Standards (NAAQS).¹⁹ Other examples of early MBI implementations are the 1980 Wisconsin's program to reduce BOD (Biochemical Oxygen Demand) discharges in the Fox River, the 1982 EPA lead reduction program for gasoline refiners²⁰ or the Regional Clean Air Incentives Market (RECLAIM, 1994) for SO_x (sulfur oxide) and NO_x (nitrogen oxide) emissions in California. However, the first nation-wide emission trading program in the US appeared in 1995 with the US Acid Rain Program (ARP), established under Title IV of the Clean Air Act Amendments of 1990. The ARP sets annual reduction targets for SO₂ emissions of power plants. SO₂ emissions of affected facilities were capped annually at about half of their 1980 levels. Ex-post evaluations of the ARP have demonstrated high cost savings with respect to previous command-and-control approaches (see Ellerman [2003]).

Emission trading schemes related to pollutants responsible for acid rains have also been implemented in Europe. On the basis of the national NO_x and SO₂ reduction targets established under the 2001/81/EC directive (the “National Emission Ceilings” directive), Slovakia (2002) and

18 Montgomery [1972] provides formal proof that such an equilibrium exists under certain conditions (competitive market, no transaction-costs, etc).

19 While the offset-mechanisms introduced a market for emissions reduction credits, it was only designed for new facilities. Thus, it was limited in size.

20 While the lead reduction program was recognized as a success with annual cost savings estimated at 200 million USD by the EPA (see Newell and Kristian [2003]), the Fox River program ended in failure with only one trade in five years due to numerous administrative requirements discouraging the trading of allowances (see Hahn [1989] and [1991]).

the Netherlands (2005) have set legally-binding caps for NO_x (the Netherlands) and SO₂ (Slovakia) emissions of industrial thermal facilities.²¹ The Slovakian SO₂ trading program came into operation in 2002. The aim was to reduce SO₂ emissions in 2010 to 36% of the 1999 emissions. It applied to sources with installed thermal capacities above 50 MW, and it represented about 90% of the Slovakian SO₂ emissions in 1998. There were very few trades. The Dutch NO_x emissions trading system applies to approximately 250 facilities with installed thermal capacities of more than 20 MW. It covers about 85% of industrial emissions and 25% of the overall Dutch emissions. Between 2005 and 2010, the Dutch government set a target of 55,000 tonnes of NO_x emissions per year for affected facilities, compared to 1995 base year emissions of 122,000 tonnes. Nevertheless, the allowance price was very low. Yet, the Dutch NO_x trading program has been prolonged until 2013. Discussions about the future of the program for after 2013 are currently under progress.²²

However, the first national MBI in Europe was the Individual Transferable Quotas (ITQ) system in the fishery sector in Iceland (1984). Between 1945 and 1983, the value of capital stock in the Icelandic fishery sector increased by 1,200%. The fishery stocks were clearly over-fished, which motivated the introduction of the ITQ system. The program allocated quotas attached to boats. However, transfers of quotas were not allowed, unless boats were wrecked or sold abroad. These restrictions have led to incentives to destroy boats in order to sell quotas. To avoid such destruction, unrestricted transfers of quotas were allowed in 1991. The ITQ system reduced the number of fishing boats in Iceland, and brought the fishery sector better in line with fish stocks (see EEA [2006]). ITQ systems were also used in Canada (1983), Australia (1984) and New Zealand (1986). In Europe, ITQ systems have been implemented in the fishery sector of Denmark, Italy, the Netherlands, Portugal and the UK (see Branch [2004]).

Another example of the MBI system which is not related to GHG emissions can be found in the packaging waste regulation. In the wake of the EU Packaging and Packaging Waste Directive (94/62/EC), the UK government implemented in 1997 the Packaging Recovery Note (PRN) system which allows affected companies to trade quotas limiting packaging discharges. So far, the UK PRN is the only application of MBIs to limit packaging.

Due to the interest in promoting renewable energies in Europe, MBIs have been designed to foster penetration of renewables. The EU adopted a directive in 2001 (2001/77/EC) to increase the

21 See EEA [2005], EEA [2006], IEA [2006] and Ecofys [2010].

22 For several years the EU has been assessing opportunities on developing an EU-wide NO_x and SO₂ trading scheme for IPPC installations, i.e. installations subject to the directives 96/61/EC and 2008/1/EC about Integrated Pollution Prevention and Control (see EC [2010]). However, in March 2011, the Commission officially announced that it will not be pursuing further work on NO_x/SO₂ trading due to potential conflicts with the Industrial Emissions Directive (the IDE directive 2010/75/EU) and uncertainties about the impact on local air quality (see Eurofer [2011]). Same questions about interferences with the IDE directive are the main topic regarding the future of the Dutch NO_x trading program.

share of green electricity in the total electricity consumption. It established different national targets for Member States in order to meet an overall objective for the EU.²³ To achieve this aim, markets for “Tradable Green Certificates” (TGCs) – or “Tradable Renewable Energy Certificates” (TRECs) – have been established in several EU Member States, including the UK, the Netherlands, Italy, Denmark, Belgium, Sweden, and Austria (see Bertoldi and Rezessy [2004]). TGC schemes impose quantified obligations on electricity buyers (e.g. retailers or consumers). The obligated buyers must surrender to an authority a number of certificates corresponding to a percentage of their total electricity sales or consumption. The authority issues (a fixed number) and distributes certificates to producers of green electricity (typically, one certificate refers to one MWh of green electricity). Certificates are sold by power producers to obligated buyers and they vanish after submission. TGC schemes can be regarded as market-based subsidies rather than pure MBIs as defined before.

MBIs are particularly appropriate for GHG emissions since greenhouse effect is a global process, and thus local differences in air concentrations do not matter. Created in 1996, the Canadian PERT (Pilot Emission Reduction Trading) program was the first emission trading scheme applying to GHG emissions. The PERT was a voluntary market for industrial emissions in the Ontario region. While the initial focus was NO_x and VOC (Volatile Organic Compound) emissions, the program was expanded in 1997 to include CO₂ and carbon monoxide emissions. It operated between 1996 and 2001, and it was directly linked to the Canadian government through supervision of the Canadian federal environmental agency. It appears that only a small number of trades were completed during the program.²⁴ The Greenhouse Gas Abatement Scheme (GGAS) is another example of emission trading scheme applying to GHG emissions. It was introduced by the New South Wales (NWS – Australia) state government in 2003 (see GGAS [2008]). It is a mandatory emission trading scheme. The program covers GHG emissions of electric generators and large consumers of power. The GGAS establishes an annual state-wide target for emissions which is converted into NSW Greenhouse Abatement Certificates (NGACs). Individual sources receive each year an initial allocation of NGACs, with the ability to buy and sell those certificates to meet their obligations. The GGAS remains operational to date.²⁵

Prior to the creation of the EU ETS, the first European CO₂ trading schemes were introduced in Denmark and in the UK.²⁶ The Danish CO₂ emissions trading system came into operation in 2000, after the “Electricity Reform” and the “CO₂ Quota Act” were passed by the Danish parliament in March and June 1999, respectively. The system covered the eight largest electricity

23 This was confirmed in 2008 with the Climate and Energy Package.

24 For further details see LECG [2003].

25 Even though it has been delayed several times since 2007, an Australian Federal Emission Trading Scheme is expected to be operational in 2013.

26 See Pedersen [2000], EEA [2005], EEA [2006], DEFRA [2006] and Green [2008].

producers in Denmark, representing approximately 90% of the CO₂ emissions from the Danish electricity production, and about 30% of the total GHG emissions in Denmark. It operated between 2000 and 2004. Legally-binding allowances were allocated each year to affected producers, representing 66% of their average annual emissions between 1994 and 1998. However, the low non-compliance fees of DKK 40 (i.e. about EUR 5.40) per tonne made the constraint less restrictive. The program obtained contrasted results with very few trades and several companies that failed to comply in 2002 and 2004, while they were collectively long of allowances. Nevertheless, efficiency was not the first objective of the program. The aim was rather to prepare the country for the EU ETS. In that respect, it was a success. The UK ETS (United Kingdom Emission Trading Scheme) was a voluntary scheme launched in the UK in April 2002 for the five-year period 2002-2006, and which formally ended in March 2007. It intended to prepare the UK companies for the EU ETS, and London's financial place for emissions trading. The UK ETS was the world's first economy-wide GHG emissions trading scheme, since it covered a wide range of sectors. The reduction targets (with respect to baseline emission levels between 1998 and 2000) were set through an auction in March 2002. Sources sold their reduction targets to the government, and received tradable allowances in exchange. The aim was to provide a financial incentive for companies to adopt emission reduction targets voluntarily. The thirty-three direct participants committed to reducing collectively their CO₂ emissions by 3.96 million tonnes by the end of the scheme. However, over the life of the program, a total of 7.2 million tonnes of CO₂ were reported.

Following the European leadership on carbon trading, several GHG emissions trading schemes have been implemented in the last few years and others are on the horizon. Examples are the Specified Gas Emitters Regulation (SGER, state of Alberta, Canada, 2007), the New Zealand Emissions Trading Scheme (NZ ETS, New Zealand, 2008) and the Regional Greenhouse Gas Initiative (RGGI, United States, 2008). There are now GHG emissions trading schemes in America, Europe and Oceania. However, the EU ETS is still, by far, the more ambitious program. The main characteristics of the EU ETS are presented in the following.

The EU ETS: characteristics and main issues

The EU ETS officially started in January 2005. It is made up of consecutive “Phases” which are trading periods of several years. Phase 1 covered the period 2005-2007. It was designed as a pilot phase to “learn by doing” and gain experience for subsequent Phases. Phase 2, which is currently in

progress, corresponds to the first Kyoto commitment period, i.e. 2008-2012. Phase 3 will start in 2013 and end in 2020. It is supposed to be part of a post-Kyoto agreement.

The EU ETS was established to help the EU Member States to fulfill their commitments in the Kyoto Protocol. Under the Burden-Sharing-Agreement of 1998 (EU Council Document 97/02/98), the EU-15 collective target (see Table 1) has been translated into differentiated national targets for each Member State (see Table 3). Moreover, ten of the twelve Member States that were not part of the EU in 1997 have individual commitments under the Kyoto Protocol (see Table 1).

Table 3: Distribution of the EU-15 Kyoto target in the Burden-Sharing-Agreement, from Guesnerie [2003]

National targets of the EU-15 countries under the Burden-Sharing-Agreement (emission reductions in the period 2008-2012 compared to the 1990 levels)					
Country	Target (in %)	Country	Target (in %)	Country	Target (in %)
Austria	-13	Germany	-21	Netherlands	-6
Belgium	-8	Greece	25	Portugal	27
Denmark	-21	Ireland	13	Spain	15
Finland	0	Italy	-6.5	Sweden	4
France	0	Luxembourg	-28	UK	-12.5

In order to meet national targets, each Member State has to set a national cap on CO₂ emissions for each Phase of the EU ETS. Indeed, the Directive 2003/87/EC establishes that each Member State has to develop a National Allocation Plan (NAP) stating the total number of allowances it intends to allocate for the Phase (the cap), how it proposes to allocate them (free allocations or auctions), what the receiving installations and the new entrant reserves are. Each NAP has to be approved by the European Commission before validation. In the case of incompatibility with criteria listed in the Directive 2003/87/EC or if allocations are judged too generous with respect to obligations, the European Commission may reject NAPs and send them back to Member States for revisions. The EU ETS is a decentralized system, in which Member States have a lot of freedom in designing their NAPs. But, on the other hand, the European Commission decides the general rules (e.g. which are the affected sectors and facilities). Thus, it is halfway between an EU centralized system and a fully decentralized system (Kruger et al. [2007]).

Allocation

The EU ETS concerns facilities with energy consumption or installed thermal capacities which exceed some thresholds (see Annex 1 of the Directive 2003/87/EC) in sectors of power and heat, refineries, cement and lime, iron and steel, pulp and paper, glass, ceramic, metal ore processing and coke ovens.²⁷ Based on accepted NAPs, each participating installation receives a certain volume of EUAs (European Union Allowances) at the beginning of each year, on 28th February. Each EUA gives the right to emit one tonne of CO₂, and can be traded on several exchanges (i.e. organized market places) across Europe.

Options for allocation of EUAs in the EU ETS are grandfathering (i.e. free distribution of allowances on the basis of historical emissions) or auctioning.²⁸ Auctioning has been widely advocated by economists,²⁹ who support that it can reduce adverse effects associated with grandfathering such as unfair distributional effects (transfer of resources “from the poor to the rich”)³⁰ or perverse dynamic incentives to emit more now in order to receive a larger allocation in the future. Moreover, auctioning is likely to be more efficient than free allocation because it ensures that more allowances are received by firms which need them more (i.e. firms with higher abatement costs) and it offers scope to reduce distortionary taxes in the economy by “recycling” the auction revenue. According to the Directive 2003/87/EC, Member States can auction up to 5% of the total number of EUAs allocated for Phase 1, and up to 10% for Phase 2. Nevertheless this only gives an upper limit and Member States can determine freely the exact volume of allowances they want to auction. During Phase 1, only four countries decided to use auctioning: Denmark (5%), Hungary (2.4%), Lithuania (1.5%) and Ireland (0.5%). For Phase 2, eleven countries decided to include auctioning in their NAPs. Examples are Germany (8.8%), the UK (7%), the Netherlands (3.7%) or Hungary (2%).³¹ There will be change in Phase 3. The Directive 2009/09/EC, which sets out changes to the EU ETS from 2013 onwards, states that 100% of the allocation will be auctioned in the electricity sector. In other industrial sectors, with limited exposure to international competition, the allocation via auction will increase from 20% in 2013 to 70% in 2020 (and 100% in 2027). Besides, firms of the newly-included aviation sector will have to buy 15% of their EUAs at auction.

²⁷ With the start of Phase 3 in 2013, new sectors will be covered by the EU ETS such as aviation, petrochemical or aluminium.

²⁸ Allocations based on benchmarking (i.e. allocations on the basis of specific benchmarks) are also allowed. They seem to yield better outcomes compared to grandfathering (see Betz et al. [2006]), that we do not discuss here. In practice, benchmarking is often used for new entrant allocations. Only France used benchmarking for existing installations in Phase 1, and very few countries in Phase 2 including Belgium, Malta and Cyprus.

²⁹ See Crampton and Kerr [2002], Hepburn et al. [2006] and Mougeot and Naegelen [2009].

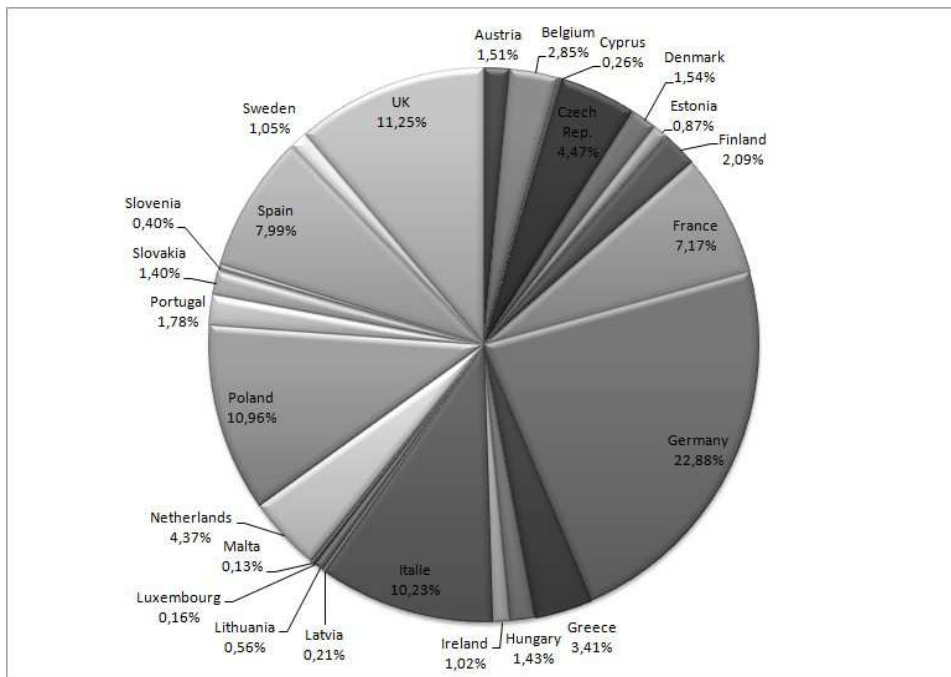
³⁰ Most of the rent from grandfathered allowances ultimately accrue to shareholders of the profiting firms, who tend to be wealthier than the general population. See Hepburn et al. [2006].

³¹ See Charpin [2009] for an overview on main characteristics of auction procedures adopted by Member States in Phases 1 and 2.

Thus, the auctioning of EUAs will sharply increase in Phase 3, with more than one billion EUAs auctioned annually, compared to less than 150 million in Phase 2.³²

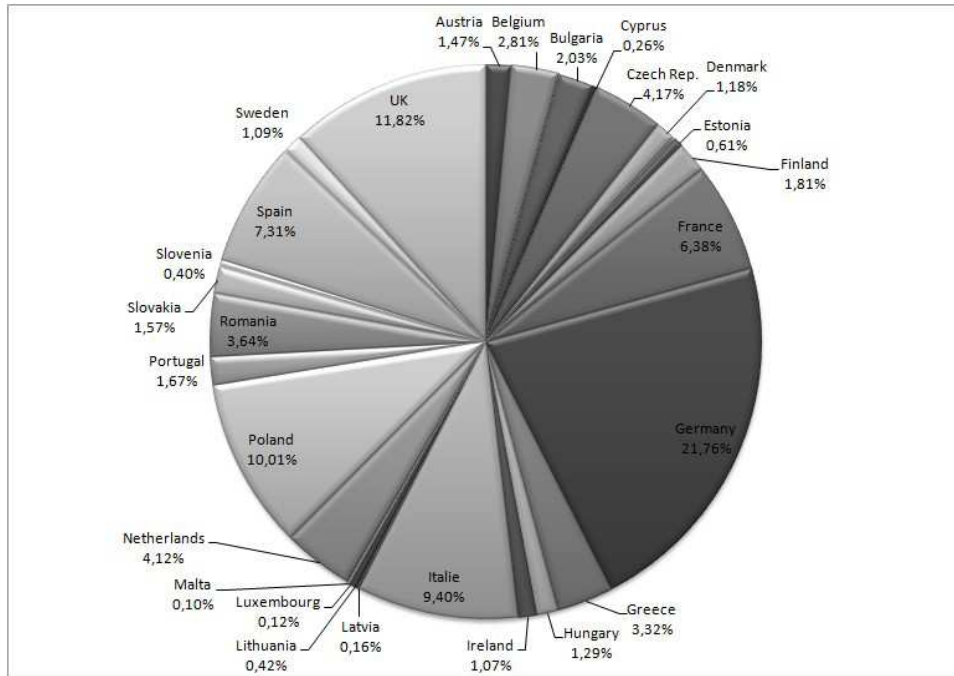
According to the Phase 1 NAPs, about 2181 million EUAs per year have been distributed between 2005 and 2007. In Phase 2, yearly allocations account for about 2082 million EUAs. This corresponds to a reduction of about 217 million EUAs per year compared to Phase 1 (excluding the Romanian and Bulgarian Phase 2 NAPs of calculation to make Phases 1 and 2 comparable since those countries did not have Phase 1 NAPs). Regarding the repartition of EUA allocations, there are strong disparities between Member States (see Figures 3 and 4). During Phase 1 Germany distributed 499 million EUAs annually, while the following countries were Italy, Poland and the United Kingdom, with about 235 million EUAs allocated a year. Six countries (France, Germany, Italy, Poland, Spain and the UK) total 70.5% of EUAs distributed in Phase 1, and 66.7% in Phase 2.

Figure 3: Phase 1 NAPs in percentages of total EUA allocations (based on CITL data, available at www.ec.europa.eu/environment/ets)



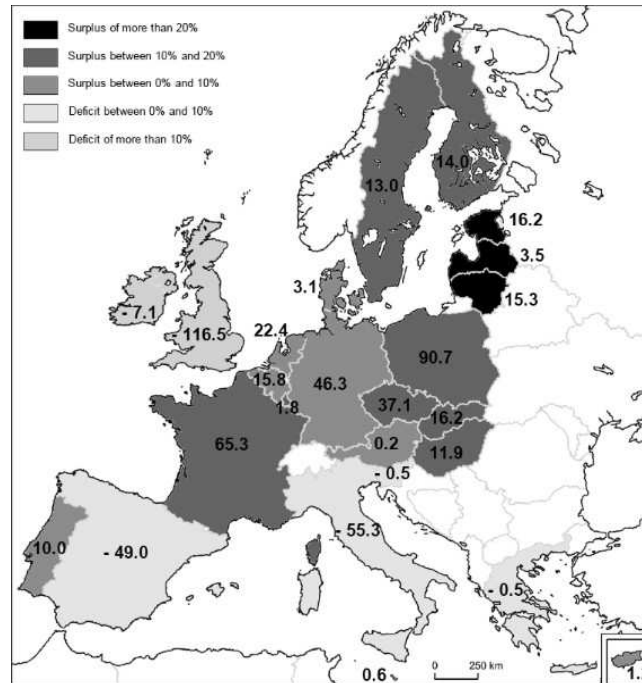
32 See Charpin [2009], Delbosco [2009], Mougeot and Naegelen [2009] and Sator [2010].

Figure 4: Phase 2 NAPs in percentages of total EUA allocations (based on CITL data, available at www.ec.europa.eu/environment/ets)



The volume of EUA allocated in Germany is particularly high due to its massive carbon emissions from electricity, which is largely generated with coal and lignite in this country. Germany is by far the biggest carbon emitter in Europe. For instance, in 2005, carbon emissions in Germany were twice as high as in the UK, the second biggest carbon emitter (see Ellerman and Buchner [2008]). Regarding differences between allocations and verified emissions, an allowance surplus of 155.7 million EUAs was recorded during Phase 1, equivalent to 2.5% of the three-year allocations (Trotignon and Delbosch [2008]). This surplus decreased from 83 million tonnes in 2005 to 36 million tonnes in 2007. However, positions are heterogeneous between Member States. Some countries recorded a net deficit of allowances (e.g. the UK, Spain or Italy), despite the overall surplus (see Figure 5).

Figure 5: Net positions of Member States in Phase 1, from Trotignon and Delbosco [2008]. Shortages and surplus are expressed as percentages of the national allocations (colored areas) and in million tonnes CO₂ (numeric values)



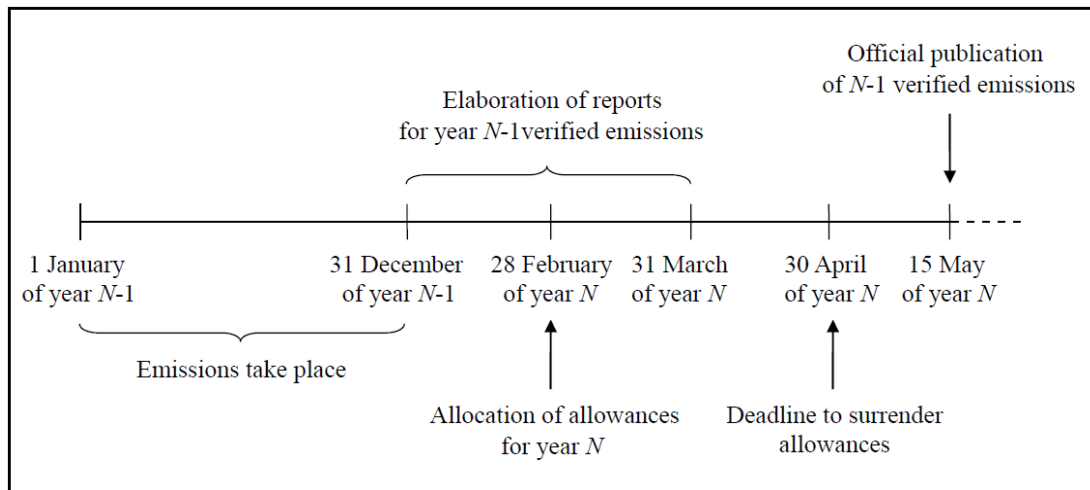
For the first time the EU ETS revealed a deficit of 115 million tonnes EUAs in 2008 (Trotignon [2009]), the first year of Phase 2, while 2009 ended with a surplus of 170 million tonnes EUAs due to reductions of CO₂ emissions that came with the economic recession (Trotignon [2010]). Excluding auctioned allowances, the 2009 net surplus is 85 million tonnes EUAs. In 2010, the economic recovery reduced the surplus to 55 million tonnes EUAs (excluding auctioned allowances) even though the EU ETS is still globally long (Trotignon and Stephan [2011]).

Monitoring, reporting and allowance trading

Rules for monitoring and reporting of emissions are defined in the Decision 2007/589/EC amending the Decision 2004/156/EC of the European Commission (Brohé [2008]). It states that each Member State has to report its previous year's verified emissions (recorded between January 1 and December 31) to the European Commission before March 31 of the following year, and that affected firms must surrender the allowances corresponding to their previous year's verified emissions before April 30 (see Mansanet-Bataller and Pardo [2008a]). For example, for the 2005 emissions, reports had to be submitted before March 31 and April 30, 2006 was the deadline to surrender allowances

corresponding to verified emissions. Once all reports have been submitted and approved, the European Commission can officially publish, on May 15 of the following year, the previous year's verified emissions (see Chevallier [2010]). This monitoring and reporting process is summarized in Figure 6.

Figure 6: The EU ETS monitoring and reporting deadlines, based on Mansanet-Bataller and Pardo [2008a] and Chevallier [2010]



In Phase 2, if an installation fails to surrender enough allowances to cover its verified emissions, it must pay a penalty of 100 Euros per tonne of CO₂ in excess (in Phase 1 the penalty was 40 Euros per tonne of CO₂). In addition to paying penalties, firms are compelled during the following year to return all allowances that were not surrendered for compliance in the previous year.

According to the European Parliament and Council Decision 280/2004/EC, each Member State has to establish a registry where the balance of bought and sold allowances of each participant is recorded, as well as verified emissions. Therefore, registries are used to check the compliance of each participant. The national registries are linked to the Community Independent Transaction Log (CITL), the European registry that centralizes all information contained in the national registries. Since October 16, 2008, the CITL is connected to the UNFCCC International Transaction Log (ITL), the international registry system under the Kyoto Protocol.³³ Thus, participants are now allowed to meet part of their obligations with international credits (CERs and ERUs).

Participants can trade allowances through organized trading platforms (exchanges) or in

³³ Information available at <http://cdm.unfccc.int/Registry/index.html>. Note that the European Commission announced on July 7, 2011 that it intends to set a single European Union registry (EUTL – European Union Transaction Log) to replace all Member States registries which are centralized in the CITL (information available at <http://ec.europa.eu/environment/ets>).

over-the-counter (OTC) transactions. Several organized exchanges exist where it is possible to trade EUAs and related financial products such as futures contracts or options. Eight are based in Europe: BlueNext (Paris), Climex (Amsterdam), EEX (European Energy Exchange, Leipzig), EXAA (Energy Exchange Austria, Vienna), GME (Gestore Mercato Elettrico, Rome), ICE-ECX (Intercontinental Exchange - European Climate Exchange, London),³⁴ NordPool (Oslo) and SendeCO₂ (Spain). Another is located in the United States: GreenX (Green Exchange, New York Mercantile Exchange). As for stock exchanges, these platforms offer standardized contracts and provide clearing and settlement services.³⁵ In terms of size, BlueNext is the most important market place for spot contracts with 73% of total spot volume in Phase 1, while ECX is the most important platform for future contracts with 96% of total transactions in Phase 1 (Mansanet-Bataller and Pardo [2008a]).³⁶ ECX and GreenX are the only platforms offering the possibility to trade options on EUAs. EUA/CER and EUA/ERU swaps are traded bilaterally, over-the-counter.

Banking, borrowing and linkage

In principle, firms have to build a compliance strategy for each year since, at the end of each year, they have to surrender a number of allowances equal to their verified emissions. However, the EU ETS rules allow them to bank and borrow allowances. Therefore, in practice, abatements can be smoothed over time, and allowances can be traded between years. Despite the Directive 2003/87/EC which gives the Member States the possibility to allow banking between Phases, all countries decided to prohibit the transfer of allowances between Phase 1 and Phase 2.³⁷ Thus, during Phase 1, it was impossible to bank EUAs in order to use them in Phase 2. Borrowing EUAs from Phase 2 to cover Phase 1 emissions was also forbidden. Banking and borrowing were only allowed within the same Phase.³⁸ Since the beginning of Phase 2, it is now allowed to bank allowances between Phases (i.e. in Phase 2 for Phase 3) in all the Member States.³⁹ By contrast, borrowing

34 ECX is a former subsidiary of the Chicago Climate Exchange (CCX). In 2006, ECX, CCX and CCFE (Chicago Climate Futures Exchange) were grouped in the "Climate Exchange Plc" holding. In 2010, ICE acquired Climate Exchange Plc, after a five-year partnership between ICE and ECX.

35 For a detailed presentation of products and services in the different exchanges, see Kristiansen et al. [2006] and Mansanet-Bataller and Pardo [2008a].

36 See also see Benz and Klar [2008] and Daskalakis et al. [2009].

37 See Alberola and Chevallier [2009] for a discussion on reasons that justified these decisions.

38 A "one-year" borrowing is allowed within the same Phase. That is firms are allowed to borrow allowances from the following year for compliance in the current year. For example, in 2005, permits could be borrowed from 2006, but not from 2007.

39 The Directive 2003/87/EC establishes that allowances allocated for a given Phase have to be canceled by Member States at the end of this Phase. For example, EUAs that were part of Phase 1 NAPs had to be canceled after April 30, 2008. However, the Directive allows Member States to replace those canceled allowances with valid allowances of the next Phase (Phase 2 in our example), which leads to an "inter-phase" banking. In other words, the Directive states that inter-phase banking is possible in principle, and it gives the Member States the responsibility to decide if

allowances between Phases is still forbidden.

Since the CITL is connected to the ITL, installations can use international credits to comply with their obligations.⁴⁰ Firms are allowed to import CERs and ERUs in the EU ETS, up to a certain percentage of their initial allocations. The rules for using international credits in the EU ETS are stated in the linking Directive 2004/101/EC, amending the Directive 2003/87/EC. The linking Directive states that Member States may allow imports of international credits by specifying it in their NAPs. If permission is given, Member States have to set a limit on how many CERs and ERUs can be surrendered by installations. Limits are expressed in terms of percentage of the allocation of allowances to each installation. This translates into an overall limit for each country. Those limits vary from 0% of allocations in Estonia, to 20% in Germany, Lithuania and Spain. This means that installations in Germany can import 450 million credits over Phase 2, representing more than a fourth of the total volume of international credits in the EU ETS. CERs and ERUs can be obtained by investing in CDM and JI projects, or by purchasing them on the secondary market. As for EUAs, it is possible to trade international credits through organized exchanges or in over-the-counter transactions. NordPool, ECX, BlueNext and GreenX are example of exchanges which offer the possibility to trade CERs and ERUs. In 2008 and 2009, the overall quantity of international credits used for compliance in the EU ETS was about 85 million tonnes CO₂. In 2010, this quantity rose by almost 65%, to reach about 140 million tonnes CO₂ (see Trotignon and Stephan [2011]). To date, about half the CERs and ERUs issued have been surrendered in the EU ETS. The use of credits is particularly high in Slovakia, Romania and Hungary, where about 50% of the total quantity allowed for the three years has already been surrendered. In other countries like Spain, Portugal, Finland and Germany, the use of credits has also not been negligible with about 30% of the allowed limit already surrendered. Here it is interesting to note that there has been a legal loophole in the EU ETS, regarding the use of international credits (Sator [2011]). The loophole allowed credits already used for compliance in the EU ETS to re-enter the market and be traded again. This problem became evident in March 2010, when some of those CERs that were still circulating on the EU ETS were identified. The Hungarian government had resold them even though they had already been used for compliance by Hungarian installations. To avoid such “dishonest dealings”, an amendment to the EU registry legislation was decided in April 2010. The amendment states that surrendered credits must be placed in a specific retirement account from which the resale is forbidden.⁴¹

it is allowed in practice. With the European Union “Climate and Energy Package” of December 2008, the European Commission decided that inter-phase banking will be clearly allowed, at the EU level, from the beginning of Phase 2. This was confirmed later in the Directive 2009/09/EC.

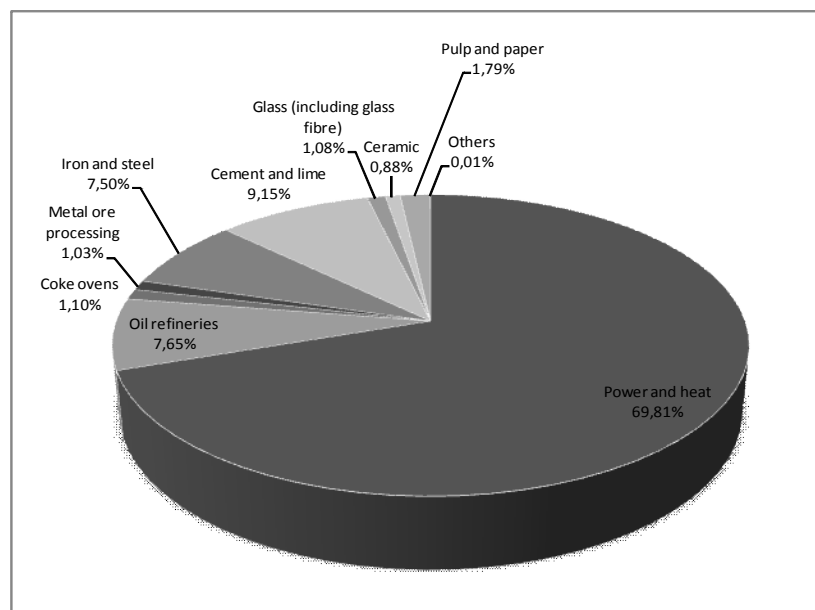
40 Before connection, issued international credits remained in the UNFCCC registries.

41 Other kinds of fraud were observed on the EU ETS in 2010 and 2011, such as VAT frauds and allowance thefts

Sectoral analysis

Among sectors covered by the EU ETS, the power sector is of special relevance. Both CO₂ emissions and allowance allocations in this sector account for more than half of the total volumes of the EU ETS (see Figures 7 and 8).⁴² Hence, the power sector represents more than half of the potential demand and supply for EUAs, and thus, understanding its position is crucial. Moreover, power plant allocations represent more than 50% of the total power and heat allocations. As pointed out in Trotignon and Delbosc [2008], the share of power plants in the power and heat allocations is even higher in some Member States. During Phase 1, it ranged from 50% in France to more than 80% in Italy and in the UK. Countries where emissions and allocations of the power sector are particularly high are those which generate large volumes of electricity with fossil fuels such as coal, natural-gas or lignite. These countries include Germany, Italy, Poland, Spain and the UK.

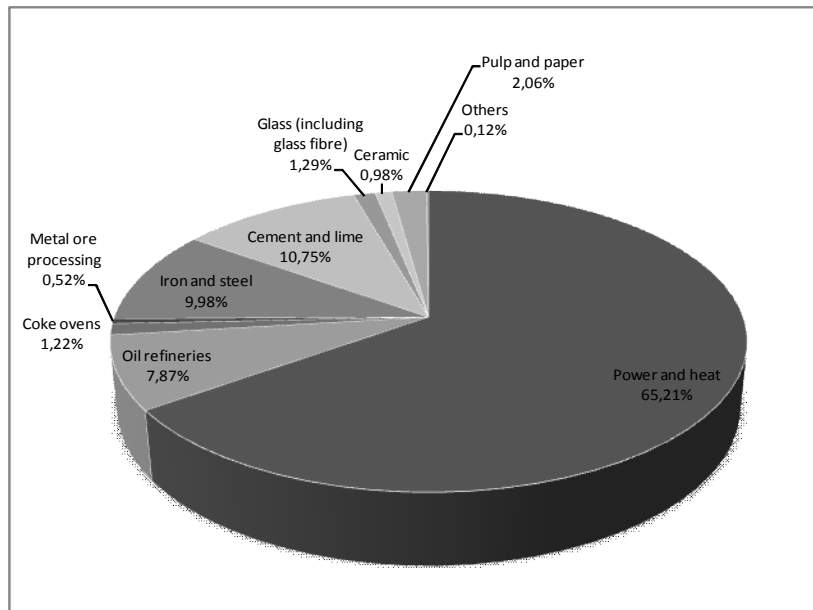
Figure 7: The 2006 EUA allocations by sector (data available at <http://dataservice.eea.europa.eu/PivotApp>)



(Sator [2011]). In VAT frauds, fraudsters set up an account in one country and buy allowances from a seller to another country without paying VAT in the purchase price (because EU VAT rules exempt cross-border sales of allowances from VAT). Next, the fraudsters resell allowances in domestic transactions with VAT added into the price. However, instead of refunding the collected VAT to the State, the fraudsters pocket it and disappear. Allowance thefts also occur when fraudsters acquire access details to accounts of some EU ETS operators. Thus, fraudsters can steal allowances by transferring them from the victim's account to another account. In order to access the victim's accounts, fraudsters can use fishing techniques (e.g. fake links or e-mails requesting access details to accounts) or trojan virus (e.g. the "Nimkey" trojan).

⁴² See Point Carbon [2006], Ellerman and Buchner [2008] and Trotignon and Delbosc [2008].

Figure 8: The 2009 EUA allocations by sector (data available at <http://dataservice.eea.europa.eu/PivotApp>)



Regarding the difference between allowance allocations and verified emissions, the position of the power and heat sector is also remarkable. In Phase 1, it was the only sector with a net deficit of allowances. The deficit accounted for about 1% of allocations in this sector, and it was mainly explained by the short position of power producers. The net deficit of power producers accounted for about 7% of the power plant's allocations, while other sub-sectors were long of allowances (see Trotignon and Delbosc [2008]). The net short position of the power and heat sector was confirmed and strengthened in Phase 2. In 2008, 2009 and 2010, the net deficit of allowances in the sector was respectively 240 (20% of allocations), 112 (9.3% of allocations) and 125 (10.2% of allocations) million tonnes CO₂. As a comparison, in 2006 and 2007 the power and heat sector net deficit was 24 (1.7% of allocations) and 33 (2.3% of allocations) million tonnes CO₂, respectively.⁴³

Price drivers

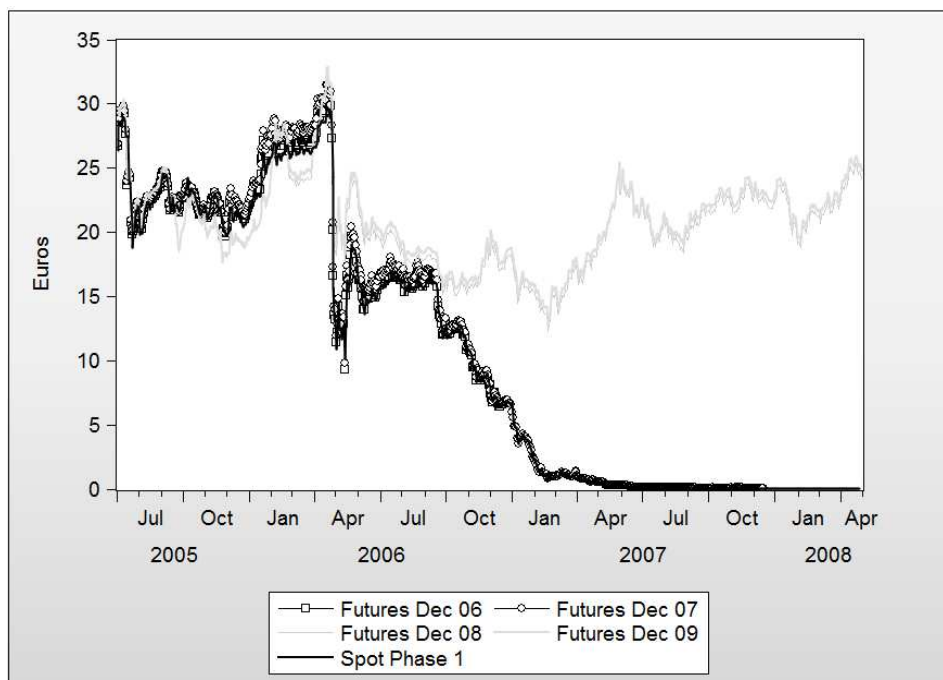
Numerous factors influence the price of CO₂ allowances. Like on other markets, the EUA price is driven by the balance between supply and demand, long-term investment decisions, market structure and institutional factors such as general rules or information disclosure.

⁴³ Data available at <http://dataservice.eea.europa.eu/PivotApp>.

On the supply side, the main price driver is the volume of EUAs allocated to installations, since it sets the overall stringency of the EU ETS. The lower the cap is with respect to business-as-usual emissions, the stricter the trading scheme will be. Uncertainties regarding the exact number of EUAs issued for a Phase may also be important. Because of special reserves for new entrants, the total amount of EUAs that would be available during a Phase is uncertain. It may be important if the market is stressed. Other factors influencing the supply side are the use of international credits and banking or borrowing between Phases. During Phase 1, both were irrelevant since inter-phases banking (and borrowing) was prohibited and the CITL was not connected to the ITL. However, as we have seen, inter-phase banking and the use of international credits are now possible in the EU ETS.

Political decisions and information disclosure also impact the EUA price. Regarding information disclosure, 2006 gave a good example. The publication by four countries (the Czech Republic, France, Spain and the Netherlands) of 2005 verified emissions (25 April 2006) and the European Commission communication announcing that the EU ETS was globally long for 2005 (15 May 2006), caused the EUA price crash of Spring 2006 (see Figure 9).

Figure 9: Spot and futures EUA prices in Phase 1. The spot price is the price of the BlueNext spot contract, and the futures prices are those of the ECX futures contracts with expiry in December 2006, 2007, 2008 and 2009 (data are available on the BlueNext and ECX websites)



Another example is the price drop that occurred in October 2006, when the European Commission announced that Phase 2 validated NAPs of 17 Member States were stricter than submitted draft versions (see Figure 9).⁴⁴ This changed the perception of market participants, which realized that Phase 1 and Phase 2 were two different markets. Consequences have been a divorce between prices for Phase 1 and Phase 2. Due to banking restrictions, the EUAs issued for Phase 1 were useless at the end of Phase 1. As information disclosures revealed that the market was oversupplied in Phase 1, the spot price of Phase 1 (and prices of futures contracts expiring in Phase 1) stabilized at around zero from Spring 2007 until the end of Phase 1. By contrast, prices of futures contracts expiring in Phase 2 ranged from 15 to 25 Euros (see Figure 9).

Market structure is also important in price formation. With a small number of large buyers and sellers, the EUA price is expected to react strongly to individual decisions. As pointed out by Trotignon and Delbosc [2008], during Phase 1 more than half of the EUAs were held by thirty companies, among which there was a majority of power producers. Some authors argued that the level of prices before the crash of Spring 2006 could be explained by incentive for power producers to exert market power on the carbon market in order to keep high prices for EUAs (Betz et al. [2006]). In doing so, power producers would have tried to increase their windfall profits by passing through a higher carbon cost to the electricity price.⁴⁵

The demand for EUAs is determined by the CO₂ emissions of covered installations. Power generation represents more than half of the total of CO₂ emissions in the EU ETS. Hence, factors that affect emissions in the power sector are the main drivers for EUA demand. They include energy prices, weather conditions (temperatures, rainfall, wind speed, etc) and economic activity. Because they determine electricity demand and the composition of power generation (i.e. the carbon-intensity of technologies that are used to produce), those factors drive the CO₂ emissions in the power sector, and thus the demand for EUAs of power producers.

Temperatures influence energy demand because they determine energy needs for heating (in winter) and cooling (in summer). As a consequence, temperatures influence carbon emissions and EUA prices. In particular, variations in carbon emissions depend heavily on extreme temperatures (i.e. extremely hot and cold temperatures) and on unexpected temperature changes (i.e. deviations

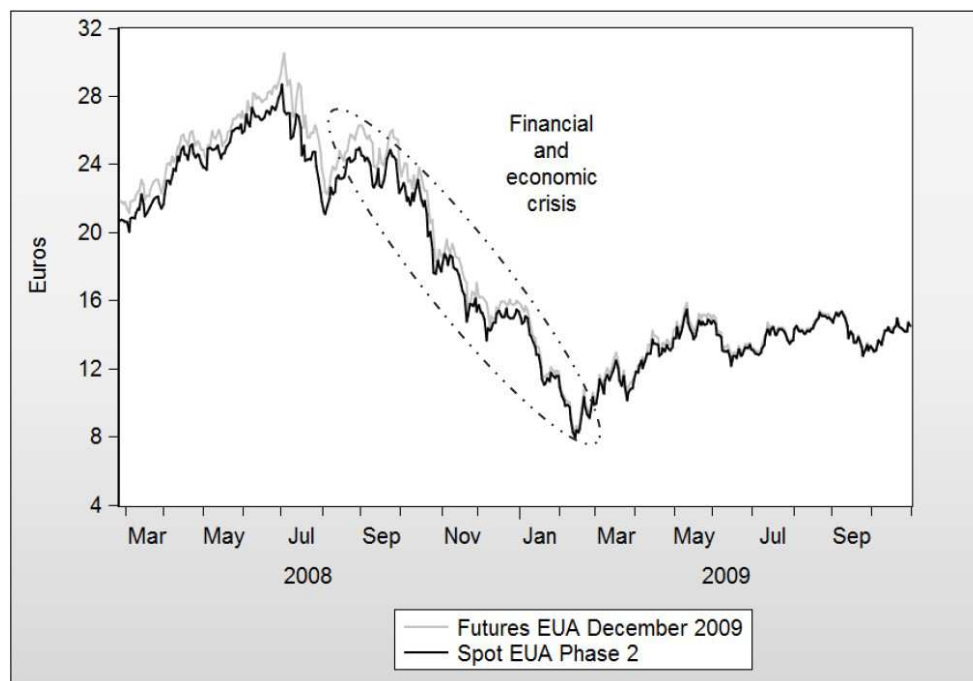
44 The econometric paper by Alberola et al. [2008] reports statistical evidence of influence of those information disclosures on the EUA price.

45 Hintermann [2010] has reported evidence of a “CO₂ bubble” in the EU ETS before the price crash of Spring 2006. He found that the EUA price was disconnected from its fundamentals (energy prices, temperatures, rainfall, etc) during this period, and driven by “self-fulfilling expectations” captured by lagged values of the EUA price.

from historical averages).⁴⁶

The relationship between CO₂ emissions and economic activity is supposed to be positive, since, for example, an economic recession is expected to decrease energy consumption. However, there may be another simultaneous opposite effect. Indeed, it is sometimes argued that recessions can create some increases in carbon emissions, simultaneously with decreases that come with cuts in production (Declercq et al. [2011]). Because energy prices tend to decrease during recessions, there is an incentive to consume more energy and so to emit more CO₂. In 2009, which was a year of recession in Europe, verified emissions in the EU ETS sectors declined by 11% (compared to 2008), while they rose by 2.5% in 2010 with the recovery.⁴⁷ This suggests that the quantity effect (decrease in CO₂ emissions due to reduced production) dominates the price effect (increase in CO₂ emissions due to lower energy prices),⁴⁸ so that there would be a net positive relationship between CO₂ emissions and economic activity. This is confirmed by the decline in EUA prices observed in 2008 and 2009 (see Figure 10).

Figure 10: Decline in EUA prices during the 2009 recession



46 Several papers have shown that extreme temperatures and unexpected temperature changes are the most important weather variables for the EU ETS (see Mansanet-Bataller et al. [2007] and Alberola et al. [2008]). They matter more than temperatures themselves, which indicates that the relationship between temperatures and the carbon price seems to be non-linear.

47 See Trotignon [2010] and Trotignon and Stephan [2011].

48 Verified emissions have revealed a decrease of emissions in the power sector over the years 2008 (-30 million tonnes CO₂ compared to 2007) and 2009 (-130 million tonnes CO₂ compared to 2008). Data are available at <http://dataservice.eea.europa.eu/PivotApp>. Note however that the power sector have been globally short of allowances during this period. See Trotignon [2010], Declercq et al. [2011].

The depressive impact of the economic crisis has been accentuated by the credit crunch that came with the financial crisis. Thanks to emission reductions, regulated firms were able to sell large amounts of unused allowances in order to raise cash during the credit crunch.⁴⁹ This has translated into a stronger price decrease, especially on the spot market.

Rainfall, wind speed and cloudiness conditions also influence carbon emissions because they determine the share of power generation that can be obtained from hydroelectricity, wind and solar plants. The more hydro, wind and solar plants available to produce, the less electricity has to be generated by burning fossil fuels, and thus the lower the CO₂ emissions are. For example, a dry year in Nordic countries is likely to increase carbon emissions, because of high use of hydroelectricity in those countries. In such a situation, power producers have to replace hydroelectric capacities (from Norway and Sweden) by fossil-fuel-based capacities (coal plants from Denmark). Therefore, carbon emissions rise.

According to literature, fuel prices are the most significant price drivers for EUAs, due to the ability of European power producers to reduce their carbon emissions by switching fuels from coal to gas in electricity generation.⁵⁰ The basic idea of fuel switching is that relative fuel prices determine the demand for carbon allowances by setting the composition of power generation. In the EU ETS, this is known as the most important short-run abatement option, since power producers are major actors in the scheme.⁵¹ Thus, fuel prices strongly influence EUA prices. Without carbon price, coal plants are usually brought on line first, because of their cheaper fuel cost. Gas plants are used next, during shorter periods, when demand for power is higher. However, with a price for carbon emissions, gas plants may be preferable to coal plants, due to their lower carbon intensity. That is, if the cost of increased carbon emissions with coal plants is higher than the additional fuel cost associated with the decision to produce with gas rather than with coal, it is cheaper to use gas plants first instead of coal plants. If such a switching occurs, carbon emissions are reduced, because coal plants are brought on line during shorter periods. Therefore, all other things being equal, a relatively high gas price encourages the use of more coal, which drives up demand for allowances and the carbon price (and vice versa).

Among energy prices, the electricity price is another important driver of EUA prices in the short-run. This is explained by the short-run rent capture theory (Keppler [2010]). According to this

49 See De Pertuis [2009], Sikorski [2009] and Charpin [2009].

50 See Bertrand [2011a] for a review of econometric and theoretical papers dealing with fuel switching.

51 Fuel switching we refer to here involves coal plants and Combined Cycle Gas Turbines (CCGTs). Of course fuel switching can also take place with other plants for other levels of load. For example, switching can occur between oil plants and open cycle gas turbines, or also between coal and lignite. However, as quantities of carbon concerning switching between coal plants and CCGTs are much higher, this type of switching is the main focus of power producers and researchers (and the main EUA price driver).

approach, the electricity price influences the carbon price in the very short-run because no carbon abatements can be performed. This implies that power producers have to reduce their production to sell allowances. In this situation, the margin between the price of electricity (set by monopolistic suppliers) and its marginal cost will be captured in the carbon price. In other words, power producers with market power have the ability to “monetize” on the carbon market their scarcity rents in the electricity market.⁵²

In the long-run, the demand for allowances strongly depends on investment decisions. Investing today in measures such as carbon capture and storage, energy efficiency or in building new low-carbon power plants, will reduce carbon emissions in the future and thus the demand for allowances. However, high investment costs, uncertainties,⁵³ the time horizon before investments produce effects and irreversibility are many discouraging factors that often lead to delay investments.⁵⁴

The long-run trends in energy markets are also important. In particular, trends in the gas market should be strongly influential, given the interest for gas in carbon abatement decisions. Thus, the EU ETS should be impacted by information about pipeline projects, non-conventional gas extraction or progresses in gas liquefaction. Regarding nuclear, the current debate in Europe about the renewal of installed capacities is of major importance for the EU ETS. Yet, Germany has already announced that it renounces to extend the life of its nuclear plants and the position of several other Member States has been uncertain since the Fukushima disaster. The consequences of those decisions would be huge for the EU ETS. This would drastically increase the demand for EUAs in Phase 3, and cancel the surplus of allowances created by recession in Phase 2.⁵⁵

52 Note that market power in the electricity market does not imply a permanent market dominance of some particular firms. This is rather a short-run rotating position during peak-load hours, depending on scarcity of capacities (see Keppler [2010]).

53 As pointed out by Chao and Wilson [1993], purchases of allowances have an intrinsic advantage compared to investments in abatement measures, because they avoid uncertainties about volumes of abatements and their costs. As a consequence, allowances have an additional value (an “option value”) with respect to investments in abatement measures, which justifies that the allowance price should exceed the marginal cost of abatements.

54 In Phase 1, the EU ETS has triggered very few large-scale investment decisions with long amortization times (e.g. building new power plants). Covered firms have been mainly engaged in allowance trading or short-run abatement decisions to meet their obligations (see Hoffmann [2007]).

55 For more details, see Berghmans [2011].

Purpose of this thesis

This thesis studies the interplay between the EU ETS and energy markets. Our objective is to understand better how the EU ETS has modified power generation, and how energy markets impact the EU ETS. In particular, we investigate the influence of fuel prices and power generation on the price of EUAs. We also examine the influence of the EU ETS on fuel and electricity markets.

This thesis is composed of four chapters. The first chapter presents the European fuel and electricity markets and their relationships with the carbon market. The next three chapters are based on personal research.

The aim of the first chapter is to provide a general introduction on interactions between the EU ETS and energy markets. We review different approaches explaining relationships between carbon, fuel and electricity prices. Additionally, the consequences of the EU ETS for power generation are discussed. A special focus is given to fuel switching, the main short-term abatement measure within the EU ETS. The main concepts and methodological tools are introduced. Most of them are well known, some are new. Thanks to this synthesis, we highlight what the important questions are about our subject, and the gaps in the literature. Notably, we identify that not one of the previous theoretical works on fuel switching has addressed the question of the influence of differences in the energy efficiency of power plants. We also find that no previous econometric work has applied a full VAR-VECM approach to analyze the dynamic of interactions between carbon, fuels and electricity prices in Phase 2 of the EU ETS. Finally, the cross-market price discovery in the European gas and CO₂ markets has not been investigated to date.

In Chapter 2,⁵⁶ we examine the implications of the fuel switching behavior of power producers, in a context where power plants used in the fuel switching process do not all have the same energy efficiency. Our aim is to identify how relationships between fuel and allowance prices are affected. To do so, we build a tractable equilibrium model along the lines of the equilibrium models for tradable permits developed since the pioneering work of Montgomery [1972]. Using a cost function that represents the expense engendered by switching from coal plants to CCGTs, we follow the same strategy as in Fehr and Hinz [2006]. Unlike them however, we explicitly model differences in the energy efficiency of CCGTs used in the fuel switching process. This differs from previous equilibrium models on the subject. As a consequence, the level of fuel switching effort

⁵⁶ This chapter is based on Bertrand [2010].

influences the marginal cost of fuel switching. The main result shows that the carbon price becomes more sensitive to the gas price when the level uncontrolled carbon emissions (i.e. “business-as-usual” carbon emissions, that determine the level of switching effort) increases. This is explained by differences in the energy efficiency of CCGTs that are used in fuel switching.

Chapter 3⁵⁷ explores interactions between carbon, coal, gas and electricity prices on the European markets. We examine the relevance of different approaches explaining relationships between energy and carbon markets through an empirical analysis in Phase 2 of the EU ETS. We estimate a Vector Error Correction Model (VECM) that enables us to investigate short-run and equilibrium relationships between carbon, coal, gas and electricity prices. The analysis includes Granger causality tests and impulse response functions. Up to now, to the best of our knowledge, no other econometric work has applied a full VAR-VECM approach to study relationships between carbon, coal, gas and electricity prices in Phase 2 of the EU ETS. Our study fills this gap in the literature. Among the main results, we find that there is a significant link between carbon and gas prices in the equilibrium. We also find that coal and gas prices appear to be sensitive to the carbon price in the short-run. This last result could be explained by the crisis.

In Chapter 4,⁵⁸ we analyze the cross-market price discovery process between the European gas and CO₂ markets. We have identified in previous chapters that there is a robust significant link between gas and CO₂ markets. The reason is that gas and EUAs can be considered as substitutable inputs in electricity generation. Indeed, during certain hours in the year, power producers can decide to increase the share of gas in their production (and reduce the share of coal) to reduce their EUA consumption. Alternatively, they can reduce the share of gas and increase their consumption of EUAs. Therefore, gas and EUAs are linked commodities, and their prices are affected by the same information. The question is which market captures incremental information first. In other words, which one is the leader in the cross-market price discovery process. This is a significant question since the price of the market which processes new information faster, may be used, in many cases, to anticipate the price fluctuations on the other market. The aim of this chapter is to investigate this process. We want to evaluate the relative contribution of each market to the cross-market price discovery. To the best of our knowledge, no other econometric work has investigated this question before. To address this objective, we use the common factor approach builds on work by Schwarz and Szakmary [1994] and Gonzalo and Granger [1995]. The first step consists in estimating a

57 This chapter is based on Bertrand [2011a].

58 This chapter is based on Bertrand [2011b].

VECM with the price series. Next, to quantify the relative contribution of each market to the cross-market price discovery, we compute the Common Factor Weights as defined Schwarz and Szakmary [1994]. We find that the carbon market is the leader in the cross-market price discovery process.

Chapter 1

Relationships between European carbon and energy markets

European power producers have a major influence on the European carbon market, given that both their CO₂ emissions and their allowance allocations account for more than half of the total volumes of the EU ETS. Moreover, as the electricity generation's basic function is to convert fuels – and other primary energies – into electricity, the links between electricity, fuel and carbon markets are obviously tenuous. The aim of this chapter is to present the main characteristics of energy markets and their interactions with the EU ETS.

1. General presentation of energy markets

We begin this chapter with a general presentation of European energy markets. We pay special attention to the electricity market, since it is at the core of all interactions between energy markets and the EU ETS. The European coal and gas markets are also presented because of their strong influence on carbon and electricity markets. Finally, we briefly describe some developments in the oil market that have influenced other energy markets and the EU ETS.

1.1. The electricity market

Electricity is an essential good for households and industry. It is available at any time, in almost every place. However, unlike other energy commodities (e.g. oil, coal, gas, wood, etc), the main characteristic of electricity is that it cannot be stored (non-storability).¹ Thus, electricity has to be produced at the same time as it is consumed.

¹ For an overview on physical characteristics of electricity, see Hansen and Percebois [2010].

Another important characteristic is that demand for electricity varies during the day, and, for any given hour of the day, it depends on the season. Typically, demand for electricity is usually lower in mid-seasons (i.e. autumn and spring) compared with summer and winter. This is due to lower power needs for heating (winter) and cooling (summer) during those seasons.²

With regard to variations of demand during the day, hours are basically classified into two categories: peak and off-peak hours. Peak hours are hours during which demand is maximal, because household appliances are switched on while factories are still running. These are, approximately, hours between 10 am and 1 pm, in the morning, and between 6 pm and 8 pm, in the evening, when households are cooking and watching TV. They correspond to levels of production that are referred to as peak-load, and which occur about 20% of the day. Off-peak hours are hours during which demand is relatively low. They represent about 80% of the day, and they correspond to levels of production that are referred to as base-load.³

Because electricity is a non-storable commodity with demand varying during the day, power plants have to be switched on and off depending on hourly demand. For example, during off-peak hours, some capacities have to be available to be brought online when demand will increase (during peak-hours). Because of these special features, the electricity supply system has to be designed for the maximal demand, i.e. installed capacities are determined by the expected maximal level of demand. Moreover, as some power plants will run more than others, the cost of production of each technology has to be considered. Accordingly, technologies are stacked in order of increasing marginal cost of production, so that power producers add more and more expensive plants to production as demand increases. This ranking of power plants is known as “merit order” or “stacking order” (see section 2.3 of this chapter).⁴ Thus, among power plants we distinguish between base-load plants, intermediate-load plants and peak-load plants (see Unger [2002]). Base-load plants run more than 80% of the time. They are hydro, nuclear, coal (the cheapest coal plants here, including lignite in countries like Germany) and renewable technologies (e.g. solar or wind). Intermediate-load plants run between 20 and 80% of the time. These are mainly coal plants and Combined Cycle Gas Turbines (CCGTs). Finally, peak-load plants run less than 20% of the time. They are mainly gas- and oil-fired open cycle turbines.⁵

2 Moreover, demand for electricity is higher in winter than in summer for any hour in the day. The reasons are that more power is needed for heating than for cooling and there is more need for (artificial) light in winter.

3 One more distinction can be made in off-peak hours between base-load and intermediate-load. Intermediate-load corresponds to levels of production that occur between 20 and 80% of the time, while base-load corresponds to levels of production occurring more than 80% of the time. See section 2.3 of this chapter.

4 Note that marginal cost of production is the most important factor explaining the merit-order, but it is not the only one. Flexibility is another determinant. Some power plants run continuously 24 hours a day (e.g. nuclear), while others (with more flexibility) can be ramped up and down more easily depending on hourly demand.

5 While base- and intermediate-load plants have high fixed costs and relatively low marginal costs, peak-load plants have lower fixed costs but higher marginal costs.

To summarize, the maximal demand of electricity is the main driver of fixed costs (since it sets the needed installed capacities), while the time of consumption impacts the variable costs (since it sets the technologies that are used to produce at a certain time).

To date, the European power generation mix is dominated by coal and nuclear, which represent about two-thirds of European electricity. Natural gas is the third source, followed by hydroelectricity, oil and renewable (see Keppler [2010]). While the share of gas is already important (it is about as much as the share of hydro, oil and renewable together), it is expected to rise strongly in the next couple of years. Indeed, the environmental constraint set by the EU ETS encourages the use of gas as opposed to coal or oil. According to the International Energy Agency's forecast, the share of gas in European electricity would double by 2030. Renewable energy is also expected to grow very fast with the EU's target of reaching 20% of renewable energy in the total energy consumption by 2020. Among renewable sources, the potential of large hydroelectric stations (reservoirs and run-of-the-river) is limited since it has been exhausted to a large extent. The growth potential is more important for wind, solar, biomass or micro-hydroelectricity. With regard to nuclear there are a lot of uncertainties. Several countries have made commitments to reduce the share of nuclear in their electricity production since the Fukushima disaster (see Introduction of the thesis). However, this would cause severe problems for energy and the environment. This is a big issue for the future.⁶

In 1997 the Directive 96/92/EC on the Internal Market in Electricity came into force (it was confirmed later in the Directive 2003/54/EC). It provided the opening of national electricity markets to competition.⁷ While transmission and distribution of electricity are regarded as natural monopolies because of the substantial economies of scales,⁸ generation and retailing are thought to be potentially competitive. Therefore, the Directive prescribed separation between the monopoly elements (transmission and distribution) and the potentially competitive segments (generation and retailing). The aim was to prevent controllers of monopoly in transmission and distribution from abusing their market power in generation and retailing. This separation is called unbundling, and it introduces competition in generation and retailing, whereas transmission and distribution are left to

6 Drawbacks of nuclear electricity are often pointed out (e.g. impacts of radioactivity, dismantling of nuclear facilities). But nuclear also creates positive externalities such as reduction of CO₂ emissions, easing of gas prices, low electricity prices and security of supply. See Chevalier and Percebois [2008].

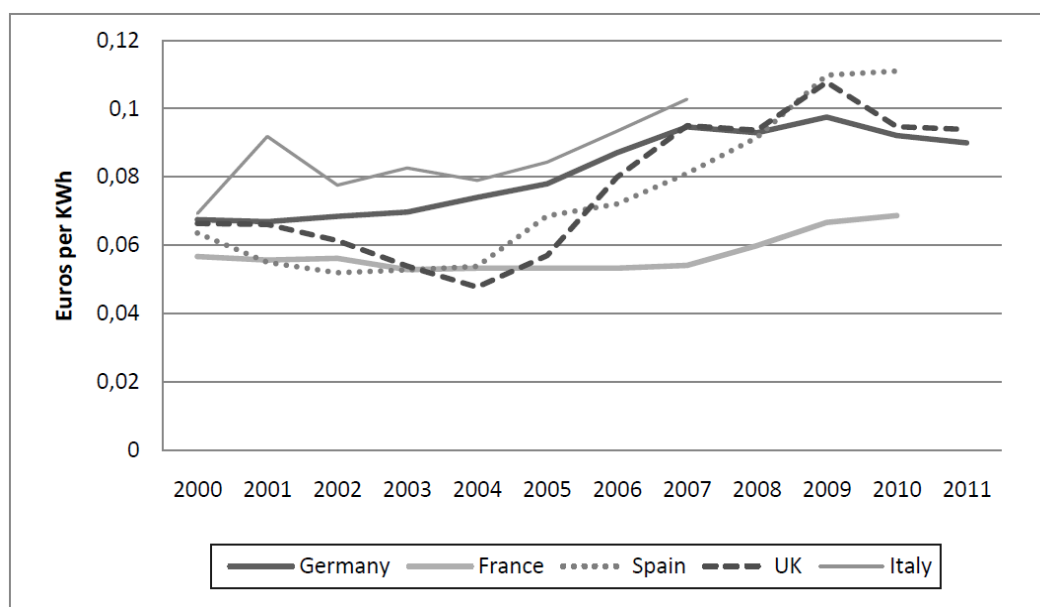
7 Competition was introduced before 1997 in a few European countries. These are England and Wales (1989), Norway (1991) and Sweden (1995).

8 Transmission is the transportation of electricity at high voltage from power plants to step-down transformers. Distribution is the transportation of electricity at lower voltage from step-down transformers to final consumers. See Unger [2002].

regulated firms (see Unger [2002]). In practice, there are still significant differences between the Member States regarding the level of competition in the power sector. While high levels of competition have been achieved in several countries (e.g. the UK, Germany, Spain and the Scandinavian countries), the degree of competition is still low in other countries where the liberalization process has been slower and is still under progress (e.g. France and Italy).

The reason that motivated the liberalization of the electricity sector in the EU was the improvement of efficiency and the reduction of prices paid by consumers. Indeed, moving from a vertically integrated industry – controlling generation, transmission, distribution and retailing – to a chain of specialized and competing firms is supposed to improve efficiency. Moreover, according to microeconomic theory, the transition from a private monopoly to a competitive market implies a price decline and an improvement in the consumer's welfare. However, in the case of electricity, introduction of competition would not necessarily result in sharp falls in prices, because electricity companies were not private monopolies before the deregulation but rather regulated monopolies. Nevertheless, there was an overall downward trend in prices until 2003 (see Kanen [2006]). Liberalization led to more competition between 1998 and 2003. As a consequence, power prices have declined in several European countries (see Figure 11).

Figure 11: Enduse electricity prices for industrial consumers in European countries (Eurostat data).



However, this changed from 2003 onwards, when increasing fuel prices started pushing power prices up. The rise in fuel prices happened in a context of increasing oil prices in the wake of the

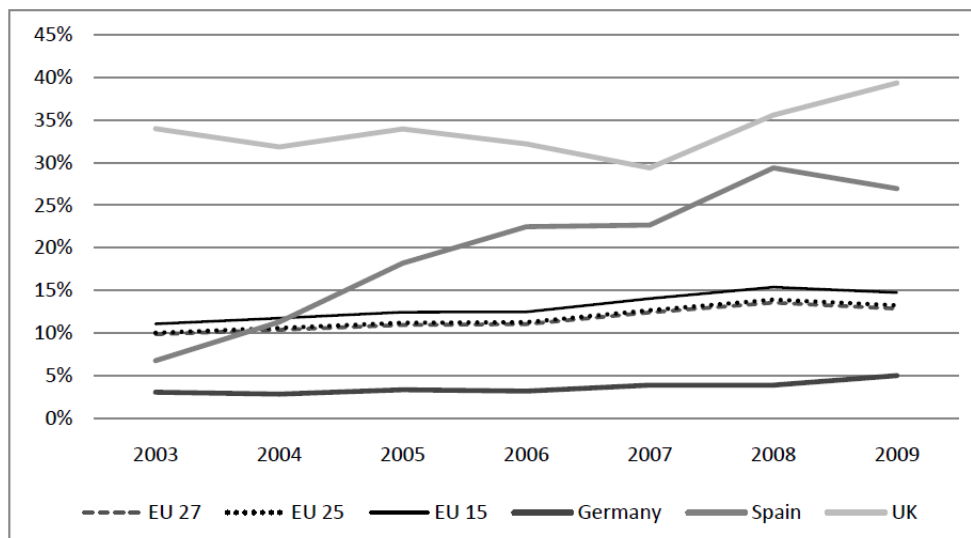
Iraq war and growing world demand for energy. The upward trend in fuel prices continued until the financial crisis of 2008 and the economic recession that occurred next. Power prices followed the same pattern (see Figure 11).

The liberalization of the electricity market has also introduced new responsibilities for power producers. Their profits are no longer determined by regulatory formulas, and thus, they are much more concerned with profitability and uncertainties. As for other commodities, the business of electricity now involves risk management and trading activities. Besides, power producers have to manage a new risk with the EU ETS. Carbon emissions are now considered as an input entering power generation. Therefore, as for other inputs, power producers are concerned with the volatility of the price of carbon.

1.2. The gas market

Natural gas is an important input for power generation in Europe. Over the last few years, the proportion of natural gas in European electricity has significantly increased (see Figure 12).

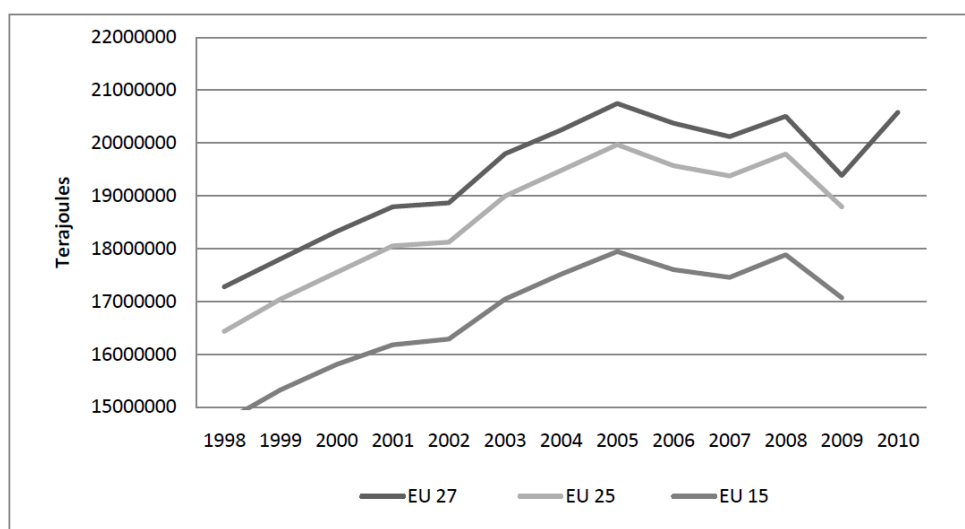
Figure 12: Proportion of natural gas in the European power generation, expressed as the ratio between the production of electricity by gas-fired plants and the total gross production of electricity (own calculations based on Eurostat data).



The growth was particularly strong in Spain, where the proportion of natural gas in electricity increased from 1% to almost 30% between 1998 and 2008. In the UK, since the beginning of the

1990s, gas has become the main energy source due to the 1980s policies encouraging the use of more gas (see Kanen [2006]). To date, about 40% of electricity comes from natural gas in the UK. The share of gas in the European power generation is still rising and it is expected to continue in the future with the tightening of the EU ETS constraint. Globally, the rise in gas consumption is a long-run trend in Europe (see Figure 13). The EU produces about 40% of its natural gas consumption⁹ and strongly depends on imports from three countries: Russia (between 40 and 50% of the European imports), Norway (21%) and Algeria (11%).¹⁰ The EU dependence on gas imports is expected to exceed 65% in 2030 (Chevalier and Percebois [2008]). Therefore, gas has acquired the same geopolitical risk characteristics as oil.¹¹ Managing this risk is probably one of the key issues for the European energy policy.

Figure 13: Evolution of gross inland natural gas consumption in Europe (Eurostat data).



Despite worries about the geopolitical risks, gas consumption is still growing in Europe. As pointed out by Keppler [2010], the rising share of gas in European electricity can be explained by some important advantages of this fuel that foster investment in gas-fired power plants and especially in CCGTs. First, CCGTs have relatively low capital costs and high efficiency. Thus, investing in CCGTs enables power producers to increase the efficiency of their parks with lower risks and shortened pay-back times compared with competing technologies. Second, producing with

9 The main gas producers in the EU are the UK (4% of world production) and the Netherlands (3% of world production and 7% of exports). See Chevalier and Percebois [2008].

10 Note that 90% of European imports come from pipelines. The remaining 10% comes from Liquefied Natural Gas (LNG) terminals. See Kanen [2006] and Hansen and Percebois [2010].

11 World reserves of natural gas are mainly located in a few countries. Among those countries, Russia controls about 30% of reserves, followed by Iran (15%) and Qatar (15%). See Chevalier and Percebois [2008].

gas often constitutes an automatic hedge against variations of prices. Indeed, gas technologies are often the marginal technologies (i.e. the last units to be brought online, which set the price of electricity) because of their high marginal costs. Thus, electricity prices are expected to be highly correlated with gas prices, which constitutes an automatic hedge for power producer. Finally, the introduction of a price for carbon emissions with the EU ETS encourages the use of more gas due to the lower CO₂ emissions.

An indirect effect of the EU ETS is to strengthen the link between gas and electricity, by rendering power generation more dependent on gas. This tends to reduce price-elasticity of demand for gas by power producers (Grubb and Newberry [2008]), which may induce unfavorable consequences such as gas price rises (Reinaud [2007]) and greater geopolitical risks (Bunn and Fezzi [2007] and Grubb and Newberry [2008]). Indeed, gas production is largely an oligopolistic market in Europe and the European imports are highly concentrated in few companies, namely Gazprom, Sonatrach and Statoil (Chevalier and Percebois [2008]). Besides, in addition to production (“upstream operators”), import and wholesale activities (“mid-stream operators”) are also dominated by a few companies (e.g. Gaz de France or Ruhrgas), which are frequently vertically integrated into electricity generation.¹² Those gas companies would exert their market power on the electricity market by raising the price of gas to increase electricity prices and hence the profits of their merged partners (Grubb and Newberry [2008]). Therefore, there would be a greater incentive to raise gas prices. All of this should be a concern for future European policies regarding both diversification of imports and the problem of vertical integrations between gas suppliers and power producers.¹³

As opposed to coal and oil which can easily be shipped all over the world, creating truly global markets, natural gas is mainly distributed through pipelines. Therefore, the gas market is more regional compared with competing fuels.¹⁴ Moreover, despite the EU liberalization process, which was introduced in 1998 (with the Directive 98/30/EC), the European gas market is still dominated by former state monopolies, except in the UK. Those historic operators sell most of their gas through bilateral long-term contracts whose prices are indexed to oil prices. Nevertheless, in the last few years, short-term contracts and trades on exchanges have developed rapidly in Europe, with

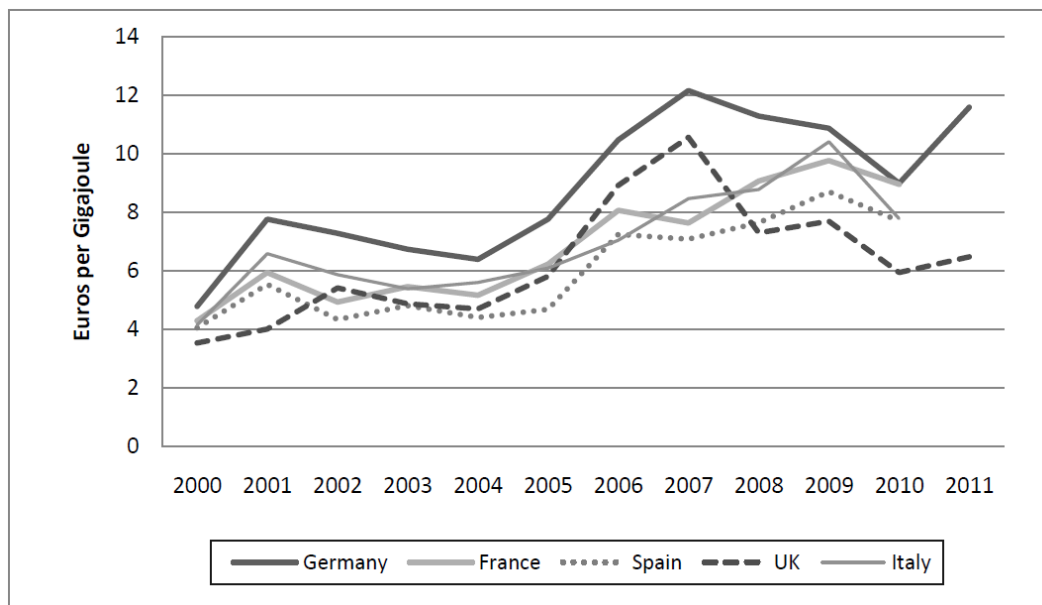
12 For example, Ruhrgas, the dominant German gas company, has merged with E.On, one of the leading power producers in Germany. Another example is the Gaz de France-Suez merger.

13 Note that this problem is very close to the one which led to the unbundling in the power sector (i.e. the separation between transmission and distribution, on the one hand, and generation and retailing, on the other hand). For further details on the vertical integration problems between gas and electricity companies and their possible regulatory remedies, see Vázquez et al. [2006].

14 However, progresses in gas liquefaction are increasingly creating a similar world market for gas, with more shipping opportunities.

prices reflecting more supply and demand of gas. Exchanges have notably developed in the National Balancing Point, in the UK, and in the hub of Zeebrugge, in Belgium, where several pipelines connect (see Kanen [2006]). As shown in Figure 14, gas prices followed the same upward trend as other energy commodities until the crisis of 2008.

Figure 14: Enduse prices of natural gas for industrial consumers in European countries (Eurostat data).



In order to diversify import sources and, particularly, to reduce exposure to Russian gas, many efforts have been made in the last few years to increase the capacity of pipelines connecting the EU to Algerian gas. Examples are the Trans-Mediterranean and the Magreb-Europe (Kanen [2006]). A new pipeline was also inaugurated in March 2011. The Medgaz pipeline, which connects directly Algeria and Spain. Another project is the Galsi, which will connect Algeria and Italy. It is expected to become operational in 2012 (Hansen and Percebois [2010]). There are also projects to connect the EU and the Southern Caspian region. Among them, there is the Nabucco pipeline, which is backed by the EU. Construction should begin in 2013 and it is expected to be operational in 2017.¹⁵ In addition to pipelines, there are more and more projects to build LNG terminals bringing non-Russian gas further into Europe. To date, Italy has started to build LNG terminals and there are advanced plans for the Netherlands, Norway and France. LNG is more expensive than gas delivered through pipelines because liquefaction is costly. In general, it becomes competitive when transported over distances greater than 5000 kilometers (Kanen [2006]). However, progresses in gas

¹⁵ See the Nabucco website: www.nabucco-pipeline.com.

liquefaction should make LGN more competitive and create more shipping opportunities. Another very important challenge for the future of the gas market regards the technological progress in the extraction of Non-Conventional Gases (NCG): shale gas, tight gas sands and coalbed methane.¹⁶ While the extraction of NCGs is problematic with current technologies – because of pollution of water tables – there is a huge potential and especially in Europe. The NCG reserves may account for more than four times those of conventional gas. The gas market should be strongly impacted.

1.3. The coal market

The coal market is a world market with international exporters such as Australia, South Africa, Columbia, the US and China. Coal resources are abundant and especially in countries such as the US, Russia, China, Indonesia and Australia.¹⁷ To a lesser extent, resources are also important in the EU (see Kanen [2006] and IEA [2010]). However, in the past forty years, many coal mines have been closed in several EU countries. This has happened because European producers had a lot of difficulties competing against international coal exporters. Therefore, the EU imports have continuously increased in the past decades.¹⁸ Antwerp, Rotterdam, Amsterdam (ARA) are the main coal-importing ports in Europe. Their prices are used as a reference for the coal price in the EU. Nowadays, the European coal production comes essentially from three countries: Poland, Germany and the Czech Republic. Notably, Germany is the biggest producers of lignite in the world.¹⁹

As we can see in Figure 15, coal prices strongly increased during the 2000s with the rise in fuel prices. European demand for coal was driven by high oil and gas prices, even in 2005 and 2006 despite high CO₂ prices. Interestingly, Figure 15 also shows that the coal market was more impacted by the crisis of 2008 compared with the gas market (Figure 14). Indeed, as opposed to gas which is almost entirely dedicated to power generation, coal is also used for steel making.²⁰ Thus, since

16 For an overview on NCGs, see Hansen and Percebois [2010].

17 The fact that Australia, China and the US are big producers and exporters of coal may explain why they are so reluctant to accept any binding agreements on climate policy. They fear that such agreements reduce the value of their coal reserves, in making coal less profitable for power generation.

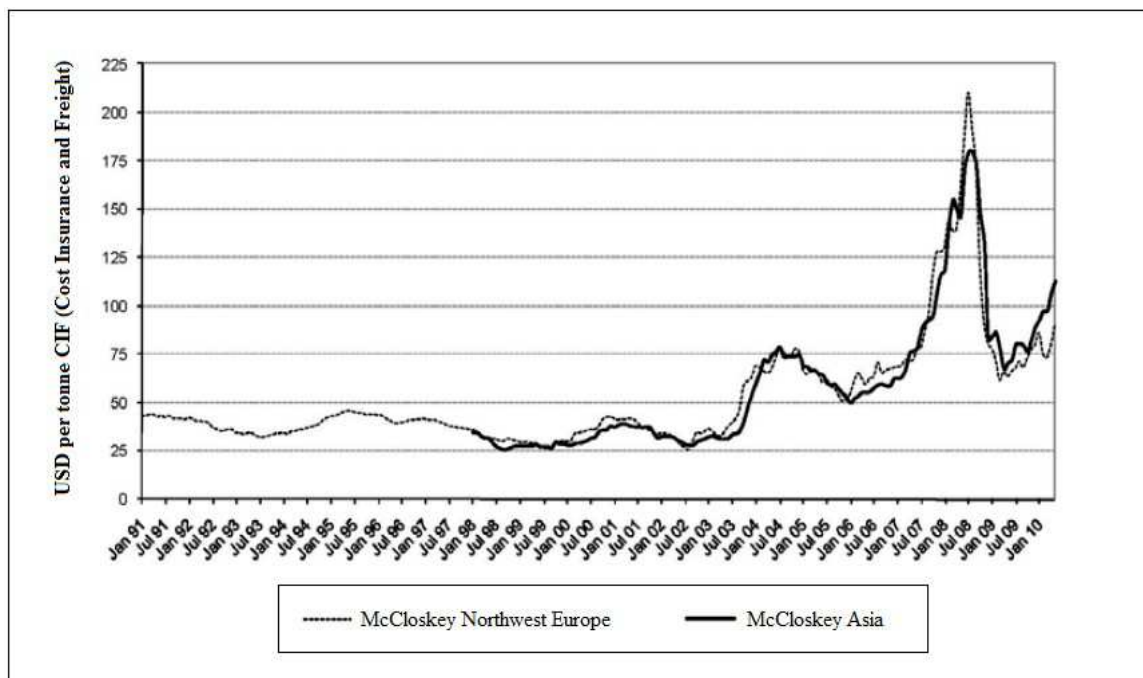
18 See Hansen and Percebois [2010] for details.

19 In Germany, subsidies are given to lignite producers to keep the industry alive for strategic and political reasons. This explains why lignite represents about 25% of the German power generation.

20 Basically, coal can be separated into three groups: hard coal, lignite (or brown coal) and peat. Hard coal has the highest calorific value followed by lignite and peat (Percebois [1989]). While hard coal and lignite are used in the power and industrial sectors, peat is dedicated to household heating. Moreover, there are two sub-categories of hard coal: coking coal (used in steel production) and steam coal (used in steam raising and power generation). See United Nations [2005].

industrial sectors were more affected by the recession than the power sector,²¹ the demand for coal has been more impacted than gas.

Figure 15: Steam coal prices in Europe and Asia (from IEA [2010]).



Over the last decades, the Eastern Europe consumption has continuously declined. Between 1996 and 2006, it fell by 26% (Kanen [2006]). Nevertheless, coal still represents an important share of European electricity. The biggest with nuclear. Poland, Germany, the Czech Republic and Estonia are the EU countries that depend most on coal for electricity, with more than 50% of power generation supplied by coal plants for each of them. In the UK about one third of electricity comes from coal, and one quarter in Spain. That can explain why countries such as Germany, Poland, Spain and the UK are the biggest CO₂ emitters in the EU (see Ellerman and Buchner [2008]).²² In addition to hard coal, lignite is also an important input for power generation in some EU countries. Thus, almost 60% of power generation comes from lignite plants in Greece, and about 25% in Germany.

21 Demand for electricity was globally more stable because the demand of households continued to rise even during the recession. See Eurostat data.

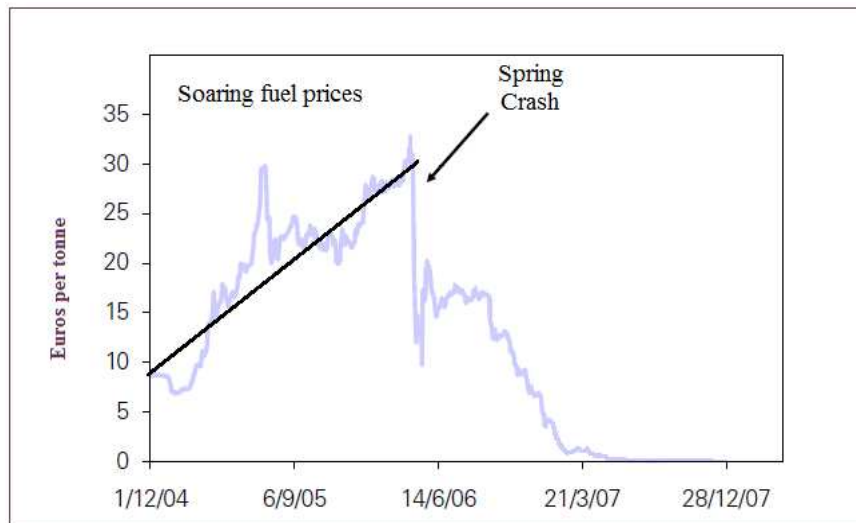
22 Note that there are technologies that can reduce CO₂ emissions from existing coal-fired plants. Some of them are available, others are under study. They rely on increasing the efficiency of plants or on carbon capture and storage. See Hansen and Percebois [2010].

1.4. The oil market

The oil market is not our main focus. However, oil prices strongly impact energy markets and, in turn, the carbon market. Therefore, the main characteristics of the oil market are presented in this sub-section. We also discuss some developments on the oil market during the last few years.

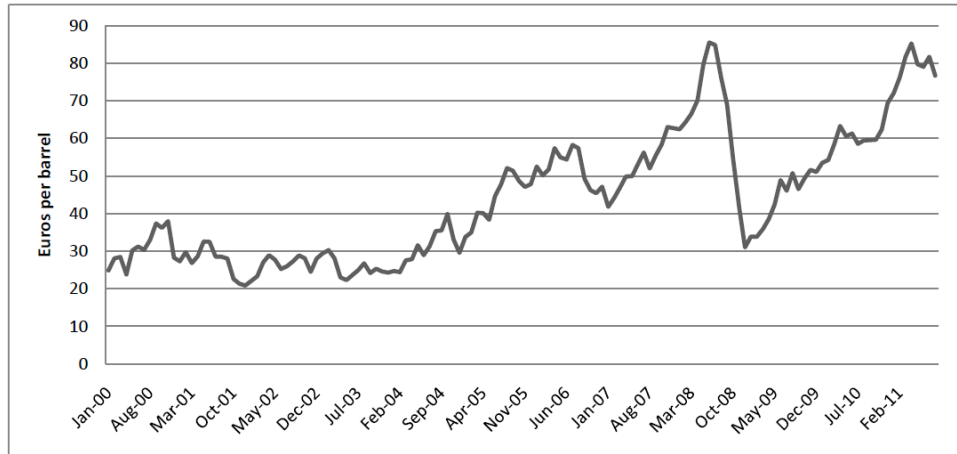
Oil is used to produce electricity during peak hours in some European countries (e.g. France and Lithuania, see Reinaud [2007]), but globally it represents a small share of European electricity. More importantly, the oil price is the main driver of the gas price which, in turn, is the main driver of power prices. Moreover, coal and gas prices also depend heavily on the price of oil, because coal, gas and oil are substitutes for many purposes (e.g. in the chemical industry). Hence, since the price of carbon depends on coal, gas and electricity prices, the price of oil also impacts the carbon market. This can be seen in Figure 16.

Figure 16: Influence of soaring fuel prices (2003-2008) on the European carbon price. The price of carbon is the EUA price of the OTC market (based on Point Carbon [2009])



As we mentioned before, there was an upward trend in the oil price from 2003 until the crisis of 2008 (see Figure 17).

Figure 17: Brent crude oil price (data available at www.indexmundi.com)



The origin of the crisis was the first liquidity crisis that occurred in August 2007, when the subprime bubble burst. However, the financial crisis really exploded in September 2008, with the failure of Lehman Brothers and the difficulties of several key firms in the financial sector. This caused a dramatic credit crunch which rapidly turned into an economic crisis with the collapse of economic activity in Europe and in the world. In response, the price of oil fell from autumn 2008 until the first signs of recovery in mid-2009 (see Figure 17).

Because oil impacts energy and carbon markets, understanding how the oil market works is an important issue in analyzing relationships between energy markets and the EU ETS. In addition to geopolitical factors and the market power of producers, supply and demand for oil have specific characteristics resulting from the centrality of oil in the economy and the depletable nature of reserves. Among those characteristics, the fact that the oil market is highly sensitive to information disclosures (due to uncertainties about reserves) and the inelasticity of supply and demand (at least in the short-run) are very important.²³

Both oil consumers and suppliers have low price-elasticity in the short-run. Thus, when the price of oil varies, changes in supply and demand do not happen immediately. Consumers do not quickly adjust their consumption when the oil price goes up. In the same way, producers cannot react rapidly because of capacity constraints. The main consequence is that shifts in demand or supply can have a huge impact on the price of oil. For example, a quick rise in demand (such as the rise in world demand during the last decade) can trigger a huge price increase with a fixed supply.

²³ We focus on those characteristics because they are particularly relevant in the short-run. We do not discuss other factors such as geopolitical risks or market concentration. For an extensive presentation of economic and geopolitical drivers of the oil market, see Percebois [1989] and Hansen and Percebois [2010].

With regard to oil reserves, the first thing to know is that their effective level depends on the price of oil. Indeed, reserves that can be exploited economically go up when oil prices are high, and vice versa. Thus, prices affect reserves and reserves affect prices. This makes estimates difficult²⁴ and sensitive to information disclosures. In addition, both producers and consumers have an interest in keeping private information from the other side. This makes the market even more sensitive to information.

24 According to IEA, peak oil (i.e. the point in time when production will decline) should occur around 2015. Note that coal and gas are also depletable resources and, therefore, their productions will also peak in the future. However, reserves are much higher than for oil, especially if we take into account the potential of non-conventional gases. If we consider the reserves-to-production ratio (= amount of known reserves / amount used per year), the world holds oil reserves for about 45 years, 65 years for natural gas and more than 150 years for coal.

2. Interactions between carbon and energy markets: theories and literature review

Relationships between fuel, electricity and carbon markets have been of growing interest since the creation of the EU ETS, and have produced a literature with theoretical, simulation and econometric studies. The economic theory offers several keys to address these questions. Basically, they can be broken down into three approaches: *the pass-through* of the carbon cost, *the short-run rent capture* and *the fuel-switching* approach. The first two concern interplay between electricity and carbon markets, while the third is relevant in explaining relationships between coal, gas and carbon prices. In this section, we present these three approaches and we review those papers dealing with these questions.

2.1. The pass-through approach

The term of “pass-through” refers to the percentage of the carbon price that is passed through to the electricity price. Carrying carbon allowances entails an opportunity cost because of profits that would be obtained if they were sold, regardless of whether allowances have been received for free or purchased at an auction (see Sijm et al. [2005], Sijm et al. [2006] and Neuhoff et al. [2006]). Therefore, power producers will integrate this opportunity cost into the cost of generating power, according to economic theory.

Since the launching of the EU ETS the question of the carbon cost pass-through has been a controversial issue because of windfall profits of power producers in a context of free allocation of carbon allowances. Sijm et al. [2005] developed a model (COMPETES – Comprehensive Market Power in Electricity Transmission and Energy Simulator) to analyze the implications of emissions trading for power prices and profits. With the same COMPETES model, Sijm et al. [2006] estimated a cost-pass-through rate between 60 and 80% depending on the country, with the highest value for Germany. They also reported empirical evidence (using OLS estimations) of pass-through rates between 60 and 117% for Germany, and between 64 and 81% in the Netherlands.

In theory, with a fully competitive electricity market, the pass-through rate would have to be 100%. Indeed, in a perfectly competitive market, all the marginal cost of production is passed-through into the price, including opportunity costs.²⁵ However, in practice, there have been significant differences between the EU Member States regarding the level of liberalization in the power sector (see section 1.1). In countries with a fully liberalized electricity market, retail prices are supposed to reflect the opportunity cost of carrying allowances. By contrast, in countries where a significant fraction of the sector is still subject to price regulations, retail prices are supposed to be less impacted by this opportunity cost. That can explain why the rate of pass-through can differ between countries. Nevertheless, even in countries with a high level of competition in the electricity market, less than 100% of the carbon cost has actually been transmitted into the price of electricity. One may think that the reason is that power prices are set under imperfect competition. Indeed, scarcity of generation capacities at certain times of the day (during peak periods)²⁶ justify the existence of some form of market power in the electricity market (see Keppler [2010]). Therefore, profit-maximizing firms under oligopolistic market-conditions will not automatically pass any increase of their marginal cost through consumers, since power prices are already relatively high above marginal costs. They actually arbitrate between their marginal revenue and their market shares. Thus, they do not fully pass on increases in the carbon cost, since it may lead to strong reductions in demand (depending on price elasticity of demand).²⁷ Hence, in less competitive markets, the effective pass-through rates tend to be less than 100%.

Other factors can also lead to pass-through rates which are lower than 100% (see Sijm et al. [2005], Sijm et al. [2006]). The main one are: changes in the merit order due to fuel switching, updating of free EUA allocations or market imperfections and non-optimal behaviors.

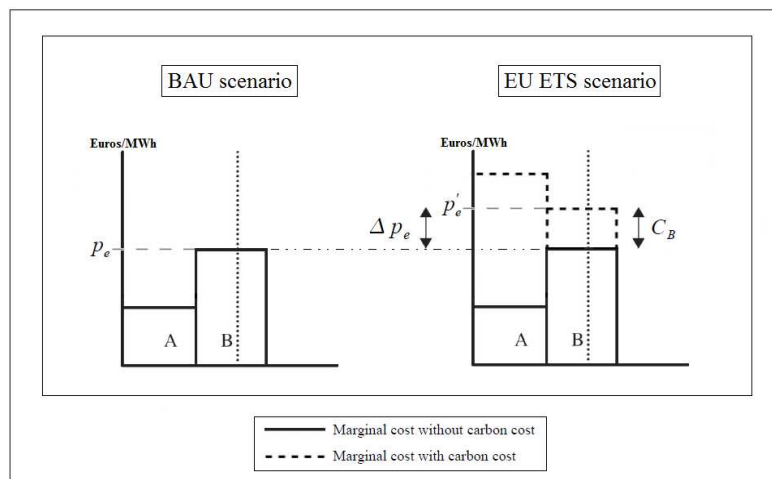
25 Theoretical justifications are available in Bonacina and Gulli [2007], Gulli [2008] and Sijm et al. [2008]. These papers develop theoretical models of carbon cost pass-through under perfect and imperfect competition. They show that the pass-through rate is 100% in the case of perfect competition, while it is lower than 100% under market power (Bonacina and Gulli [2007] show that the pass-through rate under market power may be very close to that of perfect competition when there is excess capacity, if the share of the most polluting power plants in the market is low enough).

26 Note that scarcity of capacities in peak-hours may be partially explained by investment retentions to create market power in face of rising demand. This may be a way for power producers to cover high fixed costs of peak-load plants. See Keppler [2010].

27 Price elasticity of demand for electricity is usually low. Especially, demand by households and other small-scale consumers is generally considered as inelastic, while it may be more significant for power-intensive industries. Here, differences in price-elasticity may also explain differences in pass-through rates. See Sijm et al. [2005] and Sijm et al. [2008].

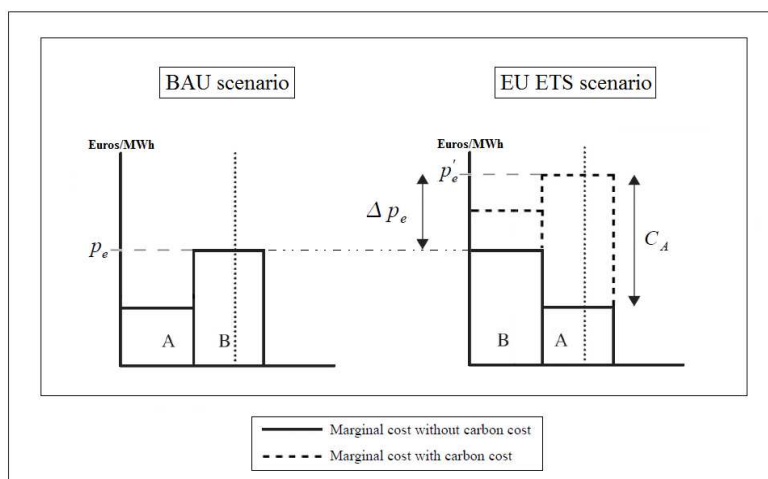
The proportion of the carbon cost which is effectively passed through to the electricity price depends on eventual changes in the merit order. To illustrate, let us take an example from Sijm et al. [2005] and Sijm et al. [2006]. We assume two technologies, A and B, which are ranked in a simplified merit order (with only two technologies). According to the merit order principle, the technology on the left is brought online first, and thus, it runs for a longer period. By contrast, the technology on the right is the last to be brought on line and it runs for a shorter period.²⁸ Thus, the technology on the right is the marginal technology which sets the electricity price. Moreover, we assume that A has a lower fuel cost and a higher carbon cost. Typically, A would be a coal plant and B a CCGT. If there is no carbon cost, in the business-as-usual (BAU) scenario, A is on the left and B on the right, due to the lower fuel cost of A. However, with a carbon cost, in the EU ETS scenario, B is on left and A on the right, due to the lower carbon cost of B (i.e. producers switch between A and B in the merit order). Finally, like Sijm et al. [2005] and Sijm et al. [2006], we make a distinction between the extent to which producers “add on” the opportunity cost of EUAs to their marginal cost (the “add-on rate”) and the extent to which the EUA costs ultimately “work on” power prices after eventual changes in the merit order (the “work-on rate”). Because of changes in the merit order, the work-on rate may be less than 100% even if the add-on rate is 100%. This is illustrated in Figures 18 and 19.

Figure 18: Pass-through rate when there is no change in the merit order (based on Sijm et al. [2005] and Sijm et al. [2006]). p_e is the electricity price in the BAU scenario, p'_e is the electricity price in the EU ETS scenario and C_B is the marginal EUA cost of the marginal technology B. The (fixed) demand is indicated by the vertical dash line.



28 The merit order principle and fuel switching are further described in section 2.3 of this Chapter.

Figure 19: Pass-through rate under changes in the merit order (based on Sijm et al. [2005] and Sijm et al. [2006]). p_e is the electricity price in the BAU scenario, p'_e is the electricity price in the EU ETS scenario and C_A is the marginal EUA cost of the marginal technology A. The (fixed) demand is indicated by the vertical dash line.



In Figure 18, when there is no change in the merit order, the change in the electricity price ($\Delta p_e = p'_e - p_e$) is always equal to the marginal EUA cost of the marginal technology B (C_B). The resulting effective pass-through rate (i.e. the work-on rate, equal to $\Delta p_e / C_B$) is always 100%. However, the situation becomes different when there is a change in the merit order. As displayed in Figure 19, in this case the change in the electricity price is smaller than the marginal EUA cost of the marginal technology A (i.e. $\Delta p_e < C_A$). Therefore, the effective pass-through rate (the work-on rate which is equal to $\Delta p_e / C_A$) is less than 100%, even if the add-on rate is still 100%.

Updating free allocations of allowances can also lead to pass-through rates less than 100%. Updating is an allocation method in which the historical basis of emissions for free allocations is updated periodically, according to verified emissions. This creates an incentive for power producers to increase their current emissions in order to get more free allocations in the future. Accordingly, power producers are encouraged to keep electricity prices relatively low in order to increase demand for electricity and thus carbon emissions. Therefore, they may limit the percentage of the

carbon price that is passed through to the electricity price.

In daily practice, power production, trading, pricing and other decisions may deviate significantly from optimal outcomes of economic models. The opportunity cost of carrying allowances may not be fully or immediately passed on to electricity prices because of a variety of reasons such as uncertainties, lack of information or objectives other than profit maximization, etc. Therefore, the pass-through rate may also be less than 100% due to market imperfections and non-optimal behaviors.

Evidence of pass-through has been found in several econometric papers. Bunn and Fezzi [2007] (see also Bunn and Fezzi [2008] and Bunn and Fezzi [2009]) were the first to address the issue of interdependence between carbon, electricity and fuel prices in a dynamic framework using a VAR-VECM approach. They estimate a VECM with temperatures, carbon, gas, and electricity prices in the UK during Phase 1 of the EU ETS. Among their results, they report that the carbon price drives the price of electricity in the long-run equilibrium (i.e. in the cointegrating relationship). For the short-run dynamic, they also show that the electricity price reacts to a shock on the carbon price. Using another VECM for relationships between weather variables (temperatures and reservoir levels for hydroelectricity), carbon and energy prices, Fell [2008] finds evidence of pass-through in the Nordic electricity market during Phase 1. He identifies that the Nordic electricity price reacts promptly and significantly to a shock on the carbon price. Zachmann and von Hirschhausen [2007] identify an asymmetric pass-through of the carbon price into the price of electricity, in the German electricity market during Phase 1. This means that a rising carbon price has a stronger impact on the electricity price than a falling carbon price. They use a VECM between carbon and electricity prices from the German markets, with the gas price taken as an exogenous variable. Chemarin et al. [2008] examine relationships between the carbon and energy markets in France during Phase 1. They estimate a VAR model in which they find no short-run interactions, and they show that including weather variables (temperatures and rainfall) does not modify their results. However, those same authors report that the carbon and electricity prices are cointegrated.²⁹

29 Chemarin et al. [2008] also investigate the volatility transmission between the carbon and electricity markets in several bi-variate GARCH models. Their results show that the own volatility spillover effects are significant on both markets, indicating that the current volatility of one market (carbon or electricity) depends on the past volatility of that same market. They also report some evidence of cross volatility spillovers (i.e. the past volatility of one market affects the current volatility in the other market). However, the results about cross volatility spillovers depend heavily on the GARCH specification which is used.

Keppler and Mansanet-Bataller [2010] were the first to analyze the dynamic of relationships between carbon and energy markets in Phase 2, and the only ones to examine the dynamic of interactions between carbon and electricity markets in Phase 2.³⁰ They perform pairwise Granger causality tests (i.e. Granger causality tests in several bi-variate VARs involving different variables) for Phase 1 and for the first year of Phase 2. However, they do not check for cointegration between variables. Their results show a significant influence of the lagged-values of the carbon price on the electricity price during Phase 1, while this does not hold in Phase 2.

More recently, Solier and Jouvét [2011] have estimated the pass-through rate in different European countries during Phase 1 and Phase 2. Those authors ran a regression analysis, where the pass-through rate is defined as the coefficient measuring the influence of the carbon price on the “spread”, i.e. electricity price minus fuel price (where fuel can be coal, gas or oil).³¹ Prices of electricity are spot and futures prices of peak and off-peak load from different European power exchanges. Fuel prices are spot and futures prices of oil (Brent), natural gas (Zeebrugge and National Balancing Point)³² and coal (ARA). The carbon price is the spot price of EUAs traded on Bluenext. The estimation results indicate that the impact of the carbon price on electricity spot prices is relatively strong in Phase 1, while it is globally less significant in Phase 2. However, using the futures electricity prices, it appears that the pass-through coefficient is much more significant in Phase 2, whatever the country. Furthermore, Solier and Jouvét [2011] find that the value of the R^2 increases when the off-peak electricity prices are used rather than those of peak. This suggests that the pass-through is more important in off-peak periods. This result is consistent with the idea of an increase in the scarcity of generation capacities during peak periods. Hence, during peak periods, electricity prices could reach very high levels which may be less connected with the carbon cost.

2.2. The short-run rent capture approach

As opposed to the pass-through approach, the short-term rent capture theory (Keppler [2010]) implies an influence of the electricity price on the carbon price. This happens in the short-run, when

30 Note here that an earlier contribution has analyzed the effects of including EUAs in a diversified portfolio during the first year of Phase 2 (Mansanet-Bataller and Pardo [2008b]). Different portfolio compositions are considered, including traditional assets (stocks and fixed income assets like bonds) and energy commodities (oil and natural gas).

31 The fuel can be coal, gas or oil depending on the country and on the load level (i.e. a single marginal fuel is assumed for each country and load level, peak or off-peak).

32 The National Balancing Point (NBP) gas hub in the UK.

no carbon abatements can be performed, implying that power producers have to reduce their output to sell more allowances (or, symmetrically, use more allowances to increase their output). As a consequence, power producers with market power have the ability to “monetize” on the carbon market their scarcity rents in the electricity market. In other words, the carbon price will be set by the difference between the electricity price and the marginal cost, i.e. what is abandoned by a power producer if it decides to sell allowances rather than to produce (see Keppler [2010]).

As an illustration, let us take the example given by Keppler [2010]. We assume an electricity market with scarce capacities (and thus market power). The price of electricity is 70 Euros per MWh while the marginal cost (including the carbon cost) is 50 Euros per MWh. As a simplification, we assume that precisely one allowance is needed to produce one MWh of electricity. Moreover, we also assume that the endowment of allowances of each producer matches its production.³³ In this situation, if a firm wants to sell allowances in the short-run, it needs to reduce its output given that it cannot reduce its emissions otherwise. Because each producer makes a 20 Euros profit per MWh of electricity (and thus per allowance used to produce), it will abandon 20 Euros per allowance which is sold rather than used to produce. Therefore, the carbon price should be 20 Euros per allowance.

Empirical evidence of the influence of the electricity price on the carbon price has been reported in some econometric studies. It has been found in single-equation estimations by Mansanet-Bataller et al. [2007], Alberola et al. [2008]. Evidence of dynamic interactions between those prices has also been reported in VAR models. Keppler and Mansanet-Bataller [2010] identify Granger causalities running from the *spreads*³⁴ to the carbon price in Phases 1 and in the first year of Phase 2. This lends support to the short-term rent capture approach since the spreads indicate what would be abandoned by a power producer if it stops producing. Moreover, Keppler and Mansanet-Bataller [2010] find that the electricity price directly impacts the carbon price in Phase 2, while they do not report this result for Phase 1. Finally, Nazifi and Milunovich [2010] identify a significant influence of the electricity price on the carbon price during Phase 1. They investigate relationships between temperatures, carbon, fuel, and electricity prices, with data from different regions of Europe (including France, the Nordic countries, ARA, and the UK). Using the Granger causality and impulse response functions in a VAR model, they detect some significant short-run

33 The example also works if endowments are less than production. However, this does not work when endowments are larger than production since the carbon price drops to zero in this case.

34 The spreads are the Clean Dark Spread (CDS, the electricity price minus the costs of coal and carbon) and the Clean Spark Spread (CSS, the electricity price minus the costs of gas and carbon).

relationships.³⁵ Notably, they find Granger causality running from the electricity price to the carbon price. Here again, this lends support to the short-term rent capture theory.

2.3. The fuel switching approach

The impact of fuel prices on the carbon price is explained by fuel switching. The basic idea of this approach is that fuel prices determine the demand for carbon allowances by setting the composition of power generation. Fuel prices determine which technology (i.e. coal plants or CCGTs, in our case) is brought online first. Therefore, since power producers are the main actors in the EU ETS, fuel prices strongly influence carbon emissions under the scheme. That is why fuel prices are often considered to be the most significant carbon price drivers.

Kanen [2006] was among the first who gave a rigorous treatment of fuel switching under the EU ETS.³⁶ He simulated the cost of switching from coal to gas (the *switching price* or *fuel switching price*), expressed in Euros per tonne CO₂, in the different countries of the EU. He used coal and gas prices for industrial consumers. Among countries where fuel switching can occur (i.e. countries with relatively high proportion of coal and gas in off-peak load), he reported particularly low switching prices in the Netherlands and in Spain (below the EU 25 average). The author also found a relatively low switching price in the UK (below the EU 25 average),³⁷ but higher than in Spain and in the Netherlands. However, its results showed a high switching price for Germany, always quite above the EU 25 average. On the other hand, using the gas prices for big industrial consumers (more than 4 million GJ a year) – whose data are unavailable for other countries – he identified that the German switching price was drastically reduced (far lower than in other countries) so that fuel switching could occur more easily. Nevertheless, as pointed out by the author, this switching price is not attainable for most industrials except for large gas companies such as the E.On-Ruhrgas merger. Moreover, as fuel switching entails an opportunity cost for a vertically integrated company such as E.On-Ruhrgas (i.e. the opportunity cost of not selling its gas to its

35 However, Nazifi and Milunovich [2010] find no significant cointegration relationship.

36 Sijm et al. [2005] also gave one of the first contributions for the EU ETS. They compared the cost of generating one MWh of electricity with coal-plants or CCGTs in several scenarios for carbon and fuel prices. The impact of fuel switching in an emission trading scheme was previously studied in the US. In this case, fuel switching is the replacement of high-sulfur coal with low-sulfur coal (see Ellerman and Montero [1998]).

37 The first half of 2006 is an exception here, because the switching price was much higher in the UK (above the EU 25 average) due to a peak in the UK gas price (see Figure 4 in section 1.2).

customers), this switching price may be not representative for Germany.³⁸

In the same spirit, Delarue and D'haeseleer [2007] and Delarue et al. [2007] showed how an efficient way of using a park of power plants under an emission trading regime leads to an indicator, the *switching point* (which corresponds to the *switching price*), expressing how advantageous fuel switching from coal to gas is at a certain point in time (see section 2.3 of this Chapter). Delarue and D'haeseleer [2008] and Delarue et al. [2008] use the E-Simulate model (developed at the University of Leuven)³⁹ to simulate, for several European countries, how the dispatch of power plants (to meet hourly demand) is modified by introducing a carbon price. They report particularly high fuel switching potential (from coal to gas) in the Netherlands, Germany, Spain, and the UK.

Fehr and Hinz [2006] (see also Carmona et al. [2009]) were the first to analyze fuel switching in an equilibrium model (see Chapter 2 for a more detailed presentation). They build a dynamic equilibrium model with a stochastic cost function representing the expense generated by switching thermal power plants from coal plants to CCGTs. As a simplification, they assume a single switching price in their cost function. With this approximation, the fuel switching process they describe corresponds to a situation where there is only one type of CCGTs (i.e. differences in energy efficiency are not taken into account).⁴⁰ They find that the carbon price is an increasing function of the gas price, and a decreasing function of the coal price (i.e. an increasing function of the switching price). They also find that the carbon price depends on the difference between the required level of carbon abatements (which is defined as the difference between carbon emissions in the “business-as-usual” scenario and initial endowments of allowances) and the optimal level of fuel switching effort. In another equilibrium model on fuel switching, Bertrand [2010] has explicitly modeled differences in the energy efficiency of CCGTs used in the fuel switching process (whereas a single type coal plants is assumed).⁴¹ It is possible, then, to analyze how the fuel switching process can affect interaction between gas and carbon prices in a context where gas plants are not all equally efficient. The main result shows that the sensitivity of the carbon price with respect to the gas price depends on the level of uncontrolled carbon emissions (i.e. “business-as-usual” emissions)

38 This opportunity cost that comes with fuel switching for vertically integrated companies may be an important question given that E.ON is one of the biggest power producers in Germany, with RWE.

39 The E-Simulate model represents a European electricity generation system that includes most European countries. The model determines the composition of power generation, for each hour of the year, by minimizing the cost of dispatching plants. For more details, see Voorspools [2004].

40 They also assume one type of coal plant.

41 The same strategy as in Fehr and Hinz [2006] is followed with a cost function representing the expense generated by switching from coal to gas.

due to differences in efficiency of gas plants.

Up to now, several econometric papers have shown in single-equation estimations that coal and gas prices were often the most significant carbon price drivers during the first Phase of the EU ETS (see Kanen [2006], Mansanet-Bataller et al. [2007], Rickels et al. [2007], Alberola et al. [2008] and Hintermann [2010]). With regard to Phase 2, Rickels et al. [2010] were the first who analyzed relationships between the carbon price and its drivers in single-equation estimations. Those authors estimate regressions with the carbon price as dependent variable, and fuel prices (coal, gas, oil, and switching prices), economic activity (stock price indexes) and weather (temperatures, wind and reservoir levels for hydroelectricity) as explanatory variables. Estimations are conducted with two switching prices, i.e. one based on spot and one based on forward fuel prices. However, only the “forward switching price” has a significant positive coefficient, in line with fuel switching. Rickels et al. [2010] conclude that their results indicate that fuel switching takes place, but not in the very short-run. When the absolute coal and gas prices are included (rather than the switching price), performances of estimations (as measured by R^2) increase. The coefficients of the spot and forward gas prices are highly significant and positive, in line with the fuel switching approach. However, the coal prices have positive coefficients, contrary to what is predicted by fuel switching (i.e. a negative influence on the carbon price). The authors note that this result does not necessarily imply that fuel switching does not take place, since fuel switching relies on relative fuel prices rather than on their levels alone.

Evidence of dynamic interactions between those prices have also been reported. Bunn and Fezzi [2007] find that the carbon price depends heavily on the gas price, in the short-run dynamic. As they find that both the gas price and the carbon price drive the electricity price (in the short-run and in the equilibrium), they conclude that one indirect consequence of the EU ETS is to strengthen the link between gas and power, due to fuel switching (see also Grubb and Newberry [2008]). Kepler and Mansanet-Bataller [2010] show that there is an indirect influence of coal and gas prices on the carbon price, through the spreads. That is, coal and gas prices influence the spreads which in turn influence the carbon price. They report this result for Phase 1 and for the first year of Phase 2. Moreover, in 2008, they identify that the carbon price directly impacts the gas price and the coal price. The relationship is bi-directional regarding carbon and coal prices. As pointed out by the authors, the influence of the carbon price on fuel prices is somewhat surprising. One would expect

the influence of fuel prices on the carbon price to be more important.⁴² They argue that this result should be explained by the economic crisis.⁴³ Nevertheless, other studies have found a significant influence of the carbon price on fuel prices in Phase 1. Thus, Fell [2008] reports that coal and gas prices react to a shock on the carbon price. However, the reaction is slow and small in magnitude in each case. Finally, Nazifi and Milunovich [2010] find Granger causality running from the carbon price to the gas price. In another early contribution for Phase 2, Bonacina et al. [2009] examined the interdependence between carbon, fuel and stock prices in 2008. The authors conducted a cointegration analysis, with the carbon price normalized as the dependent variable of the cointegrating relationship. The oil price, the switching price and an equity price index are the explanatory variables. The results show that variables are cointegrated, with significant positive coefficients for the oil price and the switching price. However, the stock price index is not significant, and the value of the switching price coefficient is very low. In order to investigate consequences of the financial crisis, the dataset is divided in two sub-periods – before and after the financial crisis (i.e. before and after August 2008) – in which ECMs are estimated.⁴⁴ The results on the full sample period show that the stock price index has a significant influence in the short-run, even though it is not significant in the cointegrating relationship. For the authors, this indicates that market players consider the carbon allowances as financial assets in the short-run, whereas the carbon market is governed by its fundamentals (i.e. energy prices) in the long-run. Indeed, in the absence of certainties concerning the future rules of the EU ETS,⁴⁵ the market players may have traded allowances mostly for speculative purposes. Regarding the sub-periods, the results show that the fundamentals have slightly changed with the crisis. Before the financial crisis, energy prices were the main drivers of the carbon price, whereas the stock price index was not significant. By contrast, the carbon market has become sensitive to stock prices after the financial crisis, whereas the switching price was not significant. The authors interpret these results as the consequences of changing behaviors of market players because of the crisis and the credit crunch. With emission reductions (consequences of production cutbacks), companies were able to sell their unused allowances to raise cash during the credit crunch. These financing strategies were the main reasons

42 While the fuel switching theory is robust to explain the influence of fuel prices on the carbon price, it is more questionable for the opposite relationships. Indeed, demand for fuels triggered by fuel switching represents a relatively small share of the overall fuel consumption in Europe. Thus, variations in demand for fuels caused by variations in the carbon price should have a limited impact on European fuel markets.

43 Due to economic recession in Europe, the carbon price fell in 2008. At the same time, there was a “de-coupling” between the European and the world fuel markets (i.e. market participants had different expectations about the European and the world fuel markets, due to the continuing economic growth in emerging countries). Therefore, once the “de-coupling” was effective, the downward pressure on the carbon market would have been transmitted to the European fuel markets. See Kepler and Mansanet-Bataller [2010].

44 Error Correction Model, see Chapter 3.

45 The precise rules for Phase 3 of the EU ETS were not known before the end of 2008.

for the volumes of trade at the end of 2008. This may explain why the carbon price was less driven by energy prices in the short-run and especially by mid-2008.

More recently, two papers have investigated the existence of equilibrium relationships (i.e. cointegration relationships) between the carbon price and several of its drivers over Phase 1 and Phase 2 (Bredin and Muckley [2011] and Creti et al. [2012]). Bredin and Muckley [2011] analyze the development of cointegration relationships in a system containing EUA futures prices and several fundamentals such as oil price, spreads (CDS and CSS), equity price index, temperatures and index of industrial production (interpolated to obtain daily data). They examine Phase 1 and Phase 2. Bredin and Muckley [2011] use conventional procedures for cointegration testing⁴⁶ and a modified Johansen test allowing to take into account ARCH effects. In any case, the carbon price is normalized as the dependent variable of the relationship. The results reveal that a robust equilibrium relationship only holds in Phase 2. The authors conclude that a new “pricing regime” has emerged since the beginning of Phase 2, which is indicative of an increasing activity and a rising level of efficiency in the carbon market. Creti et al. [2012] extend Bredin and Muckley [2011] by running a cointegration analysis taking into account the structural break that occurred in Phase 1 during Spring 2006. Moreover, the authors run Granger causality tests and derive in-sample forecasts for the carbon price, based on estimated models for Phase 1 and Phase 2. This allows them to discuss the discrepancies between the predicted and observed carbon price. The sample of data includes EUA futures prices, oil price (Brent), switching price and equity price index. However, no weather variables are considered.⁴⁷ As in Bredin and Muckley [2011], Phase 1 and Phase 2 are examined. The cointegration analysis is conducted with the carbon price normalized as the dependent variable of the cointegrating relationship. The results indicate that the variables are cointegrated for the full sample and for the two sub-periods corresponding to Phase 1 and Phase 2. Regarding Phase 1, the results are different from those of Bredin and Muckley [2011]. Whereas Bredin and Muckley [2011] find no evidence of cointegration in Phase 1, Creti et al. [2012] show that a long-run relationship exists in Phase 1 when the structural break is taken into account. However, the results suggest an increasing role of fundamentals in Phase 2 compared to Phase 1. Notably, the switching price is significant in Phase 2 – with a positive coefficient in line with the fuel switching theory – whereas it was not in Phase 1. The results of the Granger causality tests show that the carbon price is impacted by the switching price and by stock prices in Phase 2, whereas it is not influenced by any of the

46 See Chapter 3.

47 Creti et al. [2012] argue that weather variables should not necessarily be included in the analysis since their impact on carbon prices is indirect and captured in energy demand.

considered fundamentals in Phase 1. Interestingly, Creti et al. [2012] also report significant Granger causality running from the carbon price to the oil and stock prices.⁴⁸ These results are interpreted as evidence of an increasing role of the EU ETS in the economy. Finally, the results of the in-sample forecasts show that the adjustment between observed and predicted carbon prices is globally better in Phase 2. Here again this suggests an increasing role of fundamentals during Phase 2. Moreover, the results show that the observed price is close to the predicted price and globally overvalued at the beginning of Phase 2, whereas there is an overall undervaluation (i.e. predicted price higher than observed price) and a worse adjustment since the end of 2009. For the authors, this can be partially explained by production cutbacks in non-energy sectors that caused a downward pressure on the carbon price. Before October 2009 the effect of production cutbacks was diminished by the stability of power demand. However, the power demand finally decreased in October 2009, which depressed the carbon price and created the observed undervaluation. Nevertheless, Creti et al. [2012] argue that the undervaluation cannot be completely explained by the impact of the economic crisis. Uncertainties regarding the future of the international climate policy, the Copenhagen summit and the recent cases of VAT frauds and allowance thefts have also contributed to depressing the carbon market by reducing confidence in the EU ETS.⁴⁹

The question of the volatility transmission between carbon and fuel markets has also been investigated by Mansanet-Bataller and Soriano [2009]. They estimate a GARCH model for carbon, gas and oil prices during Phase 1 and the first year of Phase 2. They find that the carbon price volatility is affected by its own past volatility, and the oil and gas prices past volatility. Moreover, the gas price volatility is affected by the past volatility on the oil market and by its own past innovations, but it does not depend on the past volatility of the carbon price.

2.3.1. Merit order and fuel switching

The merit order is the ranking of all power plants of a given park by marginal cost of production. Technologies are stacked in order of increasing marginal cost of electricity production, so that power producers bring ever more expensive plants into production as demand increases.⁵⁰

48 These last results can be compared with results of Keppler and Mansanet-Bataller [2010] for Phase 2, which show that the carbon price impacts the gas price and the coal price.

49 Similar interpretations are given in Bonacina et al. [2009] and in Solier and Jouvét [2011].

50 For further details, see Unger [2002].

Without any carbon price, coal plants are usually brought on line first, because of their cheaper fuel cost. Gas plants are used next, during shorter periods, when demand for power is higher. However, with a price for carbon emissions, gas plants may be preferable to coal plants, due to their lower carbon intensity. That is, if the cost of increased carbon emissions with coal plants is higher than the additional fuel cost associated with the decision to produce with gas rather than with coal, it is cheaper to use gas plants first instead of coal plants. If such switching occurs, carbon emissions are reduced, because coal plants are brought on line for shorter periods (i.e. they are higher in the merit order). Therefore, all other things being equal, a relatively high gas price (and/or a relatively low coal price) encourages producers to use more coal, which drives up demand for allowances and the carbon price (and vice versa).

The fuel switching we describe happens in intermediate load – i.e. for intermediate levels of production that occur between 20% and 80% of the time (see Unger [2002]) – between coal plants and CCGTs.⁵¹ To illustrate this, let us assume a given park of power plants which is representative of countries where fuel switching can occur (i.e. with a high proportion of coal plants and CCGTs in intermediate load).⁵² This is given in Table 4.

Table 4: Composition of an illustrative power system.

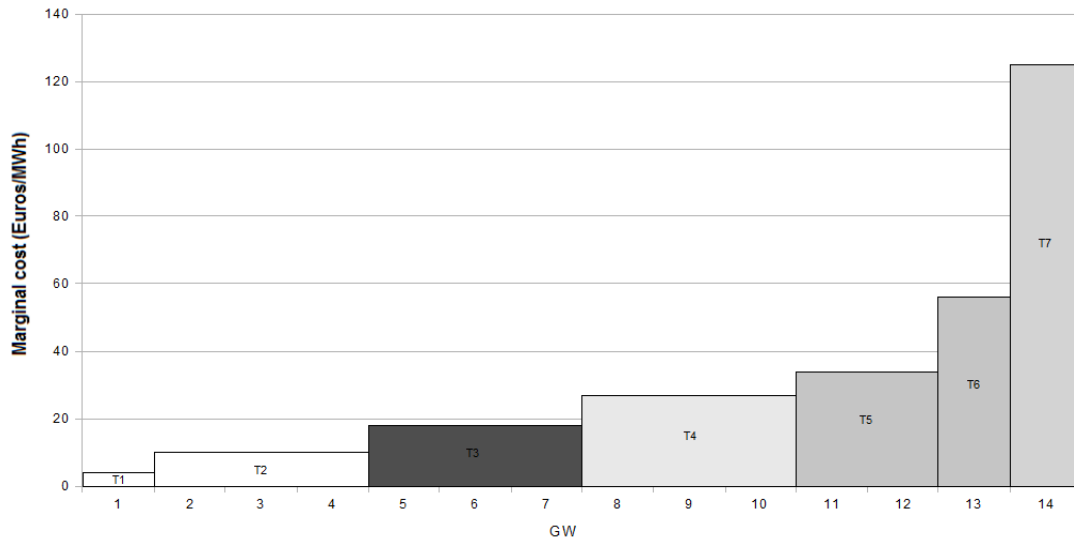
Name	Technology	Number of plants	Unit power (GW)	Total installed capacity (GW)
T1	hydro	1	1	1
T2	nuclear	3	1	3
T3	hard-coal	3	1	3
T4	CCGT	3	1	3
T5	open cycle gas turbine	2	1	2
T6	oil	1	1	1
T7	diesel	1	1	1

51 As we have already mentioned, fuel switching can also occur with other plants for other levels of load (e.g. between oil plants and open cycle gas turbines, or between hard-coal and lignite). However, as the quantities of carbon involved in switching between coal plants and CCGTs are much higher, we focus on this type of switching (as is usual in the literature about the EU ETS).

52 As pointed out by Kanen [2006], a single European merit order is a theoretical concept due to lack of interconnection between national power grids. However, with progresses in interconnection, a single European merit order is expected to become a reality. It should be close to the one presented in this section.

Applying the merit order principle to this power system, we obtain the merit order curve given in Figure 20 (values of marginal costs are arbitrary but consistent with reality, see Kanen [2006] and Delarue et al. [2008])⁵³ :

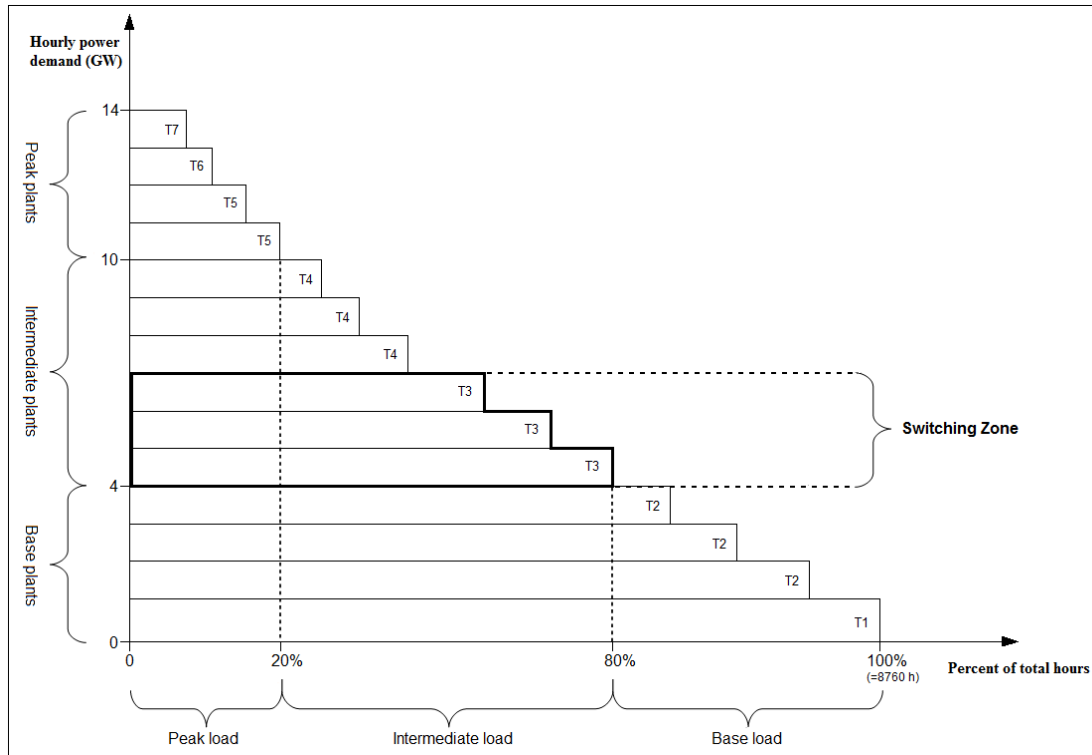
Figure 20: Merit order without carbon price (based on Voorspools [2004], Kanen [2006] and Delarue et al. [2008]).



Unger [2002] defines as base-load the load levels that occur for more than 80% of all hours in a year. Power plants that run more than 80% of the time are referred to as base plants. Intermediate load corresponds to the load levels that occur between 20% and 80% of the time, and power plants associated with intermediate load are called intermediate plants. Finally, peak load corresponds to the load levels that occur for less than 20% of the year and the corresponding power plants are called peak plants. This is illustrated in Figure 21, which shows the annual load duration curve associated with the power system in Table 4 and the merit order in Figure 20.

⁵³ Note that for thermal power plants the fuel cost makes up the great majority of the marginal cost. Other factors affecting the marginal cost of production are maintenance operations or unforeseen breakdowns (see Unger [2002]).

Figure 21: Annual load duration curve (based on Unger [2002]). It shows the cumulative frequency distribution of load levels, and associated plants. T1,...,T7 are the technologies available in the representative park of Table 4.

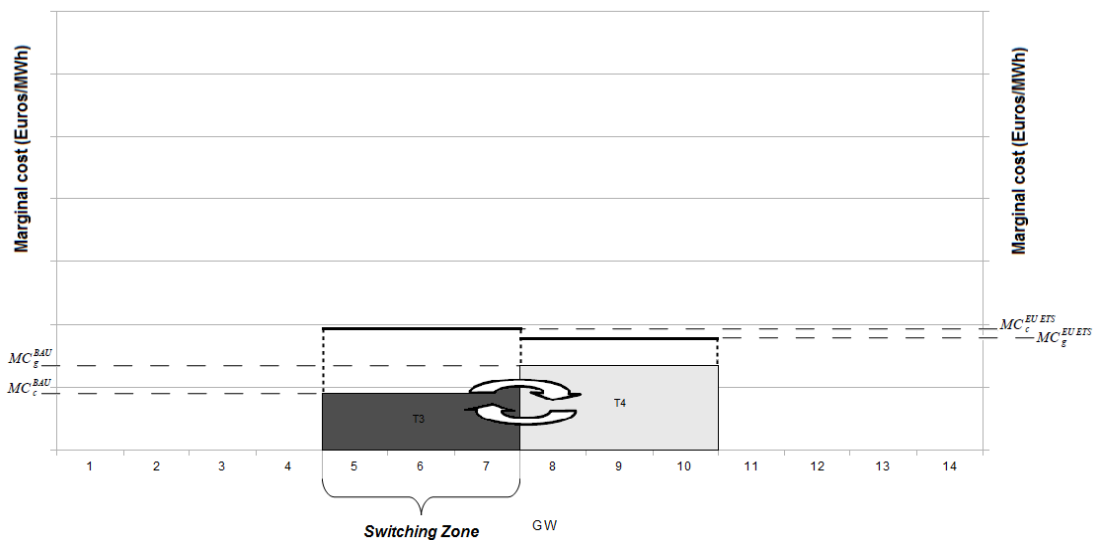


As we have mentioned, the fuel switching we describe happens in intermediate load. More exactly, it happens in the lower part of intermediate load. For convenience we call this the *switching zone* (see Figure 21). As can be seen from Figure 21, the switching zone corresponds to longer time periods than the remaining part of intermediate load. Therefore, plants which are brought online first, in the switching zone, run for longer periods, whereas other intermediate plants that are brought online next, when demand increases further, run for shorter periods. If there is no carbon cost, in the business-as-usual (BAU) scenario, coal plants are usually used before CCGTs, in the switching zone, due to their lower fuel cost. This is illustrated in Figure 20 (the merit order curve which ignores the carbon price). However, if power producers decide to use CCGTs in the switching zone, they reduce their carbon emissions compared with the BAU scenario. If such switching occurs, coal plants stand higher in the merit order than gas plants, and so carbon emissions are reduced.

If we introduce a carbon price, CCGTs may become preferable to coal plants, due to their lower carbon output. We define the marginal costs of producing one MWh of electricity (in Euros) with coal plants and with CCGTs, respectively, as: $MC_c^{BAU} = h_c COAL_t$ and $MC_g^{BAU} = h_g GAS_t$, in the BAU scenario, and $MC_c^{EU ETS} = h_c COAL_t + e_c EUA_t$ and $MC_g^{EU ETS} = h_g GAS_t + e_g EUA_t$ under the EU ETS. Here e_c and e_g are coefficients measuring the carbon emissions (in tonnes of CO₂ per MWh of electricity) from coal plants and CCGTs, respectively. h_c and h_g express how much fuel is consumed to generate one MWh of electricity with the same plants (where h_c is expressed in tonnes, and h_g in thermal MWh). $COAL_t$, GAS_t and EUA_t are the prices of coal (in Euros per tonne), gas (in Euros per thermal MWh) and CO₂ (in Euros per tonne) at time t .

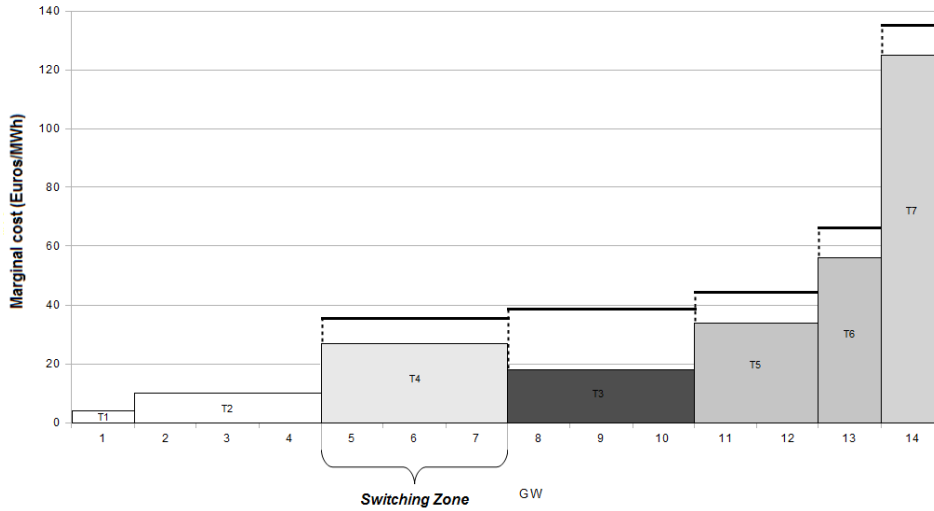
Using these notations, the decision to implement CCGTs rather than coal plants in the switching zone is made by comparing $MC_c^{EU ETS}$ with $MC_g^{EU ETS}$. Thus, it will be worth switching between the two technologies if $MC_c^{EU ETS}$ is higher than $MC_g^{EU ETS}$ (whereas MC_c^{BAU} could be lower than MC_g^{BAU}), as illustrated in Figure 22.

Figure 22: Switching between CCGTs and coal plants (based on the merit order curve in Figure 20). For simplicity technologies other than T3 and T4 have not been included in the graphic.



After fuel switching, the merit order is modified as in Figure 23.

Figure 23: Change in the merit order after switching with one type of CCGTs. The parts above the areas reflecting fuel costs (the same as in Figure 20) correspond to the costs of carbon emissions.



More specifically, if the cost of increased carbon emissions with coal plants ($EUA_t(e_c - e_g)$, for each MWh of electricity) is higher than the additional fuel cost associated with the decision to produce with CCGTs in the switching zone rather than with coal ($h_g GAS_t - h_c COAL_t$, for each MWh of electricity), it is cheaper to use CCGTs first instead of coal plants (and vice versa). Therefore, fuel switching should occur if and only if $EUA_t(e_c - e_g) > h_g GAS_t - h_c COAL_t$ (which corresponds to $MC_c^{EU ETS} > MC_g^{EU ETS}$). This last inequality allows us to derive the switching price, as defined in Fehr and Hinz [2006] (see also Kanen [2006] and Delarue and D'haeseleer [2007])⁵⁴:

$$SW_t = \frac{h_g GAS_t - h_c COAL_t}{e_c - e_g} . \quad (1.1)$$

SW_t represents the cost (in Euros per tonne CO₂ at period t) of switching from coal plants to CCGTs to abate one tonne of carbon. It can also be defined as the carbon price that makes CCGTs

⁵⁴ Following Delarue and D'haeseleer [2007], the switching price can be derived directly by equalizing $MC_c^{EU ETS}$ and $MC_g^{EU ETS}$. Kanen [2006] defines the switching price as the carbon price at which the gas and coal spreads (i.e. the clean dark spread and the clean spark spread) are equal.

and coal plants equally attractive in terms of marginal cost. Thus, fuel switching will (will not, respectively) occur at a period t if and only if $EUA_t > SW_t$ ($EUA_t < SW_t$, respectively).

2.3.2. Efficiency of plants

So far we have assumed that all plants involved in fuel switching are equally efficient. However, differences in the energy/environmental efficiency of plants matter. This has been pointed out in some previous studies. Notably, Sijm et al. [2005] estimate that the switching price declines by 22% when the efficiency rate of CCGTs involved in fuel switching is increased from 53% to 62%.⁵⁵ They also point out that the switching price would be affected by differences in the efficiency rate of coal plants. However, this is of lesser importance given that the dispersion in the distribution of efficiency rates of coal plants involved in fuel switching with CCGTs is quite small in general.⁵⁶

Taking into account these differences in the efficiency rate of plants, we have one switching price for any given pair of coal and gas plants. Thus, as pointed out by Delarue et al. [2008] (see also Ellerman and Feilhauer [2008]), for any given fuel prices, there are several switching prices associated with different pairings of coal and gas plants. There is in fact a distribution of all switching prices, that can be called the “switching band” (Ellerman and Feilhauer [2008] and Delarue et al. [2008]), and, accordingly, it may be profitable to switch certain plants (for which $EUA_t > SW_t$) and not others.⁵⁷

Switching band: illustration

The value of the switching price depends on efficiency of plants involved in fuel switching. Indeed, the value of emission rates (e_c and e_g) and heating rates (h_c and h_g) depends on the efficiency rate of plants. Therefore, the value of the switching price varies with the efficiency rate of plants (according with equation (1.1)).

55 An efficiency rate of 50% means that each thermal MWh of gas can be converted into 0.5 MWh of electricity.

56 According to the literature, in most cases, the efficiency rate of those coal plants is around 38% while it ranges from 45% to 55% (and, sometimes, and it can reach 60% or more) for CCGTs (see Sijm et al. [2005], Kanen [2006], Delarue et al. [2007] and Delarue et al. [2008]).

57 See Delarue et al. [2008] for simulations of the switching price with more or less efficient types of plants (with efficiency rates ranging from 36% to 38% for coal plants, and from 36% to 50% for CCGTs).

As an illustration, let us take the power system in Table 4 again. However, contrary to Table 4, we assume that the three CCGTs are no longer equally efficient.⁵⁸ Say that their rates of efficiency are 55, 50 and 45%, respectively. Accordingly, the values of the coefficients e_g and h_g vary depending on the type of CCGT. Using the calculation formulas, $h_g = \frac{\text{electric MWh}}{\text{thermal MWh}} = \frac{1}{\text{efficiency rate}}$ (where $\text{efficiency rate} = \frac{\text{thermal MWh}}{\text{electric MWh}}$) and $e_g = \frac{0.202}{\text{efficiency rate}}$ (where 0.202 is the quantity of CO₂ in tonnes per thermal MWh of natural gas, as provided by the Intergovernmental Panel on Climate Change),⁵⁹ the values of coefficients e_g and h_g can be calculated for each type of CCGT as in Table 5.

Table 5: Emission and heating rates (e_g and h_g) with different types of CCGTs.

Efficiency rate of CCGTs	h_g	e_g
45%	2.222	0.449
50%	2.000	0.404
55%	1.820	0.367

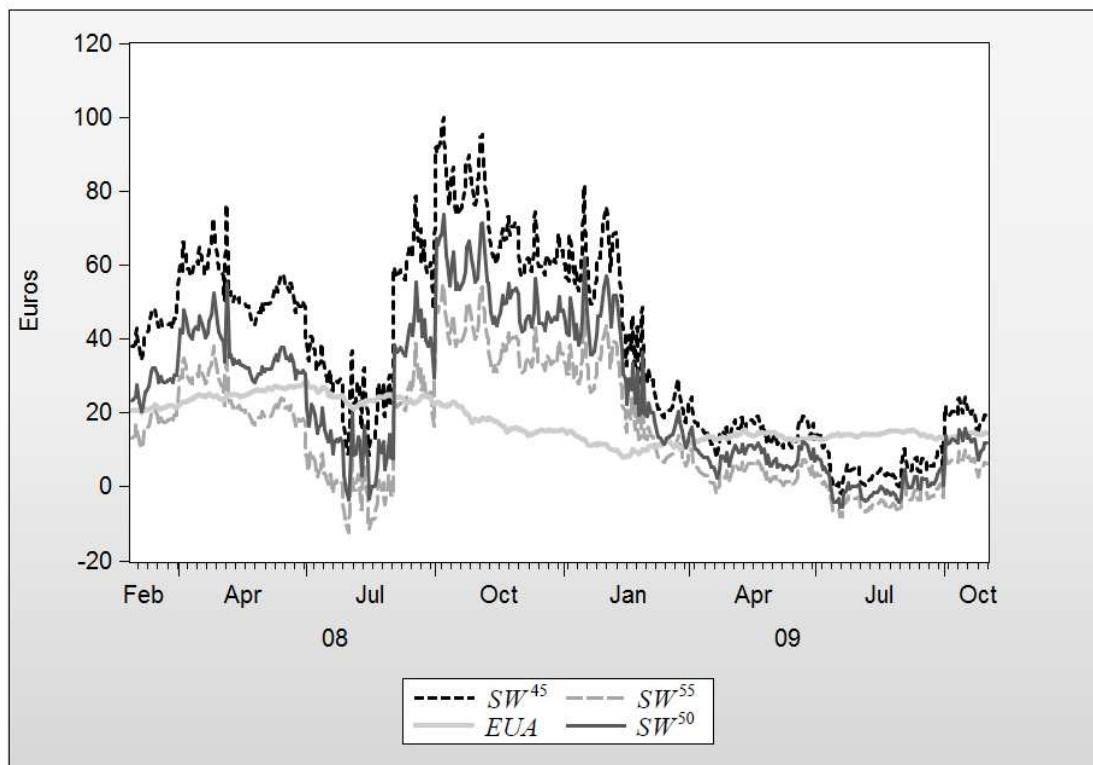
As a consequence, assuming one type of coal plant with an efficiency rate of 38% (i.e. the three T3 in Table 4 are equally efficient), we have three switching prices given by equation (1.1): SW_t^{45} , SW_t^{50} and SW_t^{55} (where SW_t^i is the switching price associated with a CCGT of $i\%$ efficiency). Thus, with $e_c=0.9$ and $h_c=0.38$ (corresponding to coal plants of 38% efficiency),⁶⁰ we obtain a “switching band” where we always have $SW_t^{45} > SW_t^{50} > SW_t^{55}$ for any coal and gas prices. This is illustrated in Figure 24.

58 For simplicity we continue to assume that there is only one type of coal plant. This assumption is justified because the dispersion in the distribution of efficiency rates of coal plants involved in fuel switching with CCGTs is very small. Of course, there are other coal plants which are very different of those used in fuel switching with CCGTs. They may be significantly more efficient (e.g. new coal plants) or less efficient (e.g. lignite plants), but they should not be used in intermediate load, and thus they are not involved in the fuel switching described here.

59 See Fehr and Hinz [2006].

60 $e_c = \frac{0.341}{\text{efficiency rate}}$, where 0.341 is the quantity of CO₂ in tonnes per thermal MWh of coal (as provided by the Intergovernmental Panel on Climate Change, see Fehr and Hinz [2006]). $h_c = \frac{\text{electric MWh}}{\text{tonne coal}} = 0.144 \times \frac{1}{\text{efficiency rate}}$, where 0.144 represents one thermal MWh of coal expressed in tonne. Since one tonne of coal corresponds to 6.961 thermal MWh (as calculated by Fehr and Hinz [2006], based on values reported by the McCloskey Group), one thermal MWh of coal corresponds to 0.144 tonne of coal. Therefore, assuming a coal plant with 38% efficiency, we find $e_c=0.9$ and $h_c=0.38$ (see Table 10).

Figure 24: “Switching band” and carbon price. Switching prices are calculated from equation (1.1), using the Zeebrugge Hub daily gas price and the CIF ARA daily coal price. The carbon price is the Bluenext daily spot price for EUAs. Data are presented in Appendix B.



The switching band shows which type of CCGT can be substituted for coal plants in the switching zone at any time. For example, if $SW_t^{45} > EUA_t > SW_t^{50} > SW_t^{55}$, it would be worth switching to 55 and 50% efficiency CCGTs, but not to 45% ones.

Static comparative analysis for switching price

The fuel switching cost represents the additional fuel cost associated with the decision to generate power with CCGTs where coal-fired plants were previously used (i.e. in the switching zone). Then, given that fuel switching consists in substituting gas plants for coal plants in power generation, its cost must increase with the gas price and decreases with the coal price. Therefore, the switching price (i.e. the switching cost expressed in Euros per tonne CO_2) is an increasing function of the gas price and a decreasing function of the coal price.

Kanen [2006] ran a series of sensitivity analyses to check the impact of changing coal and gas prices on the switching price. He confirmed that rising gas price drives the switching price up, whereas rising coal price drives the switching price down. This can be easily verified by taking the first derivatives of equation (1.1) with respect to coal and gas prices:

$$\frac{\partial SW_t}{\partial COAL_t} = \frac{-h_c}{e_c - e_g} < 0 \quad \text{and} \quad \frac{\partial SW_t}{\partial GAS_t} = \frac{h_g}{e_c - e_g} > 0, \quad (1.2)$$

since $(e_c - e_g) > 0$ for any pairings of coal and CCGT plants. Interestingly, Kanen [2006] also observed that the impact of changing gas prices is bigger than the impact of changing coal prices. He estimated that the elasticity of the switching price to the gas price is +2, while the elasticity of the switching price to the coal price is -1.

Efficiency rate of plants and switching effort

The level of switching effort has also to be taken into consideration, because it determines the efficiency of power plants involved in fuel switching. Indeed, a power producer owning several more or less efficient types of coal and CCGT plants will substitute less and less efficient CCGTs for more and more efficient coal plants, as the fuel switching effort increases. On the one hand, as the fuel switching effort increases, power producers tend to use ever less efficient CCGTs in the fuel switching process, because they want to produce first with units that are less costly to run (i.e. the most efficient). On the other hand, as the fuel switching effort increases, power producers tend to drop their less efficient coal plants first, because they want to shut down coal plants first that are more costly to run.

To illustrate this, we take the example of the power system in Table 4 again. As in our example for the switching band, we assume that we have three different types of CCGTs with efficiency rates of 45, 50 and 55%, respectively. Moreover, we assume that we have only one type of coal plant, so that the three T3s in Table 4 are equally efficient. Let us define T_4^{55} , the CCGT of 55% efficiency, T_4^{50} , the CCGT of 50% efficiency, and T_4^{45} , the CCGT of 45% efficiency. In addition, we assume three levels of switching effort: low (= one T4 in the switching zone), medium (= two T4s in the switching zone) and high (= three T4s in the switching zone). As we have

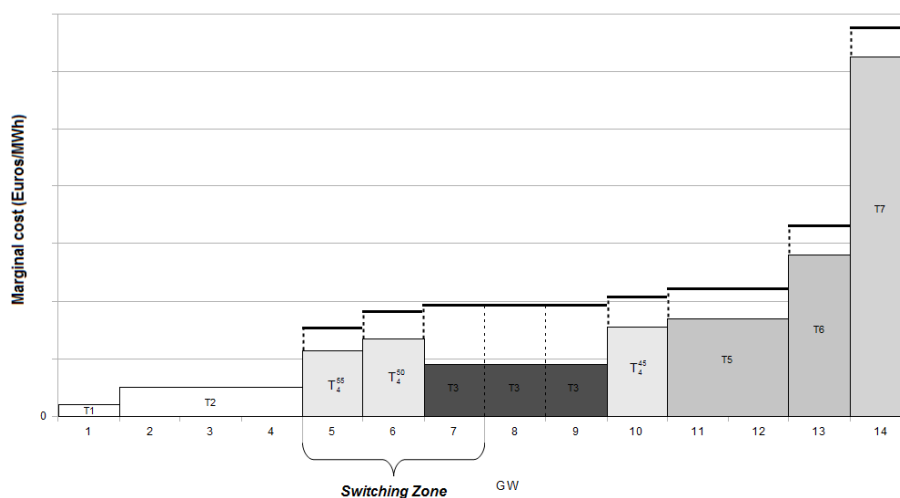
explained just before, power producers substitute ever less efficient CCGTs for coal plants, as the fuel switching effort rises. Therefore, in our example, a power producer will switch only T_4^{55} for the low level of effort, T_4^{55} and T_4^{50} for the medium level, and T_4^{55} , T_4^{50} and T_4^{45} for the high level. This is summarized in Table 6.

Table 6: Efficiency of CCGTs and level of switching effort.

Level of switching effort	Type of switching	Marginal switching
Low	T_4^{55} for one T3	T_4^{55} for T3
Medium	T_4^{55} and T_4^{50} for two T3s	T_4^{50} for T3
High	T_4^{55} , T_4^{50} and T_4^{45} for three T3s	T_4^{45} for T3

According to the switching band, depending on fuel and carbon prices, it may be profitable to switch certain plants (the ones associated with a switching price which is below the carbon price) and not others. For example, if $SW_i^{45} > EUA_i > SW_i^{50} > SW_i^{55}$, it would be worth switching to 55 and 50% efficiency CCGTs, but not to 45% ones. In such a situation, the merit order (after fuel switching) would be modified as in Figure 25, with the two most efficient CCGTs in the switching zone and the less efficient one outside. This corresponds to the medium level of effort, as defined before.

Figure 25: Change in the merit order after a medium level of switching effort.



As we can deduce from Figure 25, for any level of electricity production where switching is possible (i.e. in intermediate load, when some CCGTs are available), the proportion of CCGTs in the switching zone may vary (depending on carbon, coal and gas prices). If the proportion of CCGTs in the switching zone rises, carbon emissions decrease and, consequently, fewer allowances are used. Hence, for any level of electricity production where switching is possible, the proportion of CCGTs in the switching zone and allowances can be considered as inputs for electricity production, and they can be substituted for one another. So, defining ξ , the proportion of CCGTs in the switching zone (“switching effort”), and θ , the number of allowances required for production, we see that ξ and θ are substitutes, and, for a given level of electricity production where switching is possible, their relative cost (which depends on carbon, coal and gas prices) sets the optimal combination (ξ^*, θ^*) .

We saw that the efficiency of power plants involved in fuel switching depends on the level of switching effort. Power producers substitute ever less efficient CCGTs for ever more efficient coal plants, as the fuel switching effort increases. Therefore, the marginal fuel switching cost increases with the level of effort, due to a rising cost for gas consumption and a decreasing avoided cost for coal consumption. Moreover, the level of switching effort also influences the sensitivity of the marginal cost of switching to fuel prices. This is discussed in what follows.

The marginal cost of fuel switching: dependence on the gas price and level of switching effort

The marginal cost of switching becomes more sensitive to the gas price, as the fuel switching effort increases. Two reasons can explain this relationship⁶¹:

- Gas consumption per switched MWh increases (**effect 1**);
- Gas consumption per tonne of carbon abatement increases (**effect 2**).

As the switching effort increases, power producers use (in the fuel switching process) ever less efficient CCGTs that consume more and more gas to generate one MWh of electricity. Thus, the gas

⁶¹ For convenience, we call *switched MWh* each MWh of electricity generated by switching fuels (i.e. by using T4s in place of T3s in the switching zone).

consumption per switched MWh increases with the switching effort (effect 1). Moreover, the carbon emissions per MWh of electricity generated with CCGTs increase (because of decreasing efficiency of CCGTs), and thus the carbon abatements per switched MWh decrease. Therefore, more switched MWhs have to be generated to abate one tonne of CO₂, so that the gas consumption needed to abate one tonne of CO₂ increases (effect 2). Taking into account effect 1 and effect 2, we see that gas consumption increases when switching effort increases. As a consequence, the marginal cost of fuel switching becomes increasingly dependent on the gas price as the switching effort increases.

In order to illustrate effects 1 and 2, let us take an example. We define $e_{g,55}$, $e_{g,50}$ and $e_{g,45}$, the emission rates of CCGTs with 55, 50 and 45% efficiency, respectively. Using the same calculation formulas as before, we get $e_{g,55}=0.37$, $e_{g,50}=0.4$ and $e_{g,45}=0.45$ (see Table 5). Moreover, assuming one type of coal plant with 38% efficiency, we have $e_c=0.9$ (see Table 10). Thereafter, we can show that, when the switching effort increases, more switched MWhs have to be generated to abate one tonne of CO₂. This is illustrated in Table 7.

Table 7: Switching effort – with different types of CCGTs – and volume of “switched MWh” needed to abate one tonne of CO₂.

Level of switching effort	Marginal switching (see Table 6)	Abatements (in tonnes of CO ₂) per switched MWh	Gas consumption (h_g) per switched MWh – see Table 5 – (effect 1)	Volume of switched MWh needed to abate one tonne of CO ₂ ^a (effect 2)
Low	T_4^{55} for T3	$e_c - e_{g,55} = 0.53$	1.820	1.890
Medium	T_4^{50} for T3	$e_c - e_{g,50} = 0.5$	2.000	2.000
High	T_4^{45} for T3	$e_c - e_{g,45} = 0.45$	2.222	2.222

^a $(e_c - e_g) \times \text{Volume of switched MWh needed to abate one tonne of CO}_2 = 1 \text{ tonne CO}_2$

Columns 3 and 4 in Table 7 indicate that, as the level of switching effort increases, each switched MWh comes with a higher gas consumption (effect 1) and less carbon abatement. Therefore, more switched MWhs have to be generated to abate one tonne of CO₂ (column 5 in Table 7).⁶² As a consequence, the gas consumption needed to abate one tonne of CO₂ increases (effect 2), and the marginal cost of fuel switching becomes increasingly dependent on the gas price.

⁶² Note that the switching potential – defined as the volume of carbon abatements (in tonnes CO₂) that can be obtained by fuel switching – is higher with the more efficient CCGTs. Indeed, for example, the volume of switched MWh needed to abate one tonne of CO₂ is smaller with a T_4^{55} than with a T_4^{50} (see column 5 in Table 7). Therefore, one can get more carbon abatements with one installed GW of T_4^{55} than with one installed GW of T_4^{50} .

The marginal cost of fuel switching: dependence on the coal price and level of switching effort

We have seen that when the switching effort rises the marginal cost of switching depends more on the gas price due to higher gas consumption. With coal plants, the reasoning should be reversed. When the fuel switching effort increases, power producers tend to drop their less efficient coal plants first. So, the greater the fuel switching effort, the more efficient the abandoned coal plants, and so the smaller the avoided cost for coal consumption. Therefore, one may conclude that the coal price should influence the marginal fuel switching cost less as the fuel switching effort increases. However, as in the case of gas, two effects have to be considered. On the one hand, when the switching effort increases, the avoided coal consumption per switched MWh decreases (effect 1) because more efficient coal plants are shut down. Therefore, each switched MWh depends less on the coal price as the switching effort rises.⁶³ This contributes to reducing the influence of the coal price on the marginal cost of switching. On the other hand, the volume of switched MWh needed to abate one tonne of CO₂ increases (see Table 8, which is analogous to Table 7). In other words, more MWhs generated with coal have to be replaced by MWhs generated with gas to abate one tonne of CO₂. Therefore, neglecting effect 1, the avoided coal consumption per tonne of CO₂ abatement increases (effect 2). This contributes to making the marginal cost of switching more (negatively) dependent on the avoided cost for coal consumption (which is increasing), and thus, on the coal price.

Table 8: Switching effort – with different types of coal plants – and volume of “switched MWh” needed to abate one tonne of CO₂. Coal plants are T₃³⁶, 36% efficiency, T₃³⁸, 38% efficiency, and T₃⁴⁰, 40% efficiency.

Level of switching effort	One type of CCGTs			Different types of CCGTs		
	Marginal switching	Abatement (in tonnes of CO ₂) per switched MWh	Volume of switched MWh needed to abate one tonne of CO ₂	Marginal switching	Abatement (in tonne of CO ₂) per switched MWh	Volume of switched MWh needed to abate one tonne of CO ₂
Low	T ₄ ⁵⁰ for T ₃ ³⁶	$e_{c,36} - e_{g,50} = 0.55$	1.82	T ₄ ⁵⁵ for T ₃ ³⁶	$e_{c,36} - e_{g,55} = 0.58$	1.72
Medium	T ₄ ⁵⁰ for T ₃ ³⁸	$e_{c,38} - e_{g,50} = 0.5$	2	T ₄ ⁵⁰ for T ₃ ³⁸	$e_{c,38} - e_{g,50} = 0.5$	2
High	T ₄ ⁵⁰ for T ₃ ⁴⁰	$e_{c,40} - e_{g,50} = 0.45$	2.22	T ₄ ⁴⁵ for T ₃ ⁴⁰	$e_{c,40} - e_{g,45} = 0.4$	2.50

⁶³ A switched MWh depends less on the avoided cost for coal consumption which is decreasing. Therefore, it depends less on the coal price.

To summarize, the total effect can be decomposed into two effects, as for the gas price. However, unlike what happens with gas, those two effects work in opposite directions. Indeed, when the switching effort increases:

- The avoided cost for coal consumption per switched MWh decreases (**effect 1**);
- The avoided cost for coal consumption per tonne of carbon abatement increases (**effect 2**).

Thus, it is difficult to conclude on the total effect of a rise in efficiency of coal plants. Nevertheless, it should be recalled that effect 1 has been neglected in effect 2. So, taking into account effect 1, we see that, as the switching effort rises, more MWhs generated with coal have to be replaced by MWhs generated with gas to abate one tonne of CO₂, but, at the same time, the avoided coal consumption per switched MWh decreases. Taking the example of Table 8 again, one can conclude that the net effect is that the avoided cost for coal consumption per tonne of carbon abatement increases (i.e. effect 2 dominates effect 1). This is illustrated in Table 9.

Table 9: Avoided cost for coal consumption per tonne of CO₂ abatement and switching effort (based on Table 8)

Level of switching effort	One type of CCGTs			Different types of CCGTs		
	Coal consumption (h_c) per switched MWh – see Table 10 – (effect 1)	Volume of switched MWh needed to abate one tonne of CO ₂ (effect 2)	Cost factor ^a for coal consumption per tonne of CO ₂ abatement (total effect)	Coal consumption (h_c) per switched MWh – see Table 10 – (effect 1)	Volume of switched MWh needed to abate one tonne of CO ₂ (effect 2)	Cost factor ^a for coal consumption per tonne of CO ₂ abatement (total effect)
Low	0.400	1.82	0.728	0.400	1.72	0.688
Medium	0.379	2	0.758	0.379	2	0.758
High	0.360	2.22	0.799	0.360	2.50	0.900

^a Avoided cost for coal per tonne of CO₂ abatement = Cost factor × coal price (in Euro per tonne)

In Table 9, the increasing cost factor (columns 4 and 7) indicates that effect 2 seems to dominate effect 1 (i.e. the avoided cost for coal consumption increases).

Interestingly, looking at the first derivatives of equation (1.1) (as given in equations (1.2)) can give more insights that help us to understand the shape of the total effect. More exactly, looking

at the absolute value of the first derivative of equation (1.1) with respect to the coal price, we can see how the influence of the coal price on the switching price (i.e. on the marginal cost of switching) is affected when the efficiency of coal plants varies. The absolute value of the first derivative of equation (1.1) with respect to the coal price is given by:

$$\left| \frac{\partial SW_t}{\partial COAL_t} \right| = \left| \frac{-h_c}{e_c - e_g} \right| = \frac{h_c}{e_c - e_g}. \quad (1.3)$$

When the efficiency of coal plants increases, the values of h_c and e_c decrease. So, we again find two opposite effects on (1.3) that make the total effect unpredictable: the decrease in h_c tends to decrease the value of (1.3) (which corresponds to effect 1), while the decrease in e_c (where $(e_c - e_g) > 0$, necessarily) tends to increase the value of (1.3) (which corresponds to effect 2). Once again we cannot conclude. Nevertheless, looking at the values of h_c and e_c associated with different types of coal plants, we see that, when the efficiency of coal plants increases, the value of e_c decreases more and faster than the value of h_c (see Table 10 and Figures 26 and 27).

Table 10: Emission and heating rates (e_c and h_c) with different types of coal plants. Variations of e_c and h_c when efficiency of coal plants increases are also included in the table. They are reported as $\Delta e_{c,i} = e_{c,i} - e_{c,i-1}$ and $\Delta h_{c,i} = h_{c,i} - h_{c,i-1}$, where $e_{c,i}$ and $h_{c,i}$ are emission and heating rates associated with coal plants of $i\%$ efficiency.

Efficiency rate of coal plants	e_c	h_c	$\Delta e_{c,i}$	$\Delta h_{c,i}$
36%	0.947	0.4	-	-
37%	0.922	0.389	-0.025	-0.011
38%	0.897	0.379	-0.025	-0.01
39%	0.874	0.37	-0.023	-0.009
40%	0.8525	0.36	-0.0215	-0.01

Using the values for emission and heating rates in Table 10, the changes in h_c and e_c when the efficiency of coal plants increases can be represented as in Figures 26 and 27.

Figure 26: Evolutions of e_c when efficiency of coal plants increases.

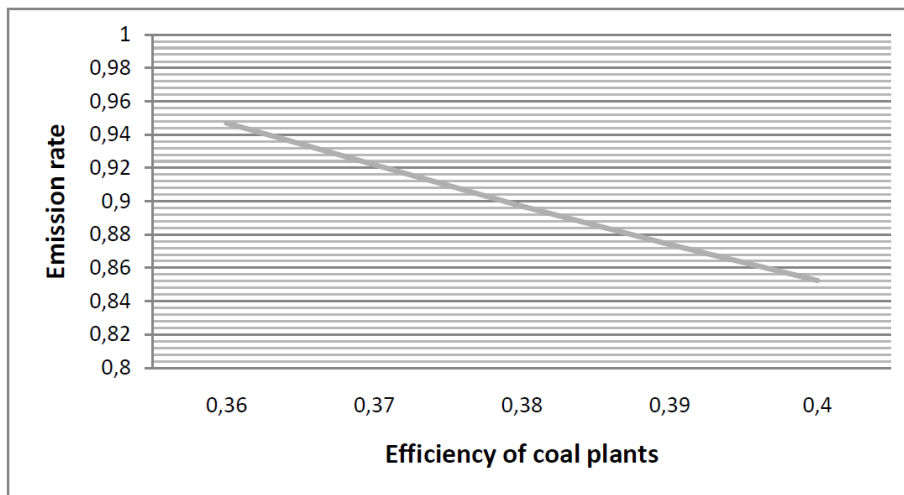
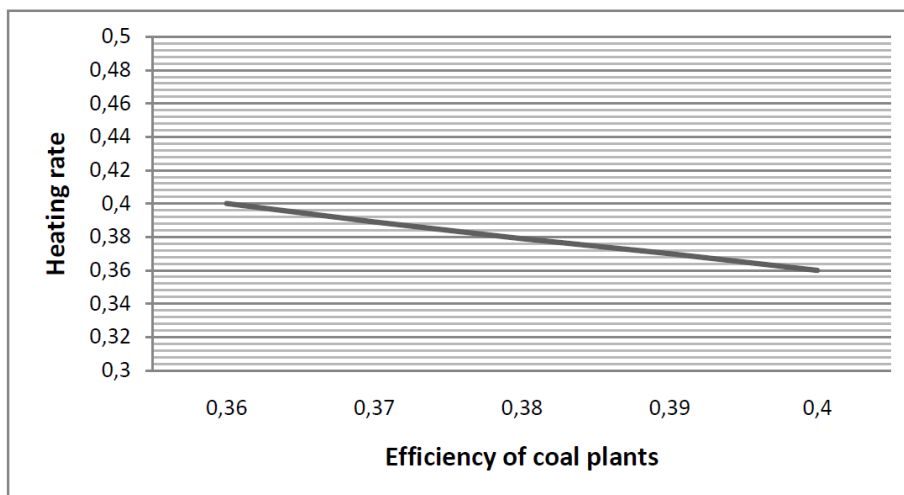


Figure 27: Evolutions of h_c when efficiency of coal plants increases.



As can be seen in Table 10 and in Figures 26 and 27, effect 2 seems to dominate effect 1 (because the value of e_c decreases more and faster than the value of h_c) so that the net effect must be an increase of **(1.3)**. This means that the total effect of a rise in efficiency of coal plants should be a rise in the influence of the coal price on the marginal cost of switching. However, even if **(1.3)** increases, the net effect should be small (contrary to the case of gas where the two effects work in the same direction). Moreover, as the dispersion in the distribution of the efficiency rates of coal plants is very small, the net effect should be still smaller.⁶⁴ Accordingly, we think that the influence of differences in efficiency of coal plants can be ignored.

⁶⁴ The distribution of efficiency rates we take in our example (from 36 to 40%) has been chosen for illustration only. It has not been chosen to fit reality where, in most cases, the efficiency rate of those coal plants (i.e. the ones involved in fuel switching with CCGTs) is around 38%.

With regard to the gas price, using the absolute value of the first derivative of equation (1.1) gives a result which is unambiguous: the switching price becomes increasingly dependent on the gas price when the efficiency of CCGTs decreases. The absolute value of the first derivative of equation (1.1) with respect to the gas price is given by:

$$\left| \frac{\partial SW_t}{\partial GAS_t} \right| = \left| \frac{h_g}{e_c - e_g} \right| = \frac{h_g}{e_c - e_g}. \quad (1.4)$$

When the efficiency of CCGTs decreases, the values of h_g and e_g increase. So, we find two effects on (1.4) that work in the same direction: the increase in h_g tends to increase the value of (1.4) (which corresponds to effect 1), and the increase in e_g contributes to increasing the value of (1.4) (which corresponds to effect 2). Therefore, we can conclude unambiguously that when the efficiency of CCGTs decreases, the marginal cost of switching becomes more dependent on the gas price. Besides, as the dispersion in the distribution of efficiency rates is far higher for CCGTs (compared with coal plants) the impact of differences in the efficiency of CCGTs must be much more significant. Accordingly, we think this must not be neglected. This will be an important question for the model presented in Chapter 2. Interestingly, as we previously mentioned, Kanen [2006] identified that the impact of changing gas prices is bigger than the impact of changing coal prices regarding the switching price. Similarly, Sijm et al. [2005] have shown that differences in efficiency of CCGTs produce a significant effect on the switching price.⁶⁵ One may consider these results as further evidence of the special relevance of the gas price to explain the fluctuations in the carbon price.

2.3.3. Availability of CCGTs

For any given carbon price, the volume of CO₂ abatements that can be obtained by fuel switching depends on the availability of CCGTs that can be substituted for coal plants. Thus, at any time, the fuel switching potential depends on load conditions and on the relative price of coal and gas.⁶⁶ On the one hand, the availability of CCGTs in each hour of the year is heavily dependent on the hourly demand for electricity. On the other hand, a very low gas price – compared to the coal price – may cause all the CCGTs to be brought online before the coal plants, even neglecting the cost of CO₂ emissions (BAU scenario). In this case, power producers are unable to reduce CO₂ emissions by

⁶⁵ In Sijm et al. [2005], the switching price is referred to as the “CO₂ breakeven price”.

⁶⁶ For a detailed analysis of those effects, see Delarue et al. [2008].

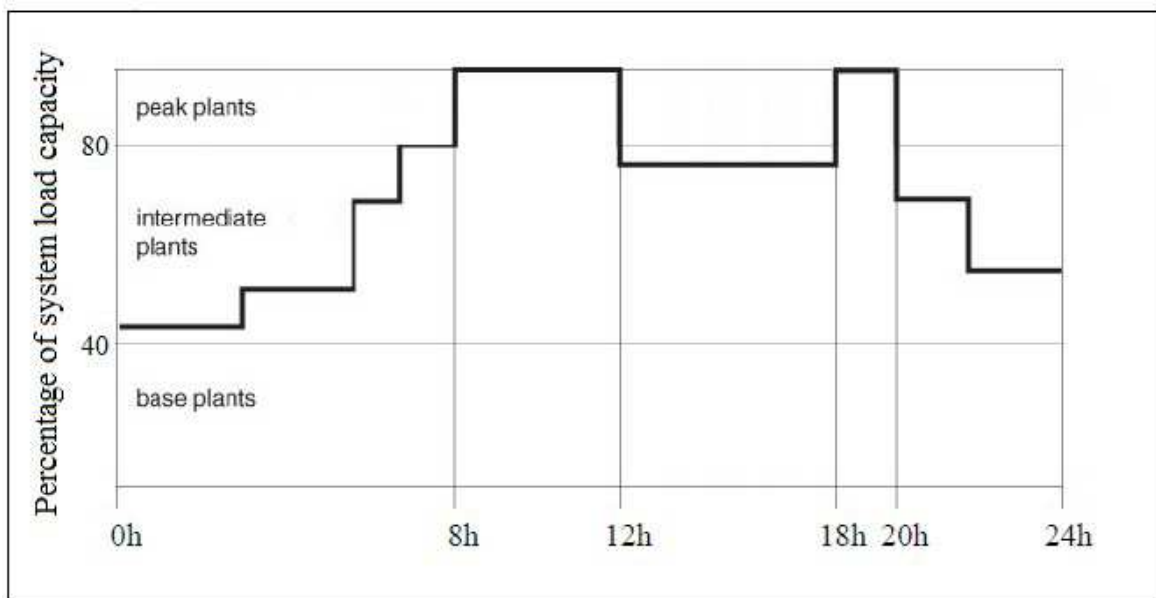
fuel switching because no CCGT is available. These relationships are discussed in this sub-section.

The load curve effect: daily, weekly and seasonal cycles

The volume of CO₂ abatements that can be obtained from fuel switching is heavily dependent on the hourly load, which varies over daily, weekly, and seasonal cycles. In other words, there is a “topography of fuel switching” that indicates the hours in which fuel switching can occur (Delarue et al. [2008]).

To be able to continuously meet changing demand for power, generation systems are usually based on the merit order principle, meaning that power plants are sequentially loaded according to increasing marginal costs. This means that during peak hours (say between 8 am and 12 am, in the morning, and between 6 pm and 8 pm, in the evening)⁶⁷ the system is running at its full capacity, while during off-peak hours, when load is relatively low, only the power plants with the lowest marginal costs are in service. Figure 28 provides an example. It depicts the load curve of a typical electric system during a single week-day, with the fields of action of different generation units.

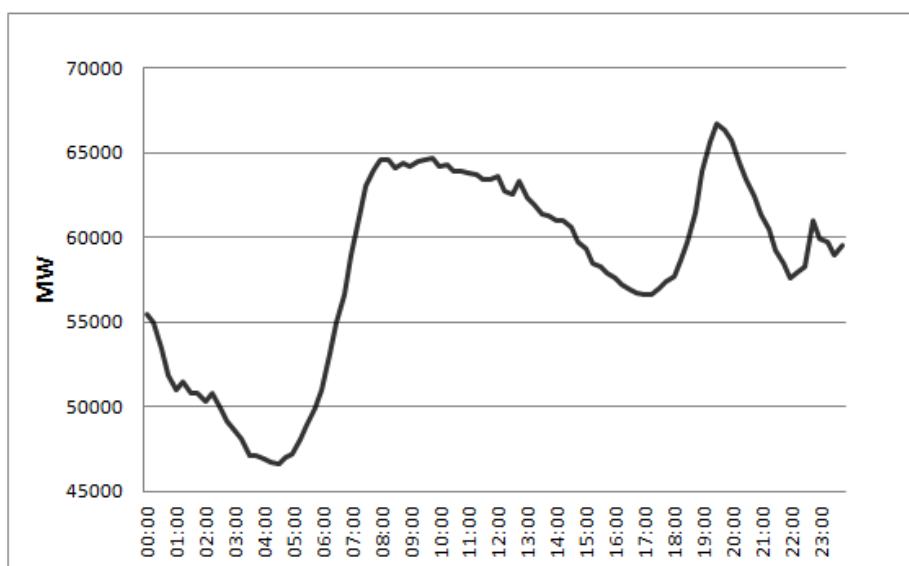
Figure 28: Typical daily load curve. Based on Nag [2001] and UIE [2009].



⁶⁷ Peak hours usually differ from one country to another since they depend on economic activity, weather conditions and other country-specific factors affecting power demand (e.g. load management measures or tariff with lower prices for off-peak consumption). For example, peak hours are 8:30-10:30 (morning) and 16:30-18:30 (evening) in Italy, 9:00-11:00 (morning) and 18:00-20:00 (evening) in France and 7:00-13:00 (morning) and 19:00-21:00 (evening) in Switzerland. See UIE [2009].

During peak hours, when all the power plants are running, there is no fuel switching opportunity, whereas during off-peak hours, if some CCGTs are available, fuel switching can occur. In addition, fuel switching cannot happen in base load since, in this case, no coal plant is running (i.e. none of the hard-coal plants which are involved in fuel switching) and so no coal plants can be replaced by CCGTs. So based on a daily load curve like the one in Figure 28, we can highlight the hours of the day when fuel switching may occur. As an illustration we take the example of the load curve for a typical week-day in France (see Figure 29).⁶⁸

Figure 29: French load curve for a typical week-day (20 October 2010). Data available at www.rte-france.com/lang/fr/visiteurs/vie/courbes.jsp.



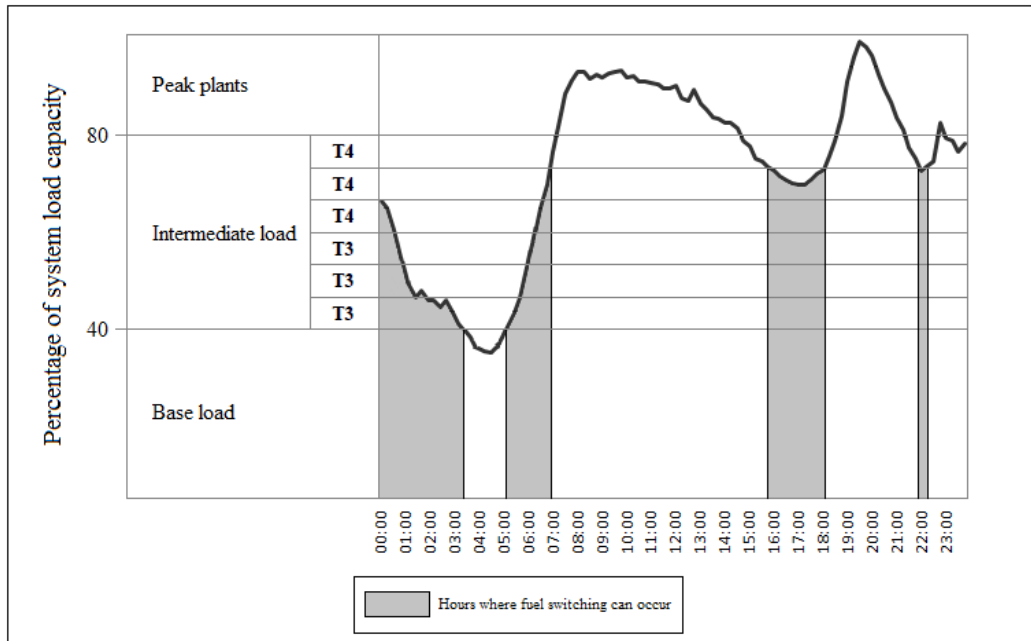
So, neglecting the effect of the relative price of coal and gas (this will be discussed further in this section) and assuming that only coal plants (T3) and CCGTs (T4) are in intermediate load,⁶⁹ the hours of the day in which fuel switching is possible can be represented based on the load curve of Figure 29. This is illustrated in Figure 30.⁷⁰

⁶⁸ Although the fuel switching potential is very limited in France, due to the high proportion of nuclear in the French production mix (see Delarue and D'haeseleer [2008]), we use this country for our illustrative example since data is fully available on the RTE website (Réseau de Transport d'Électricité, www.rte-france.com). The exact load levels in countries where the fuel switching potential is high may be slightly different but the shape of the load curve is similar to the one in Figure 29 (see UIE [2009]).

⁶⁹ The example in Figure 30 is an illustrative case which does not reflect the French power generation where coal and gas are very marginal and absent from off-peak load. Moreover, the partition between base, intermediate and peak load levels – expressed as a percentage of the power system which is in service (“percentage of system load capacity”) – has been chosen arbitrarily but is consistent with what can be observed in practice (see Nag [2001]).

⁷⁰ The aim of Figure 30 is to give some intuitions about how the fuel switching potential can vary during a day with load fluctuations. Thus, as our objective is not to give an exact representation of a load profile, the values of installed capacities of coal plants (T3) and CCGTs (T4) are left unspecified. Moreover, we assume that each group of CCGTs (there are three groups of CCGTs and three groups of coal plants in Figure 30) can be substituted for one group of coal plants (which corresponds to the previous examples developed in this chapter).

Figure 30: Hourly load, daily cycle and fuel switching potential (applied to Figure 29 and based on Nag [2001] and UIE [2009]).



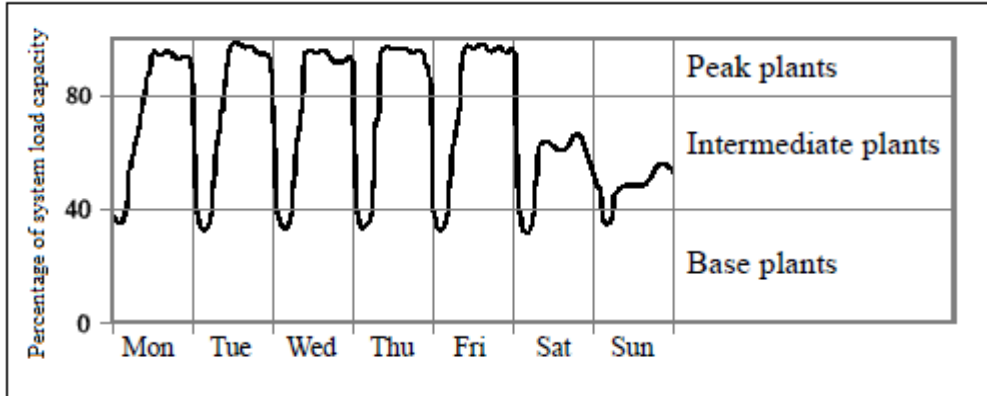
As shown in Figure 30, fuel switching can occur when some coal plants (T3) are running and some CCGTs (T4) are available. Plainly, if CCGTs are to be substituted for coal plants, some coal plants have to be in service. On the other hand, fuel switching cannot occur when all the power plants are running.

In some cases, the fuel switching opportunities in Figure 30 may be theoretical if they correspond to situations where the time interval in which fuel switching can occur is so short that CCGTs would not be able to start quickly enough (e.g. around 10 pm, in Figure 30). In such situations, power producers may not be able to switch because they would not have enough time to start CCGTs. In numerous cases the start-up time of CCGTs varies between one and three hours, for a hot start cycle, and up to 24 hours for a cold start cycle (PSIG [2001]). However, new generation CCGTs have much better performances with start-up times of only a few minutes, and intensive research is being pursued by manufacturers (e.g. Alstom, General Electric and Siemens) to increase the flexibility (and efficiency) of plants.

In addition to daily fluctuations, the load level varies over the course of the week. Typically, demand for electricity is higher on week-days than at weekends. Accordingly, load levels are lower on Saturdays and Sundays, and so more fuel switching opportunities are available at weekends. As an illustration let us take the example of a weekly load curve for a typical power system (see Nag

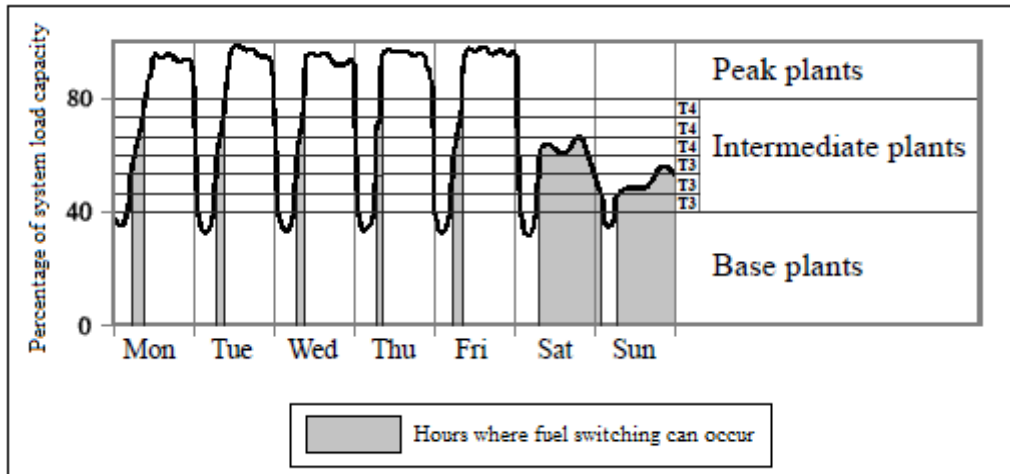
[2001] and UIE [2009]). This is depicted in Figure 31.

Figure 31: Weekly load curve for a typical power system. Based on Nag [2001] and UIE [2009].



Applying the same procedure to Figure 31 as was applied to Figure 29 to derive Figure 30, we can represent the fuel switching potential of each day of the week (see Figure 32).⁷¹

Figure 32: Weekly cycle and fuel switching opportunities (applied to Figure 31).



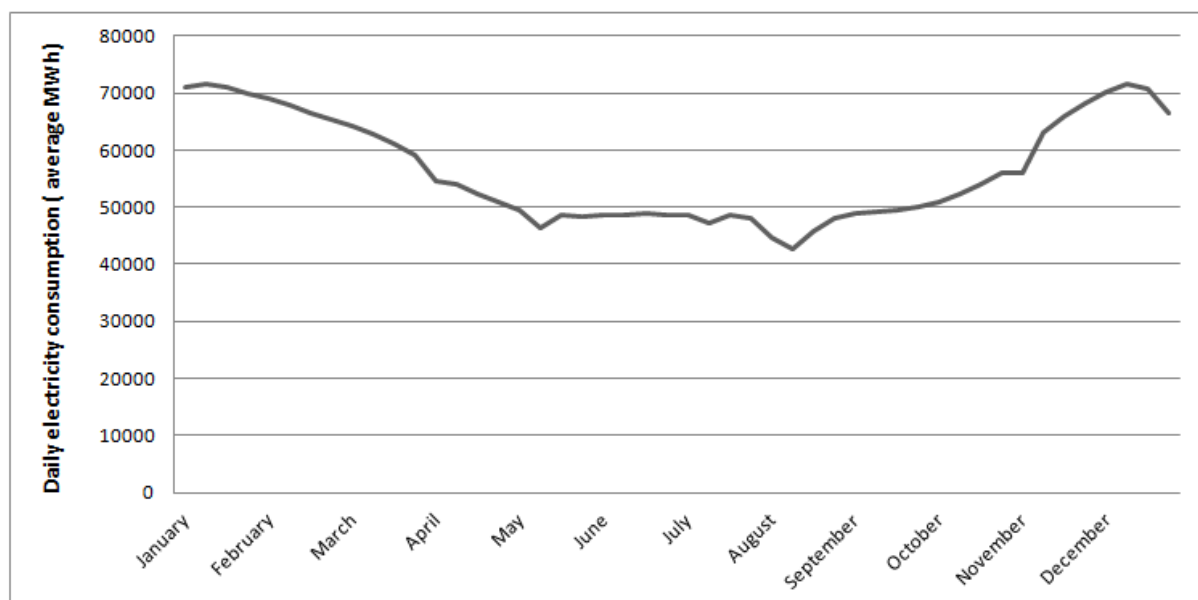
So, as explained before, we observe there are more fuel switching opportunities on weekend-days because of lower load levels.

Finally, to conclude on the influence of load levels on the fuel switching potential, we point

⁷¹ As before, we ignore the effect of the relative price of coal and gas and we assume that only coal plants (T3) and CCGTs (T4) are in intermediate load. The values of installed capacities are left unspecified, and we assume that each group of CCGTs can be substituted for one group of coal plants.

out that fuel switching opportunities also vary with the seasons. Since load levels are far higher in winter than in summer – due to higher demand for electricity in winter (see Figure 33)⁷² – the intermediate load levels where fuel switching can occur are more frequent in summer.

Figure 33: French daily electricity consumption in 2010 (taken the first day of each week). Data available at www.rte-france.com/lang/fr/visiteurs/vie/courbes.jsp.



To summarize, fuel switching opportunities are much more numerous on a typical weekend during the summer than on a week-day during the winter (see Delarue et al. [2008]).

The effect of the relative price of coal and gas

Another important question with regard to the availability of CCGTs is the relative price of coal and gas. This has to be taken into account when assessing whether fuel switching can occur. Indeed, at any time when load levels allow fuel switching, it can effectively occur only if the gas/coal price ratio lies within a certain range (Delarue et al. [2008]). Evidently, there are ratios which are high enough to make fuel switching economically unattractive. However, interestingly, there are also ratios which are so low that fuel switching cannot happen. Indeed, a very low fuel price ratio would cause all the CCGTs to be brought online before coal plants even with a carbon price of zero.⁷³ In

⁷² See section 1.1 of this chapter.

⁷³ In this case, the use of CCGTs before coal plants cannot be considered as an abatement effort because this would be

such a situation, power producers cannot reduce their emissions by fuel switching – even if they need to – since no CCGT is available. Thus, for fuel switching to take place, the fuel price ratio needs to be high enough to ensure that some CCGTs are available. On the other hand, if the fuel price ratio is very high, fuel switching may not be a profitable option. Accordingly, as pointed out by Delarue et al. [2008], fuel switching abatement profiles have a characteristic shape: “*the emission reduction associated with any given carbon price rises, peaks, and then falls as the fuel price ratio increases. This characteristic shape reflects the interaction between the switching opportunities created by the fuel price ratio as it increases and the exploitation of those opportunities that can be economically justified by the carbon price. Higher fuel price ratios cause less gas and more coal capacity to be in service thereby creating opportunities for switching and thus abatement with an appropriate CO₂ price. In effect, higher fuel price ratios create switching or abatement opportunities until the technical maximum [...] is reached. [...] From that point on, abatement falls as the still higher fuel price ratios reduce the number of switching opportunities that can be economically justified at the assumed carbon price.*”⁷⁴

In practice, the decision to use CCGTs before coal plants is based on the comparison between the cost of producing one MWh of electricity with gas and the cost of producing one MWh of electricity with coal. So, a cost ratio may be a better indicator than the price ratio. To illustrate, let us define $Cost_{coal}^{BAU}$ and $Cost_{gas}^{BAU}$ as the cost of producing one MWh of electricity in the BAU scenario, with coal and gas, respectively. Moreover, we call $Cost_{coal}^{EU ETS}$ and $Cost_{gas}^{EU ETS}$ as the cost of producing one MWh of electricity under the EU ETS regime, with coal and gas, respectively. So, if $Cost_{gas}^{BAU} < Cost_{coal}^{BAU}$ (and thus a fortiori $Cost_{gas}^{EU ETS} < Cost_{coal}^{EU ETS}$), CCGTs are used first in the BAU scenario. As a consequence, $BAU\ emissions = EU\ ETS\ emissions$, i.e. carbon emissions cannot be reduced under the EU ETS regime (despite $Cost_{gas}^{EU ETS} < Cost_{coal}^{EU ETS}$) because no CCGT is available for switching. By contrast, if $Cost_{gas}^{BAU} > Cost_{coal}^{BAU}$, CCGTs are available and thus fuel switching can occur (i.e. $BAU\ emissions > EU\ ETS\ emissions$) if $Cost_{gas}^{EU ETS} < Cost_{coal}^{EU ETS}$. In other words, at any time where load levels allow fuel switching, CO₂ emissions can be effectively reduced if and only if $Cost\ Ratio = (Cost_{gas}^{BAU} / Cost_{coal}^{BAU}) > 1$.

done even in the BAU scenario (i.e. without regulation of carbon emissions). It becomes clear by defining carbon abatements as $\Delta = EU\ ETS\ emissions - BAU\ emissions$, where $EU\ ETS\ emissions$ are the carbon emissions (net of abatements) under the EU ETS regime.

74 See Delarue et al. [2008] for simulations of the induced abatement potentials with different carbon prices.

Chapter 2

Fuel switching process and efficiency of power plants: a theoretical analysis

The strong influence of the power sector on the EU ETS gives major importance to carbon abatement decisions of European electricity producers. The fuel switching behavior of power producers – which consists in substituting CCGTs for coal plants – is thus an important issue. This chapter studies how differences in the efficiency of power plants involved in fuel switching can affect the allowance price. We build a tractable equilibrium model, which enables us to observe the impact of fuel switching, in a context where CCGTs are not all equally efficient. The main result shows that the allowance price becomes more sensitive to the gas price when the level of “uncontrolled” CO₂ emissions (i.e. “business-as-usual” CO₂ emissions) increases, due to differences in efficiency of CCGTs that are used in the fuel switching process. This is because power producers substitute ever less efficient CCGTs for coal plants, as the switching effort increases. Then, more gas must be consumed to abate each tonne of CO₂, and the marginal cost of switching becomes more dependent on the gas price. Therefore, a rise in uncontrolled CO₂ emissions will affect the allowance price, not only because it makes the constraint on CO₂ emissions more stringent, but also because it induces a rising gas cost for abatement purposes and a higher exposure to the gas price.

1. Introduction

Since the creation of the European Union Emission Trading Scheme (EU ETS) in January 2005, there has been a price for CO₂ emissions in Europe, and regulated firms (which are firms that are part of the European carbon market) have had to cope with it. Firms have to be able to predict the carbon price accurately so as to adopt efficient compliance strategies, which consist of abating carbon physically or buying and selling permits on the market. Yet, these companies are not alone in being interested by this new market. As the European Union Allowances (EUAs, the carbon certificates from the European market) are tradable instruments, they have become de facto financial assets (or even commodities, depending on one's point of view) that have created a great

number of opportunities for the financial sector. What is now commonly called “carbon finance” is becoming an important issue for financial companies that provide trading facilities (exchanges, clearing houses, etc) and financial services (analyses, brokerage, portfolio and risk management, etc). Banks and investment funds are also interested in the carbon market because it provides new opportunities for making money and for portfolio diversification.

Up to now, many papers have shown that coal and gas prices are often the most significant carbon price drivers (see Chapter 1 for references). European power producers have a major influence on the European carbon market, given that both their CO₂ emissions and their allowance allocations account for more than half of the total volumes of the EU ETS. Accordingly, coal and gas prices are particularly relevant in explaining EUA price fluctuations because electricity in Europe is mostly generated by burning coal and gas. The power sector is even more influential in Germany¹ and in some other European countries, due to particularly high shares of fossil fuels in their electricity mixes, and the resulting massive carbon emissions.

If we look at the importance of the power sector in several European countries,² it seems quite logical to consider that electricity producers' decisions in these countries will have a strong impact on the EU ETS. It is well known that the easiest way for European power producers to reduce their carbon emissions in the short-term lies in their ability to switch fuels from coal to gas in electricity generation. This is particularly true for the aforementioned countries. These fuel switching behaviors must have a very strong influence on the relationship between fuel and allowance prices. Moreover, it could be of great importance that not all the power plants used in the fuel switching process are equally energy efficient. Accordingly, we focus on these compliance strategies of power producers. In particular, we want to enhance our understanding of how differences in the energy efficiency of thermal power plants can rule interactions between fuel and carbon prices.

Relationships between EUA price and fuel prices have been of growing interest since the creation of the EU ETS. To date, there are many econometric studies on this topic (see Chapter 1 for references). On the contrary, theoretical models are very scarce. For example, Delarue et al. [2007]

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- 1 Germany is by far the biggest carbon emitter in Europe. For instance, carbon emissions in Germany are twice as high as in the United Kingdom, the second biggest carbon emitter in Europe. Unsurprisingly, Germany has also the most EUA allocations in the EU ETS.
 - 2 The countries involved here are those emitting high levels of CO₂ because they generate power mainly with fossil fuels such as coal and gas. These countries include notably Germany, the United Kingdom, Spain, Italy and Poland.

show how an efficient way of using a park of electricity generating plants leads to an indicator, the “switching point” (which corresponds to the switching price), expressing how advantageous fuel switching from coal to gas is at a certain moment. Hintermann [2010] uses the well-known result which states that each firm equalizes its marginal abatement cost to the price of permits in equilibrium to develop an expression for the carbon price with coal and gas prices as explanatory variables. However, to the best of our knowledge, only Fehr and Hinz [2006] (see also Carmona et al. [2009]) have analyzed these relations in an equilibrium model. They build a dynamic equilibrium model with a stochastic cost function representing the expense generated by switching thermal power plants from coal plants to CCGTs. As a simplification, they assume a single type of CCGTs (i.e. differences in energy efficiency between CCGTs are not explicitly taken into account). They also assume one type of coal plant. As expected, their results demonstrate that the carbon price is an increasing function of the gas price, and a decreasing function of the coal price (i.e. an increasing function of the “fuel switching price”). They also find that the carbon price depends on the difference between the required level of carbon abatements (which is defined as the difference between carbon emissions in the “business-as-usual” scenario and initial endowments of allowances) and the optimal level of fuel switching effort.³

This work differs from previous theoretical studies on the subject, because it explicitly considers the fact that power plants used in the fuel switching process do not all have the same energy efficiency. Our aim is to identify the implications for the relation between fuel and allowance prices in that context. To do so, we present a tractable equilibrium model along the lines of the equilibrium models for tradable permits developed since the pioneering work of Montgomery [1972]. Using a cost function that represents the expense engendered by switching power plants from coal plants to gas plants (throughout the paper, when we refer to gas plants, we mean CCGTs), we follow the same strategy as in Fehr and Hinz [2006]. Unlike them however, we will use a cost function in which the level of the fuel switching effort influences the sensitivity of the marginal switching cost with respect to fuel prices, whatever their realized values (i.e. in a deterministic setting). Accordingly, the relation between carbon and fuel prices will be dependent on the level of switching effort (where the level of switching effort is determined by “uncontrolled” emissions of CO₂),⁴ due to the fact that power plants are not all equally efficient.

³ See section 2 of this Chapter for further details.

⁴ Uncontrolled carbon emissions are those which are given exogenously for power producers (determined by their level of production which is set by electricity demand), before any effort of abatement.

As in previous papers, we find that the carbon price increases with the gas price and decreases with the coal price. We also find that uncontrolled carbon emissions influence the allowance price and that the time of their occurrence in the Phase matter. But our real contribution to the literature is to show that the influence of the gas price on the price of allowances depends on the level of uncontrolled carbon emissions, due to differences in energy efficiency between gas plants that are used in the fuel switching process.

The remainder of this chapter is organized as follows. In section 2, we present a review of theoretical papers dealing with the modeling of emission allowance markets. Section 3 introduces the cost function we will use to model the cost of fuel switching. We also demonstrate in this section that mutually beneficial trading opportunities may exist among power producers that own different types of CCGTs (i.e. CCGTs with different rates of efficiency). The theoretical model and the results are presented in section 4. To conclude, section 5 summarizes the main findings and their value for practical applications.

2. Modeling of emission allowance markets: a literature review

Numerous theoretical studies on the modeling of emission allowance markets have developed since the pioneering work of Montgomery [1972]. Montgomery proves that in a competitive permit market with perfect information and no transaction costs, an efficient market equilibrium exists. The efficient equilibrium achieves any emission reduction target at the lowest cost for society (i.e. at the least total cost over all firms) and is independent of initial allocation of allowances. This “least-cost” solution implies equalization of the marginal cost of abatement among polluters. That is to say that the price of allowances must always be equal to marginal abatement costs in market equilibrium: $C'_i(a_i) = p, \forall i$, where $C'_i(a_i)$ is the marginal abatement cost of firm i associated with abatement effort a_i , and p is the price of allowances. This statement underpins that emission trading induces firms to exploit any differences between the price of allowances and their marginal costs of abatement. On the one hand, firms with lower abatement costs can make profits by abating more CO₂ than they would need to comply with a command-and-control regulation (see Introduction of the thesis). This allows them to sell unused allowances at a higher price than their marginal abatement costs. On the other hand, firms with higher abatement costs can reduce their compliance costs by abating less CO₂ than they would need to comply with a command-and-control regulation, and then buying the lacking allowances on the market at a lower price than their marginal abatement costs.

Montgomery [1972] also investigates the case of ambient permit markets, i.e. permit markets for pollutants with non-uniform assimilation rates among different affected regions (see also Atkinson [1983] and Tietenberg [1985]). In this case the location of pollution sources is crucial because a same volume of emissions does not produce the same effect in all locations. Thus, a target has to be specified for each specific location in terms of a ceiling on concentration of the pollutant at this specific region. This is equivalent to say that there are as many permit markets as the number of different locations affected by pollution. So, an equilibrium on permit markets exists and leads to the least-cost solution⁵ which implies that each firm equates its marginal abatement cost with a weighted sum – where the weights are the transfer coefficients associated with each affected location – of prices of permits at each location: $C'_i(a_i) = \sum_j h_{ij} p_j, \forall i$, where h_{ij} are the transfer coefficients⁶ and p_j is the price of allowances in location j .

5 In the least-cost solution, each firm equates its marginal abatement cost with a weighted sum of the marginal costs of concentration reductions at each location. The weights are the transfer coefficients associated with each affected location.

6 The coefficients h_{ij} translate emission increases by firm i into changes in the concentration at location j .

Based on static models similar to the one introduced by Montgomery [1972], many papers have investigated a number of factors that can affect the market equilibrium or even prevent permit market from achieving efficiency. Among the most important issues, the question of market power in the permit market has been addressed by Hahn [1984]. He shows that the market equilibrium can deviate from the first-best optimum (i.e. the least-cost solution obtained by Montgomery [1972] in a competitive market) in this case. Moreover, Hahn identifies that the degree of inefficiency observed in the market is related to the initial distribution of permits, whereas Montgomery [1972] found that first-best optimality is independent of initial allocations in the perfect case.⁷ Stavins [1995] has investigated the presence of transaction costs in the permit market. The author shows that significant transaction costs reduce the volume of tradings of permits. As a consequence, the market equilibrium can deviate from the first-best optimum and is sensitive to initial distributions of permits.⁸ Conrad and Kohn [1996] have provided a formal treatment of factors that explained the low price of SO₂ permits in the early years of the US Acid Rain Program. They show that the price was lower than expected because of excess allowances. These surpluses were explained by the creation and distribution of more permits than were initially authorized – due to political pressures – and more stringent air quality standards in some areas (e.g. near national parks) preventing high cost abaters in those areas from buying more permits in order to increase their emissions. Maeda [2004] (see also Maeda [2001]) was the first who formally includes random GHG emissions in a one-period equilibrium model. He pointed out that GHG emissions – and especially carbon emissions – are closely related to energy use which, in turn, is closely related to random factors such as economic activity and weather conditions. He assumed a single random variable reflecting macro-factors that affect emissions. Emissions from various firms are all correlated with this random variable. It can be the GDP of one or more countries, an industrial production index, temperatures, rainfall, etc. In addition to this “single factor”, Maeda [2004] introduced firm-specific random variables reflecting uncertainties that are specific to each firm and that have no correlation to each other. Unsurprisingly, Maeda found that uncertainties about the price of allowances depends entirely on uncertainties about emissions. More importantly, he showed that uncertainties that are specific to each firm are diversified and disappear when there is a large number of firms in the

7 Hahn [1984] shows that optimality can be restored by distributing to the firms with a dominant position a number of permits exactly equal to what they need to cover their emissions. Therefore, cost functions of those firms need to be known, which may be very costly. By contrast, there is no restriction about initial allocations for firms in the competitive fringe.

8 Interestingly, this result is consistent with the Coase theorem which states that the first-best optimum is achieved regardless of who initially received the permits, if and only if there are no transaction costs (see Introduction of the thesis).

market. This indicates that for a large number of emission sources, the probabilistic nature of the price of allowances would only depend on a “single factor” to which emissions of all firms are correlated. Accordingly, random macro-factors such as economic activity and weather conditions should be of major importance to explain stochastic fluctuations of the permit price in a multi-period setting.

In the wake of papers dealing with the modeling of permit markets in a static framework, several authors have developed multi-period models to study the theoretical properties of inter-temporal trading of permits. The first contributions on this topic are those of Tietenberg [1985] and Cronshaw and Kruse [1996]. Both consider a dynamic equilibrium model of permit markets – in non-stochastic environments (i.e. without introducing uncertainty in emissions) – with banking and in discrete-time. Tietenberg [1985] characterizes the joint least-cost allocation of abatement efforts, given a single constraint on the total amount of emissions over time.⁹ He also states that a permit market (i.e. a decentralized solution) can yield this least-cost allocation. In this case, the permit price must rise at the rate of interest. Tietenberg assumes that all permits are issued at the beginning of first period, so that some permits will always be in the bank. By contrast, Cronshaw and Kruse [1996] consider that permits are allocated to firms in each of T periods. Additionally, they investigate the effect of profit regulation on the firms' behavior. They show that the permit market achieves the least-cost solution if there is no profit regulation, but may not do so if firms are subject to profit regulation in their output market.¹⁰ Cronshaw and Kruse also find that, without profit regulation, firms are willing to bank permits if the permit price rises over time with the rate of interest. However, firms do not desire to bank if the price rises by less than the rate of interest.

Rubin [1996] extends the work of Tietenberg [1985] and Cronshaw and Kruse [1996] by providing a more general treatment of inter-temporal trading in continuous time through the use of optimal-control theory.¹¹ Instead of limiting inter-temporal trading to banking, Rubin allows both borrowing and banking. He analyzes the case of a regulator (i.e. a central planner) minimizing the inter-temporal joint-cost of reducing pollution of N heterogeneous firms subject to emission constraints. He considers a finite time horizon with deterministic emissions (i.e. non-stochastic

9 In Tietenberg [1985], there is a single constraint on the total amount of emissions over the T time periods, and all permits are issued at the beginning of the first period. Therefore, firms can freely transfer permits across time periods. In other words, both banking and borrowing are allowed.

10 Cronshaw and Kruse [1996] consider the case of firms which are subject to two types of regulation: environmental and profit regulation in the market of their output.

11 For a review on optimal-control theory see Kappen [2007], Arrow and Intrilligator [1981] and Malliaris and Brock [1982].

emissions). As a special case, Rubin also investigates the consequences of restrictions on borrowing. While the constraint on borrowing is not explicitly taken into account in the optimization problem, some insight into the effect of the inability to borrow are derived.

Rubin [1996] defines $S_{i,t}$, the endowment of permits received by a firm i – so that $\sum_{i=1}^N S_{i,t} = S_t$, $-C_i(e_{i,t})$, the abatement cost function of a firm i (where the marginal abatement cost, $-C'_i(e_{i,t})$, is increasing and convex with respect to abatement effort) associated with the chosen level of emissions $e_{i,t}$,¹² and $B_{i,t}$, the number of permits that are in the bank. Thus, $e_{i,t}$ is a control variable, while $B_{i,t}$ is a state variable. Finally, defining $B = \sum_{i=1}^N B_{i,t}$ as the aggregate stock of banked permits, \dot{B} as the rate of change of B (where dots denote time derivatives), and T as the terminal time period, the joint-cost problem of a central planner can be written as:

$$\left\{ \begin{array}{l} \min_{e_{i,t}} \int_0^T e^{-rt} \sum_{i=1}^N C_i(e_{i,t}) dt \\ \text{s.t. } \dot{B} = \sum_{i=1}^N (S_{i,t} - e_{i,t}) \\ B_0 = 0, B_T \geq 0, \\ e_{i,t} \geq 0, \forall i, \end{array} \right. \quad (\text{A})$$

where r is a risk-free rate of interest. Solving the problem yields necessary conditions that indicate that the regulator allocates abatement efforts so that all firms have equal present discounted marginal abatement costs, i.e. $-e^{-rt} C'_1(e_{1,t}) = -e^{-rt} C'_2(e_{2,t}) = \dots = -e^{-rt} C'_N(e_{N,t})$. Besides, all firms have present discounted marginal abatement costs equal to the marginal value of an additional unit of banked emissions, i.e. equal to the costate variable on the state equation $\dot{B} = \sum_{i=1}^N (S_{i,t} - e_{i,t})$ (reflecting the shadow value of a unit of emissions in the bank). Thus, the abatement effort of each

12 Following Montgomery [1972], Rubin defines $C_i(e_{i,t})$ as the difference between unconstrained profits and profits under the cap-and-trade regime (this difference is equal to $C_i(e_{i,t}) + P_t y_{i,t}$ when trading is allowed, see problem (B) below). However, he does not explicitly define abatements ($a_{i,t}$) and “business-as-usual” emissions ($u_{i,t}$), even though they are implicitly taken into account, since $e_{i,t} = u_{i,t} - a_{i,t}$ with $e_{i,t} \leq u_{i,t}$. Accordingly, the optimization problem is solved by minimizing $C_i(e_{i,t})$, i.e. by lowering emissions $e_{i,t}$ so as to minimize the difference between constrained and unconstrained profits, with $C'_i(e_{i,t}) < 0$ and $C''_i(e_{i,t}) > 0$. Equivalently, the problem could be solved by minimizing $C_i(a_{i,t})$, where $C_i(a_{i,t})$ is an abatement cost function. In this case, the action of minimizing the difference between constrained and unconstrained profits would be controlled by choosing an abatement effort, $a_{i,t}$, with $C'_i(a_{i,t}) > 0$ and $C''_i(a_{i,t}) > 0$. As pointed out by Rubin, using the cost function $C_i(e_{i,t})$, the abatement cost can be defined as $-C_i(e_{i,t})$, and therefore the marginal abatement cost is $-C'_i(e_{i,t})$.

firm is increased as long as the cost of one more unit of abatement is lower than its value in the bank. Finally, results show that if, in total, permits are banked and borrowed over time, then the discounted marginal abatement cost is constant in time. In this case, the marginal abatement cost rises over time with the rate of interest. By contrast, if firms, in total, would like to borrow but are not allowed to do so, the discounted marginal abatement cost would decrease in time.¹³ In this case, the rate of growth in the marginal abatement cost must be less than the interest rate.

Next, Rubin [1996] explores the consequences of introducing emission trading in the model, with price taking firms. The author wants to look at how individual firms will make their decisions (abatements and trading), given that they take permit prices as exogenous. Formally, letting P_t be the instantaneous price of permits $y_{i,t}$ purchased or sold by a firm i at period t (where $y_{i,t} > 0$ if permits are bought, and $y_{i,t} < 0$ if permits are sold), and $A_{i,t}$ and $D_{i,t}$ be bounds on $y_{i,t}$,¹⁴ the problem of a firm i can be characterized. Thus, the joint-cost problem (A) is modified as follows:

$$\left\{ \begin{array}{l} \min_{y_{i,t}, e_{i,t}} \int_0^T e^{-rt} [C_i(e_{i,t}) + P_t y_{i,t}] dt \\ \text{s.t. } \dot{B}_i = S_{i,t} - e_{i,t} + y_{i,t} \\ B_{i,0} = 0, B_{i,T} \geq 0 \\ e_{i,t} \geq 0, \\ -A_{i,t} \leq y_{i,t} \leq D_{i,t}, A_{i,t} > 0, D_{i,t} > 0. \end{array} \right. \quad \text{(B)}$$

The last constraint provides bounds ($A_{i,t}$ and $D_{i,t}$) on the maximum number of permits that can be instantaneously bought and sold by a firm i . This is a necessary technical requirement to avoid corner solutions, since the objective function is linear in $y_{i,t}$ (see also Cronshaw and Kruse [1996] and Kling and Rubin [1997]). As pointed out by Rubin [1996], rather than explicitly taking into account this constraint in the resolution, an alternative approach is to consider price paths for which an internal solution exists (i.e. a non-bounded solution over the entire time horizon).¹⁵ This is

13 Here, the author assumes a central planner that would like to borrow but which is not allowed to do so. So, he looks at the impact of an “ex-post” constraint $B_i \geq 0$ (i.e. not explicitly taken into account in optimization) – meaning that borrowing is not allowed in any period – on necessary conditions.

14 A firm i cannot buy (sell, respectively) more than $D_{i,t}$ ($A_{i,t}$, respectively) permits at any period t . Assuming these bounds in a technical requirement, as explained below.

15 The economic intuition of this assumption will be further discussed in the model of section 4 of this chapter.

equivalent to assuming that the firm has an internal solution in each period. Therefore, in order to simplify the analysis, the author assumes that the firm has such a non-bounded solution.

Solving problem **(B)**, Rubin shows that an inter-temporal market equilibrium exists, and that, in equilibrium, each firm equates the marginal cost of pollution abatement with the price of permits, i.e. $-C'_i(e_{i,t})=P_t$. Thus, when allowed to trade with one another, firms collectively behave like a central planner who efficiently allocates emission permits to each firm so as to minimize the overall compliance cost (i.e. the total compliance cost over all firms). In other words, a decentralized equilibrium solution exists and it is efficient in the sense of achieving the least-cost solution attained by a central planner: equalization of marginal cost of abatement among polluters. Moreover, as for the joint-cost problem, all firms have present discounted marginal abatement costs equal to the marginal value of an additional permit in the bank.

As explained above, for firm i to have an internal solution over the entire time horizon, the permit price must follow along a singular path. Rubin shows that, on the one hand, for a particular firm to have a non-bounded solution, the permit prices must grow at the rate of interest (i.e. the price path of permits must follow a Hotelling's rule) when each firm can bank and borrow permits. In this case the present-value price of permits must be constant in time. On the other hand, if firms face a binding constraint on the borrowing of permits ($B_{i,t} \geq 0$),¹⁶ the rate of growth in prices must be less than the interest rate. In this case, the present-value price of permits is decreasing through time.¹⁷ Note that this required price path has the same shape as in the case of a central planner, where the present-value marginal abatement cost was shown to be constant in time when each firm can bank and borrow permits, and decrease in time when borrowing is not allowed.

Using the same deterministic continuous time model as in Rubin [1996], Kling and Rubin [1997] have explored consequences of inter-temporal trading on social damages of pollution.¹⁸ They identify the socially optimal emission path and show that, in many cases, firms have an incentive to borrow more permits than needed at the social optimum. To restore the social optimality, Kling and Rubin propose a modified inter-temporal trading system, which provides firms with disincentives to

16 Here again, as in the case of a central planner, constraint $B_{i,t} \geq 0$ is not explicitly taken into account in optimization, but the author investigates the impact of this constraint on necessary conditions.

17 This last results on the required price path for an internal solution is close to the one obtained by Cronshaw and Kruse [1996] in a discrete-time model with banking. Cronshaw and Kruse show that the permit price can rise no faster than the rate of interest (regardless of whether banking is allowed or not) in a perfectly competitive market equilibrium with perfect foresight and full efficiency of information. Otherwise, there could be corner solutions.

18 Inter-temporal trading may increase damages from pollution by concentrating emissions in one time period. For example, if emissions are concentrated in one time period, interactions with other pollutants may be a concern. Moreover, concentration of emissions in one period may induce unfavorable effects (e.g. irreversibility or acceleration of damages) creating more and more damages for subsequent time periods.

borrow to much permits (i.e. disincentives to borrow more permits than the socially optimal amount). Their solution consists in allowing borrowing but only at a discount rate. Thus, for one permit borrowed in the current period more than one permit must be surrendered in a subsequent time period. Therefore, if the permit discount rate is chosen so as to match the private decisions with the socially optimal emission path, the social optimum can be restored.

Schennach [2000] explores the consequences of constraints on borrowing. She wants to take into account an important feature of the Title IV of the US Clean Air Act Amendments of 1990: borrowing of permit is not allowed. Using an approach similar to the one of Rubin [1996], Schennach considers a continuous time model with a single central planner (representing all affected firms) who faces an infinite-horizon optimization problem. Moreover, the author explicitly takes into account a non-negativity constraint on banking (i.e. $B_t \geq 0$) meaning that borrowing is not allowed. Her aim is to identify the consequences of this constraint on the path of the permit price and of emissions. Solving the problem in the case of deterministic emissions, Schennach [2000] shows that the evolution of emissions and permit prices can be divided into two periods. The first is a banking period where part of permits allocation (permits are allocated annually) are saved for future use and the permit prices must grow at the rate of interest. This is followed by a period where all permits allocated each year are used immediately (banking stops) and emissions and permit prices are set by electricity demand.¹⁹ Finally, more importantly, the author introduces uncertainty in the model, by considering stochastic emissions. Thus, she provides the first attempt to model the permit price dynamic in continuous time with stochastic emissions. Though Schennach does not provide an exact analytic solution for the problem with stochastic emissions, the dynamic behavior of the permit price is analyzed implicitly. First, she explains that the expected price path may rise with rates between zero and the interest rate. Second, she conjectures that the paths of price and emissions need to be continuously updated as new information becomes available. This may generate discontinuity in the paths of price and emissions.

Innes [2003] and Maeda [2004] (see also Maeda [2001]) are among the first studies that explicitly took into account the stochastic nature of emissions in a multi-period setting. Innes [2003] considers the impact of costly government enforcement actions in a two-period model with stochastic emissions. He shows that when pollution is stochastic and inter-temporal trading is not allowed, emission trading necessarily leads to some regulatory violations (i.e. some firms will necessarily have higher emissions than their number of permits). In such a situation, regulatory fines must be imposed to non-compliant firms. However, inter-temporal trading can avoid

¹⁹ Schennach [2000] considers the case of power producers whose SO₂ emissions are constrained under the US Title IV. Thus, here, the demand for electricity at time t stands for the SO₂ emissions at time t (i.e. the SO₂ emissions are emissions needed to satisfy the demand for electricity).

regulatory fines (by allowing non-compliant firms to borrow lacking permits rather than being sanctioned) and costs of their imposition. Accordingly, Innes [2003] concludes that when emissions are stochastic, if regulatory sanctions and other government enforcement actions are costly, environmental regulators can increase economic efficiency by allowing unrestricted inter-temporal trading of permits, despite possible higher damages of pollution if emissions are concentrated in one time period.²⁰ In another two-period model with stochastic emissions, Maeda [2004] analyzes the permit price behavior in a trading system with regulated firms (“emitters”) and speculators (“non-emitters”).²¹ Moreover, he assumes that banking is allowed while borrowing is prohibited. Interestingly, Maeda shows that the permit price is increasing with respect to the number of regulated firms, and decreasing with respect to the number of speculators. He also finds that the permit price volatility depends on the ratio between regulated firms and speculators.

Based on literature about inter-temporal trading, some authors have developed equilibrium models for emission trading in continuous time, in order to investigate how various factors (e.g. stochastic emissions, stochastic fuel prices, asymmetric information, etc) can affect the price dynamic of tradable allowances.

Seifert et al. [2008] focus on the dynamic price behavior of EUAs based on a continuous-time stochastic process for uncontrolled emissions.²² They develop a stochastic equilibrium model, in continuous time, reflecting the main features of the EU ETS.²³ Rubin [1996] formally proved that the market equilibrium in an emission trading scheme is equivalent to the solution of a central planner minimizing total cost of reducing emissions over the relevant time horizon. Accordingly, in order to avoid complication, the authors assume that all market participants are aggregated into one representative agent. Therefore, Seifert et al. [2008] model a representative agent who choose the optimal abatement trajectory, $\{u_t\}_{t \in [0, T]}$, so as to minimize the overall expected compliance cost over time horizon T . The representative agent has an initial endowment of EUAs, e_0 , at the beginning of the T periods, and continuously emits CO₂, at a rate given by a continuous stochastic process y_t , over the whole “Phase” $[0, T]$.²⁴ At every time period t , the central planner decides

20 This conclusion contrasts with previous literature that was built under assumptions of deterministic emissions and non-costly government enforcement actions, and that proposed modified inter-temporal trading systems allowing borrowing only at a discount rate to increase economic efficiency (Kling and Rubin [1997]).

21 Here “speculator” refers to unregulated firms which operate in the permit market only to make money (e.g. banks).

22 For an introduction to stochastic processes in continuous time, see Neftci [1996] and Hull [2005]. Notably, Neftci [1996] describes behavior of several processes (e.g. standard Brownian motion – or Wiener process –, arithmetic Brownian motion, geometric Brownian motion, Ornstein-Uhlenbeck process, etc) with illustrative examples.

23 These features are detailed in the model of section 4 of this Chapter.

24 Here “Phase” is used as an analogy with the EU ETS.

whether to costly abate some of the CO₂ emissions or not. At the end of the Phase $[0, T]$, realized – net of abatements – accumulated emissions, x_T , are determined. For every tonne of CO₂ not covered by an EUA from the initial endowment, a penalty has to be paid. Formally, the central planner minimizes the overall compliance cost (the authors choose to maximize a negative cost, which is equivalent to minimizing a positive cost):

$$\max_{\{u_t\}_{t \in [0, T]}} E_0 \left[\int_0^T e^{-rt} C(t, u_t) dt + e^{-rT} P(x_T) \right]$$

where r is a risk-free rate of interest, $E_t[\cdot]$ denotes the expectation operator conditional on the information set F_t available at time t ,

$$C(t, u_t) = -\frac{1}{2} c u_t^2$$

describes the abatement costs per unit of time, where c is a constant cost coefficient;

$$P(x_T) = \min \{0, p(e_0 - x_T)\}$$

stands for the potential penalty cost at the end of T .²⁵ Besides,

$$x_t = -\int_0^t u_s ds + E_t \left[\int_0^T y_s ds \right]$$

are the total expected emissions – net of abatements – over the whole Phase $[0, T]$, given the emission rate y_t for “business-as-usual” or “uncontrolled” emissions. The uncontrolled emission evolves according to a stochastic process of the general form $dy_t = \mu dt + \sigma dW_t$ (an arithmetic Brownian motion in this case), where μ is a drift coefficient, σ is the empirical variance of y_t and dW_t is the stochastic increment of a standard Wiener process.

Given a stochastic process for y_t , the authors apply the Itô's Lemma²⁶ to the above equation of x_t . They derive a stochastic process for x_t given by $dx_t = -u_t dt + G(t) dW_t$, where $G(t)$

25 When realized emissions are higher than initial endowments (i.e. $e_0 < x_T$), the penalty costs p per lacking EUA have to be paid. This penalty cost coefficient p does not represent just the penalty payment itself. It describes all costs a company faces when it fails to comply with the EU ETS, i.e. it includes the potential cost of having to deliver lacking EUAs at a later point.

26 For more details on derivation of Itô's Lemma, see Neftci [1996] and Hull [2005].

depends on the stochastic process chosen for the underlying emission rate y_t .²⁷ Next, applying the Hamilton-Jacobi-Bellman approach of stochastic optimal control²⁸ to their optimization problem, and using equation obtained for dx_t , the authors derive a partial differential equation which describes the dynamic of chosen emission x_t . The partial differential equation is:

$$V^{(t)} = -\frac{1}{2}(G(t))^2 V^{(xx)} - \frac{1}{2c}(V^{(x)})^2,$$

with boundary condition $V(T, x_T) = e^{-rT} P(x_T)$, where $V(t, x_t)$ is the expected value of the optimal abatement trajectory $\{u_t\}_{t \in [0, T]}$ expressed with x_t (i.e. the “optimal cost to go” from t to T). Moreover, $V^{(t)}$, $V^{(x)}$ and $V^{(xx)}$ denote the partial derivatives of $V(t, x_t)$. Seifert et al. [2008] also show that the optimal value of u_t is given by $u_t = -\frac{1}{c} e^{rt} V^{(x)}$. Thus, they deduce the expression of the price of EUAs, $S(t, x_t)$, using the marginal abatement cost: $-\partial C(t, u_t) / \partial u_t = c u_t = -e^{rt} V^{(x)}$. Hence, the optimal dynamic price behavior of EUAs can be obtained by solving the partial differential equation. The partial differential equation can be solved analytically only when $r = 0$ and $G(t) = \sigma$ (which occurs when y_t follows a white noise process). Numerical techniques are required for other stochastic processes (i.e. arithmetic Brownian motion and Ornstein-Uhlenbeck process).²⁹

Unfortunately, there is no clear interpretation of the analytical solution. However, based on graphical representations for numerical and analytical solutions (where values of parameters are chosen so as to take into account some stylized facts in the EU ETS), the authors get several insights about the solution (see Figure 34). Notably, the price of EUAs, $S(t, x_t)$, at each instant $t \in [0, T]$ is bounded in the interval $(0, p e^{-r(T-t)})$ (i.e. $(0, p]$ when $r = 0$), and depends on expected emissions x_t . On the one hand, the carbon price may not rise above the discounted penalty cost because, when the carbon price reaches $S(t, x_t) = -\partial C(t, u_t) / \partial u_t = p e^{-r(T-t)}$ (because x_t is very high), the representative agent would no longer increase efforts but would rather pay the cheaper penalty. On the other hand, the carbon price never reaches zero, because the probability that realized emissions, x_T , will be above the initial endowment of EUAs, e_0 , is always positive. Indeed, because of stochastic nature of emissions, there is always a positive probability of having

27 Seifert et al. [2008] consider three different processes for y_t : white noise, arithmetic Brownian motion and (mean reverting) Ornstein-Uhlenbeck process.

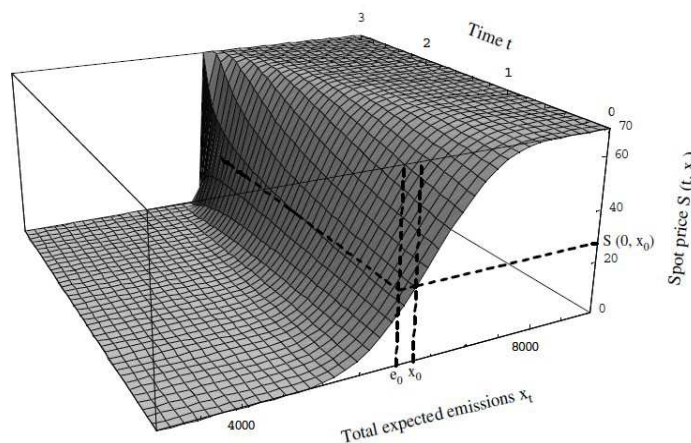
28 See Kappen [2007] and Malliaris and Brock [1982].

29 For a review on partial differential equations, see Garabedian [1964], Strauss [1992], Tyn Myint [1987] and Zauderer [1989]. See also Neftci [1996] for a simpler presentation of analytical and numerical methods for solving partial differential equations.

fewer allowances than realized emissions at the end of T , and thus having to pay penalty costs. Therefore, the firms are always willing to abate some emissions in order to mitigate some of these expected penalty costs, resulting in a positive carbon price.

Still based on graphical analysis, Seifert et al. [2008] detect that the allowance price becomes more sensitive to x_t when we move toward the end of the Phase $[0, T]$. In other words, shocks that can affect uncontrolled carbon emissions have a stronger impact on the price of EUAs if they occur in a period t which is closer to the last period T . The logic arises from the fact that the ability to adapt to a rise in uncontrolled emissions – by smoothing abatements across time – is smaller in periods that are close to the end of the Phase.³⁰ Graphically, it appears in the slopes of the x -directional characteristic curves of the surface representing the solution for $S(t, x_t)$ (see Figure 34).

Figure 34: Surface representing the carbon price dynamic in Seifert et al. [2008]. Initial endowment $e_0=6000$, initial total expected emissions $x_0=6240$, and expected spot price level $S(0, x_0)=27.46$ are indicated by dashed lines. The penalty cost coefficient is $p=70$ (reflecting the penalty payment in Phase 1 – Euros 40 per lacking EUA – plus the cost of delivering lacking allowances at a price of Euros 30), $r=0$, y_t follows a white noise process and $T=3$.



Indeed, looking at Figure 34 we see that when we move along the t -axis, from $t = 0$ toward T , we observe, in the zone where x_t is around e_0 , an increasing x -directional steepness. Finally, at time T , when any uncertainty is resolved, $S(t, x_t)$ is either zero (if realized emissions are lower than the initial endowment) or p (if realized emissions are higher than the initial endowment).

³⁰ See also Hintermann [2010].

With regard to price volatility, Seifert et al. [2008] show that it increases when coming closer to T , while, at the same time, it decreases when the price is close to its bounds.³¹ As pointed out by the authors, traders of EUAs should select an underlying spot price process reflecting this increasing volatility structure in order to give a good valuation of option contracts.³² Another interesting result is obtained using the partial differential equation. The authors show that the price $S(t, x_t)$ follows a martingale (i.e. $E_t[dS(t, x_t)]=0$), and that this result is independent of the specification of the process chosen for y_t . This indicates that the stochastic process followed by the carbon price is not affected by any trend.³³ In summary, Seifert et al. [2008] conclude that an adequate process for the price of EUAs does not have to follow any trend or seasonal patterns, and should exhibit a time- and price-dependent volatility structure.

As in Seifert et al. [2008], Hintermann [2010] shows that the equilibrium price of allowances exhibits time dependency. More precisely, Hintermann identifies that shocks on exogenous variables that influence “business-as-usual” (BAU) emissions increasingly affect the permit price as we move towards the end of the Phase.³⁴ Following the same strategy as in Maeda [2004] (see also Maeda [2001]), the author uses the fact that, in equilibrium, each firm equalizes its marginal abatement cost to the price of permits, to derive an expression for the carbon price. Moreover, Hintermann extends the model of Maeda by introducing dynamic in considering several time periods.

Hintermann [2010] considers a permit market with N participants and fixed time horizon T . The marginal abatement cost function of each firm i in each time t is given by:

$$MAC_{it}(a_{it}, G_t, C_t, BAU_{it}) = b a_{it} + d_1 G_t + d_2 C_t + g BAU_{it}, \quad (\text{A})$$

where the time index $t = 1, \dots, T$ refers to days so that T corresponds to the end of a Phase in the EU ETS, BAU_{it} are BAU emissions, a_{it} denotes abatements (defined as $a_{it} = BAU_{it} - e_{it}$ where e_{it} is the chosen level of emissions), and C_t and G_t are coal and gas prices. Moreover, $b > 0$,

31 Dependence of the price volatility on the price level can be observed in the price surface of Figure 34. Indeed, we see that the slope of the x -directional characteristic curves approaches zero when departing from the region around e_0 . As noted by Seifert et al. [2008], this is equivalent to saying that the price volatility decreases and finally reaches zero when the price moves toward either of its bounds.

32 For illustrative examples on how to select an appropriate spot price process in order to price option contracts, see Neftci [1996].

33 A martingale is a stochastic process without drift. It has the property that its expected value at any future time is equal to its value today. Therefore, the expected change in a martingale process over a time interval is zero. Formally speaking, a stochastic process S_t is a martingale if $E_t[dS_t]=0$ (or $E_t[S_{t+s}-S_t]=0$ in discrete-time), see Neftci [1996].

34 Seifert et al. [2008] report the same result.

$d_1 > 0$, $d_2 < 0$ and $g > 0$ are parameters, and BAU_{it} is modeled as a stochastic variable which is a function of a stochastic risk factor Ψ_t shared by all firms:

$$BAU_{it}(\Psi_t) = E_{t-1}[BAU_{it}(\Psi_t)] + \beta_{it}(\Psi_t - E_{t-1}[\Psi_t]) + v_{it}, \quad (\mathbf{B})$$

where $\beta_{it} = \frac{Cov(BAU_{it}, \Psi_t)}{Var(\Psi_t)}$, $E[\Psi_t \cdot v_{it}] = E[v_{it} \cdot v_{jt}] = 0$ with $i \neq j$ and $E[v_{it}] = 0, \forall i$.³⁵

Finally, the environmental regulation requires that aggregate abatement has to equal the difference aggregate BAU emissions and the emission cap D :

$$\sum_{k=1}^T \sum_{i=1}^N a_{ik} = \sum_{k=1}^T \sum_{i=1}^N BAU_{ik} - D. \quad (\mathbf{C})$$

Using the fact that, in equilibrium, each firm chooses a level of abatements such that its marginal abatement cost is equal to the permit price p_t , the optimal expression of a_{it} can be derived as follows:

$$a_{it}^* = MAC_{it}^{-1}(p_t, G_t, C_t, BAU_{it}(\Psi_t)). \quad (\mathbf{D})$$

Combining **(D)** and **(A)** and aggregating gives:

$$\sum_{i=1}^N a_{ik}^* = \frac{p_t}{b} - \frac{d F_t + g \sum_{i=1}^N BAU_{it}}{b}, \quad (\mathbf{E})$$

where $d F_t \equiv d_1 G_t + d_2 C_t$.

Substituting **(E)** in **(C)** yields:

$$\frac{1}{b} \sum_{k=1}^T p_k - \frac{d}{b} \sum_{k=1}^T F_k - \frac{g}{b} \sum_{k=1}^T \sum_{i=1}^N BAU_{ik} = \sum_{k=1}^T \sum_{i=1}^N BAU_{ik} - D. \quad (\mathbf{F})$$

Taking expectation of each variable at time t , subtracting them from **(F)**³⁶ and re-arranging gives:

35 v_{it} are firm-specific random variables reflecting uncertainties that are specific to each firm and that have no correlation to each other. See Maeda [2004].

36 In doing so, differences for period t cancel out because, in this case, expectations are taken ex-post and so expected values are the same as realizations. In the same way, the differences are equal to zero in each period for variable D , because, since D is a deterministic variable, $D - E_t(D) = 0, \forall t$.

$$\sum_{k=t+1}^T (p_k - E_t[p_k]) = d \sum_{k=t+1}^T (F_k - E_t[F_k]) + (g+b) \sum_{k=1}^T \sum_{i=1}^N (BAU_{ik} - E_t[BAU_{ik}]). \quad (\mathbf{G})$$

Substituting **(B)** in **(G)**, dividing by N and re-arranging yields:

$$\frac{1}{N} \sum_{k=t+1}^T (p_k - E_t[p_k]) = \frac{d}{N} \sum_{k=t+1}^T (F_k - E_t[F_k]) + \frac{(g+b)}{N} \sum_{k=1}^T \sum_{i=1}^N \beta_{it} (\Psi_k - E_{k-1}[\Psi_k]) + \frac{(g+b)}{N} \sum_{k=t+1}^T \sum_{i=1}^N v_{it}. \quad (\mathbf{H})$$

As shown in Maeda [2004], the variance of v_{it} goes to zero when N goes to infinity. This indicates that for a large number of emission sources, the probabilistic nature of the price of allowances would only depend on Ψ_t . The intuition behind this is that uncorrelated firms specific shocks cancel each other out in a large market. Accordingly, the term $(\frac{g+b}{N}) \sum_{k=t+1}^T \sum_{i=1}^N v_{it}$ is neglected in **(H)**. Thus, **(H)** can be simplified as follows:

$$\sum_{k=t+1}^T p_k = \sum_{k=t+1}^T E_t[p_k] + d \sum_{k=t+1}^T (F_k - E_t[F_k]) + h \sum_{k=1}^T (\Psi_k - E_{k-1}[\Psi_k]), \quad (\mathbf{I})$$

where $h = N(g+b)\bar{\beta}$ with $\bar{\beta} \equiv \bar{\beta}_t = (\frac{1}{N}) \sum_{i=1}^N \beta_{it}$.

If markets are efficient with respect to information, current prices fully incorporate all information concerning their future values, implying that $E_t[P_{t+1}] = (1+r)P_t \equiv \rho P_t$, where $\rho = 1+r$ is a discount factor associated with the interest rate r and P_t refers to any price.³⁷ Moreover, as this applies only to prices, Hintermann partitions Ψ_t into prices, denoted by Ψ_t^P , and non-price determinants (such as weather), denoted by Ψ_t^{NP} (i.e. $\Psi_t = \Psi_t^P + \Psi_t^{NP}$). Applying this to **(I)**, and solving recursively for all $t \in [1, \dots, T]$, the author derives an expression for the equilibrium price of permit in any time³⁸:

$$p_t = \rho p_{t-1} + d(F_t - \rho F_{t-1}) + h(\Psi_t^{NP} - E_{t-1}[\Psi_t^{NP}]) + h \cdot \frac{\Psi_t^P - E_{t-1}[\Psi_t^P]}{\sum_{k=t+1}^T \rho^{T-k}}. \quad (\mathbf{J})$$

Equation **(J)** shows that the allowance price is determined by its own lagged value, changes in fuel prices and shocks on the common risk factor Ψ_t . More importantly, Hintermann [2010] identifies

³⁷ See Fama [1965] and Malkiel [2003].

³⁸ We use the same procedure in the model of section 4 of this Chapter to derive the expression of the equilibrium price in any period $t \in [1, \dots, T]$.

that shocks on exogenous variables that influence BAU emissions (i.e. shocks on Ψ_t) increasingly affect the permit price as we move towards T .³⁹ As for Seifert et al. [2008], this result can be explained by the fact that the ability to adapt to a rise in uncontrolled emissions – by smoothing abatements across time – is smaller in periods that are close to the end of the Phase. Likewise, one can also argue that if a shock appears in a period which is close to T , the probability that it will be neutralized by an opposite shock in a later period is smaller, and so it has a stronger impact.

More recently, a few papers have sought to extend the analysis of Seifert et al. [2008] by taking into new features of the EU ETS, namely the fact that inter-phase banking is now allowed (i.e. it is now allowed to transfer allowances from Phase 2 to Phase 3). By contrast, inter-phase borrowing is still forbidden. Thus, Hitzemann and Uhrig-Homburg [2010], propose a stochastic equilibrium model in continuous time (similar to the one of Seifert et al. [2008]), taking into account a sequence of consecutive finite trading periods (or Phases) with inter-phase banking allowed but not inter-phase borrowing.⁴⁰ The authors find that the price of allowances and its volatility depend on upcoming Phases, and identify that each additional Phase leads to an additional component in the current carbon price. Moreover, the relative share of each component depends on the relative share of expected emissions for that component.⁴¹ Hitzemann and Uhrig-Homburg also identify an analogy between emission permits and options, when several Phases are taken into account and inter-phase banking is allowed. They show that, in this case, an allowance is equivalent to “a strip of binary options” – each one reflecting a Phase, and thus a risk of non-compliance – written on net cumulative emissions over all the Phases. However, in contrast to classical financial options, the underlying process is not exogenous since it is derived endogenously through abatement measures.

An alternative approach to Seifert et al. [2008] is taken by Fehr and Hinz [2006] (see also Carmona et al. [2009]), who model an equilibrium among N market participants. Although the setting is more realistic (compared with the case of a central planner), the model only gives a characterization of the carbon price behavior but does not provide an explicit solution. The authors

39 Note that this applies only to price determinants of BAU emissions, Ψ_t^P . In **(J)**, this appears in the summation term in the denominator of $\Psi_t^P - E_{t-1}[\Psi_t^P]$, which decreases as time progresses.

40 See Peluchon [2011] for a similar approach in a discrete-time setting.

41 Hitzemann and Uhrig-Homburg [2010] point out that this result can explain why the price of EUAs did not reach zero during the recession of 2008-2009. During this period, the market was globally long, and thus the carbon price could have been close to zero. However, the carbon price stayed relatively high because it was mainly driven by expected emissions in the future Phases.

focus on the cheapest short-term abatement measures in the power sector, i.e. the coal-to-gas fuel switching. They have produced the first contribution analyzing fuel switching in an equilibrium model. Fehr and Hinz consider N firms producing electricity from fossil fuels (i.e. from coal plants and CCGTs) and trading carbon allowances at times $t \in [0, T]$. The entire time horizon corresponds to one compliance period (a “Phase”), that is, at maturity T , all firms have to cover their carbon emissions by allowances or pay penalties. In order to comply with the regulation, each firm i can decide its abatement levels, $\xi_{t,i}$, at times $t \in [0, T]$. This corresponds to the fuel switching effort. Firms can also trade permits, $\theta_{t,i}$, at a price A_t . Moreover, the difference between allowances allocated at the beginning of the Phase and the expected uncontrolled carbon emissions over the whole Phase, F_i , is modeled as a random variable.⁴² This corresponds to the required level of effort for firm i , and F_i can take either positive or negative realizations depending on realized uncontrolled emissions. Accordingly, at the end of T , each firm i must face a penalty cost if $F_i - \theta_{t,i} - \sum_{t=0}^T \xi_{t,i} > 0$, where the penalty per tonne of CO₂ which is not covered by an allowance is equal to p . Finally, at time t , the fuel switching effort of firm i , $\xi_{t,i}$, yields an expense equal to $\varepsilon_{t,i} \xi_{t,i}$, where $\varepsilon_{t,i}$ is the actualized value of the switching price, as defined in Chapter 1 (see equation (1.1) of Chapter 1). Moreover, as a simplification, Fehr and Hinz assume a single type of CCGTs for each firm i (i.e. differences in energy efficiency between CCGTs are not taken into account). They also assume that each firm i owns only one type of coal plant. Thus, the marginal abatement cost, $\varepsilon_{t,i}$, is stochastic – because it depends on coal and gas prices which are modeled as stochastic variables (see Chapter 1) – but it does not depend on the level of switching effort (i.e. on the value of $\xi_{t,i}$).⁴³ Indeed, heating and emission rates of coal and CCGT plants are constant whatever the level of switching effort, because differences in efficiency of power plants are not taken into account. Therefore, in a deterministic environment (i.e. when coal and gas are fixed), the marginal abatement cost is constant, equal to $\varepsilon_{t,i}$, whatever the value of $\xi_{t,i}$.⁴⁴

Based on all of these notations, the profit/loss of a firm i (from the trading scheme), over the whole Phase, can be expressed as follows:

42 F_i is not modeled as a stochastic variable. It is a simple random variable whose realization is known at the end of T .

43 While previous papers considered marginal abatement cost as a deterministic function increasing in abatement efforts, Fehr and Hinz [2006] introduce a stochastic cost function which do not depend on abatement efforts. In this chapter, we investigate consequences of considering a cost function for fuel switching which is dependent on the level of switching effort (see section 3 and 4 of this Chapter).

44 This is fully described in Chapter 1.

$$\Pi_i(\theta_i, \xi_i) = \sum_{t=0}^{T-1} \theta_{t,i} (A_{t+1} - A_t) - \theta_{T,i} A_T - p \left(\Gamma_i - \sum_{t=0}^T \xi_{t,i} - \theta_{T,i} \right)^+ - \sum_{t=0}^T \varepsilon_{t,i} \xi_{t,i}, \quad (\mathbf{K})$$

where $\theta_i = (\theta_{t,i})_{t \in [0, T]}$ and $\xi_i = (\xi_{t,i})_{t \in [0, T]}$. Moreover, $\theta_i = (\theta_{t,i})_{t \in [0, T-1]}$ is defined as a trading strategy on forward contracts, while $\theta_{T,i}$ is the number of spot contracts which firm i purchases at time T . Interestingly, the penalty cost does not depend on positions held on forward contracts. Implicitly, this means that the strategy on forward contracts is a pure hedging strategy with financial settlement on each contract (i.e. without physical delivery of the underlying EUAs). Thus, in equation **(K)**, $\sum_{t=0}^{T-1} \theta_{t,i} (A_{t+1} - A_t)$ gives the wealth of hedging strategy $\theta_i = (\theta_{t,i})_{t \in [0, T-1]}$,⁴⁵ while $\theta_{T,i}$ corresponds to the number of allowances bought or sold for compliance purposes.

The individual optimization problem of a firm i is given by:

$$\max_{\theta_i, \xi_i} E_t[\Pi_i(\theta_i, \xi_i)]$$

where $E_t[\cdot]$ denotes the expectation operator conditional on the information available at time t . Accordingly, an equilibrium carbon price process $A^* = (A_t^*)_{t \in [0, T]}$, given a fuel switching price process $\varepsilon_i = (\varepsilon_{t,i})_{t \in [0, T]}$ for each firm i , can be defined as combinations of trading and switching strategies, (θ_i^*, ξ_i^*) for each firm i , so that:

$$E_t[\Pi_i(\theta_i^*, \xi_i^*)] \geq E_t[\Pi_i(\theta_i, \xi_i)], \quad \forall (\theta_i, \xi_i) \text{ with } i \in [1, \dots, N],$$

and

$$\sum_{i=1}^N \theta_{t,i}^* = 0, \text{ at any time } t \in [0, \dots, T] \text{ (the market-clearing condition).}$$

Fehr and Hinz show that this equilibrium is connected to the solution obtained by a central planner. Finally, and more importantly, they characterize the shape of the equilibrium price as follows:

$$A_t^* = p \cdot E_t \left[\mathbf{1}_{\{\Gamma - \Xi^* \geq 0\}} \right], \quad (\mathbf{L})$$

where $\mathbf{1}_{\{\Gamma - \Xi^* \geq 0\}}$ is an indicator function, $\Gamma = \sum_{i=1}^N \Gamma_i$ and $\Xi^* = \sum_{i=1}^N \sum_{t=0}^T \xi_{t,i}^*$. Thus, although they

⁴⁵ Note that holding position $\theta_{t,i}$ from t to $t+1$ yields a payment equal to $\theta_{t,i} (A_{t+1} - A_t)$. Accordingly, at the end of T , the payment of $\theta_i = (\theta_{t,i})_{t \in [0, T-1]}$ is equal to $\sum_{t=0}^{T-1} \theta_{t,i} (A_{t+1} - A_t)$.

do not provide an explicit solution, the authors demonstrate that the equilibrium price of allowances depends on the difference between the aggregated required level of abatements, Γ , and the aggregated optimal switching effort, Ξ^* . Besides, since at each instant t , for each firm i , $\varepsilon_{t,i}$ is an increasing function of the gas price and a decreasing function of the coal price, equation (L) shows that the probability of having a positive carbon price is an increasing function of the gas price and a decreasing function of the coal price.⁴⁶ This demonstrates that, in equilibrium, the carbon price should be an increasing function of the gas price and a decreasing function of the coal price.

All the papers we have reviewed so far identify abatement- and production-decisions as the key drivers of the carbon price behavior. Some of them give a special importance to inter-temporal trading of allowances. Other authors model trading and abatement strategies of firms that emit CO₂ according to a stochastic emission process (and which are subject to stochastic fuel prices, in the case of Fehr and Hinz [2006]). In all the cases an equilibrium price for allowances results from the strategies chosen by firms in equilibrium. Chesney and Taschini [2008] belong to this literature. However, contrary to the papers mentioned above, the model of Chesney and Taschini accounts for the presence of asymmetric information in the market for permits. Another particularity arises from the fact that no abatement measures are considered in the model, and thus, carbon emissions are fully exogenous to firms. Solving their dynamic optimization problem, the authors show that an equilibrium price for allowances exists. Moreover, Chesney and Taschini show in numerical simulations that the higher the probability of each firm being in shortage by the end of the Phase, the higher the permit price. This confirms previous studies.

To conclude with this literature review, one can also mention the paper of Çetin and Verschuere [2009]. Those authors derive an expression for the spot price of carbon allowances by exploiting an arbitrage relationship between prices of spot and forward contracts, given a forward price process which is exogenous to the model. This relation holds only when banking is not allowed. The authors also demonstrate that the permit price is sensitive to information release.

⁴⁶ Because, in each time t , for each firm i , $\xi_{t,i}^*$ is a decreasing function of $\varepsilon_{t,i}$.

3. Efficiency of CCGTs and fuel switching process: abatement cost function and trading opportunities

We saw in Chapter 1 that when the switching effort rises the marginal cost of switching increases and becomes more dependent on the gas price, for any given fuel prices. This is due to differences in efficiency of CCGTs involved in fuel switching. However, the influence of differences in efficiency of coal plants can be neglected.⁴⁷ In this section we discuss how these characteristics can be modeled in a cost function for fuel switching. We also show that mutually beneficial trading opportunities may exist among firms which own different types of CCGTs. Once a proper cost function is derived, it will be used in the model we present in the following section of this chapter.

Cost function for fuel switching with stepwise constant and increasing marginal cost

Using the switching price as defined in Chapter 1, we can derive a first cost function for switching with the appropriate properties as mentioned above. However, in this case, the curve of the marginal cost of switching is stepwise constant. Each step corresponds to a constant marginal cost equal to a certain switching price. In other words, as long as a certain type of CCGTs is substituted for coal plants, each tonne of carbon abatement comes with a constant marginal cost which corresponds to the switching price associated with that type of CCGTs. Next, when dirtier CCGTs are involved, we move to a higher switching price, i.e. a higher step reflecting a higher constant marginal cost of switching. To illustrate, let us take a switching price equation close to the one introduced in Chapter 1:

$$SW_i = \frac{h_{g,i}G - h_c C}{e_c - e_{g,i}}, \quad (2.1)$$

where SW_i is the switching price (in Euros per tonne CO₂) associated with CCGTs of $i\%$ of efficiency. Heating and emission rates associated with CCGTs of $i\%$ are $h_{g,i}$ and $e_{g,i}$. Finally, C and G are fixed coal and gas prices (i.e. we assume here a deterministic setting). Thus, assuming different types of CCGTs with efficiency rates ranging from 45 to 55%, and one type of coal plants

⁴⁷ We saw in Chapter 1 that the total effect of a variation in efficiency of coal plants is unpredictable and, in addition, it should be very small.

(say coal plants of 38% of efficiency), we get a stepwise constant curve for the marginal cost of switching, as in Figure 35.

Figure 35: Stepwise constant curve for the marginal cost of switching. Switching prices are obtained from equation (2.1) with fixed coal and gas prices.

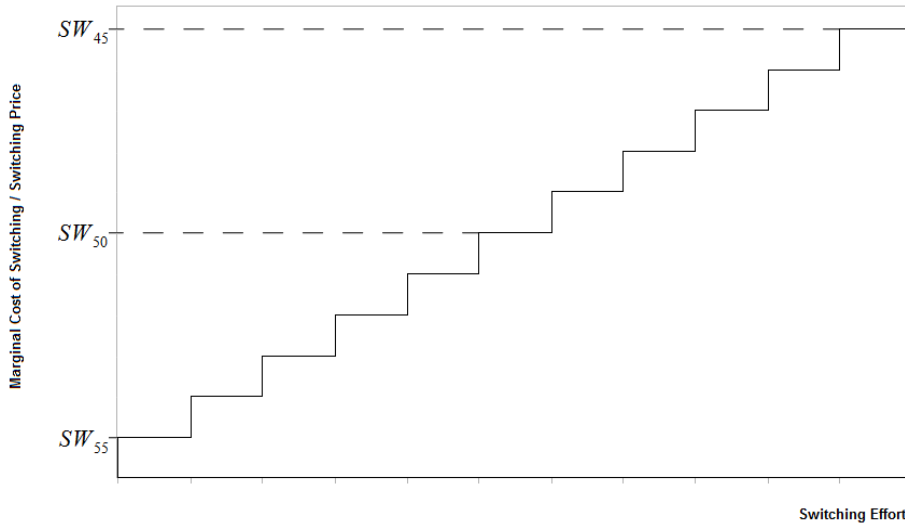


Figure 35 shows that, as the switching effort increases, we move to higher switching prices (i.e. switching prices associated with dirtier CCGTs) reflecting higher (constant) marginal costs of switching. Moreover, since heating and emission rates increase when efficiency of CCGTs decreases, the switching prices become more dependent on the gas price. In summary, when the efficiency rate of CCGTs involved in fuel switching moves from $i\%$ to $i-s\%$ – with $s>0$, meaning that efficiency of CCGTs decreases – we have:

- $SW_{i-s} > SW_i$, the marginal cost of switching increases;
- $|\partial SW_{i-s} / \partial G| = h_{g,i-s} / (e_c - e_{g,i-s}) > |\partial SW_i / \partial G| = h_{g,i} / (e_c - e_{g,i})$, the marginal cost of switching becomes more dependent on the gas price.

In Figure 35, we implicitly assumed that the volume of switching effort (i.e. the “switching potential”, defined as the number of tonnes of carbon abatement that can be obtained by fuel switching) is equivalent for all types of CCGTs, implying that installed capacities are very similar for each type of CCGTs (but not equivalent).⁴⁸ This is a simplification. Indeed, in reality,

⁴⁸ For equivalent installed capacities, the switching potential is higher with more efficient CCGTs. Indeed, since the quantity of switched MWhs needed to abate one tonne of CO₂ is smaller with more efficient CCGTs (see Chapter 1),

there may be significant differences in installed capacities of each type of CCGTs, so that the switching potential may differ significantly from one type of CCGTs to another. For example, installed capacities may be significantly more important for T_4^{50} (the CCGTs of 50%, as defined in Chapter 1) than for T_4^{45} , implying a higher switching potential with T_4^{50} than with T_4^{45} .

Now, let us assume two power producers, A and B. Each one owns a park of power plants with CCGTs and coal plants, all dedicated to intermediate load production.⁴⁹ Moreover, we assume that each producer has three different types of CCGTs and only one type of coal plants. Finally, CCGTs of A are globally more efficient than CCGTs of B. We say that A has a “profile” of CCGTs which is more efficient than that of B. By contrast, there is a unique profile of coal plants for both A and B in which units are all equally efficient (i.e. all the coal plants of A and B have the same efficiency rate, say 38%). Table 11 presents profiles of CCGTs for A and B which are consistent with our example.

Table 11: Profiles of CCGTs for firms A and B. T_4^i represents CCGTs of $i\%$ of efficiency.

Profile of A (more efficient)	Profile of B (less efficient)
T_4^{55}	T_4^{52}
T_4^{50}	T_4^{44}
T_4^{45}	T_4^{40}

Based on Table 11, we can deduce the shape of the marginal switching cost curves of A and B, in the case of stepwise constant marginal costs (see Figure 36).⁵⁰

one can get more tonnes of carbon abatement with more efficient CCGTs (e.g. for one installed GW of CCGTs, one can get more abatements with CCGTs of 55% than with CCGTs of 45%). Accordingly, an equivalent switching potential between CCGTs of i and $i-s\%$ (with $s>0$) does not mean that installed capacities are equivalent for both types. This means that installed capacities are very similar (but not equivalent), so that their switching potentials are equivalent.

49 For simplicity, we do not speak about other technologies dedicated to peak and base load production.

50 Here again we implicitly assume that all the CCGTs have the same switching potential. This appears in Figure 36 because we have the same volume of carbon abatements, whatever the type of CCGTs.

Figure 36: Stepwise constant marginal switching cost curves of firms A and B. Switching prices are obtained from equation (2.1) with fixed coal and gas prices.

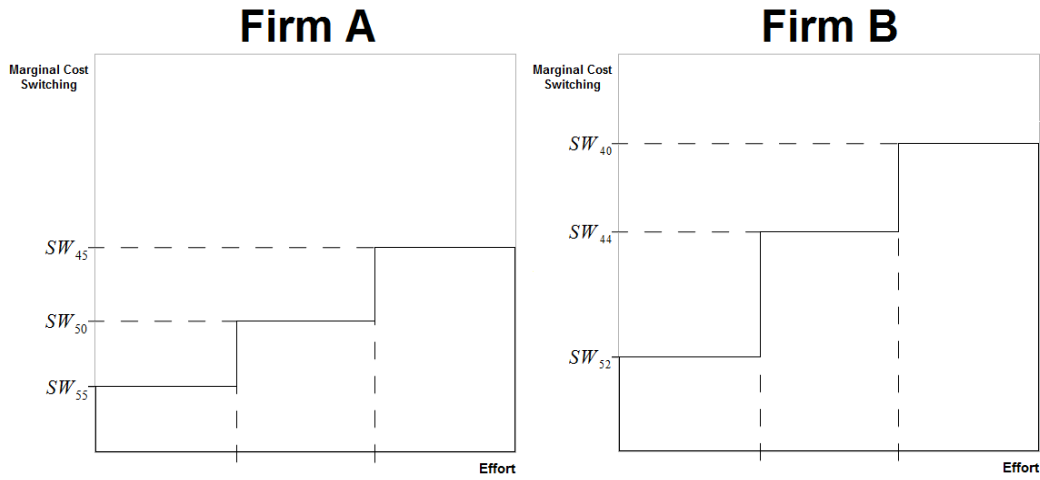
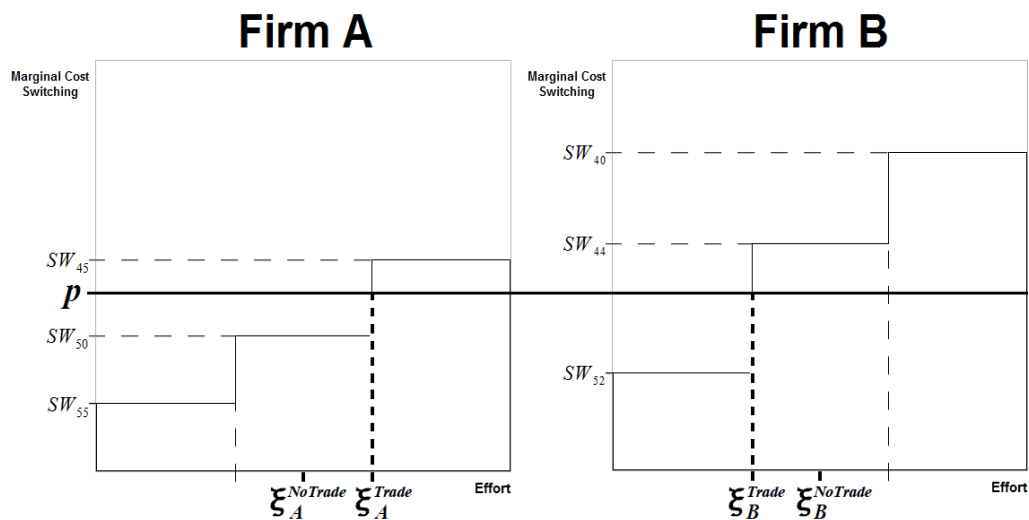


Figure 36 shows that A is more efficient than B in abating CO₂ emissions by fuel switching. Thus, for example, if $SW_{50} < p < SW_{44}$, where p is an allowance price, A abates more emissions than B (see Figure 37). In fact, there are mutually beneficial trading opportunities between A and B due to differences in their profiles of CCGTs. This is illustrated in Figure 37.

Figure 37: Mutually beneficial trading opportunities between firms A and B in the case of stepwise constant marginal switching cost curves.



Let us define Ξ , the overall switching effort (in tonnes of CO₂) that A and B have to achieve in a policy to reduce CO₂ emissions. So, $\Xi = \xi_A^k + \xi_B^k$, where ξ_A^k and ξ_B^k are the switching efforts of A and B, respectively, with $k = \{Trade, NoTrade\}$. If emission trading is not allowed, half of the overall effort is assigned to each producer by authorities. Therefore, $\xi_A^{NoTrade} = \xi_B^{NoTrade} = \Xi/2$.⁵¹ However, when emission trading is allowed, if $SW_{50} < p < SW_{44}$, A can make profits by increasing its switching effort, while it is profitable for B to reduce its switching effort. Accordingly, $\xi_A^{NoTrade} < \xi_A^{Trade}$ and $\xi_B^{NoTrade} > \xi_B^{Trade}$ (see Figure 37). On the one hand, when $SW_{50} < p$, it is worth switching all the T_4^{50} units that are available. Thus, A increases its switching effort from $\xi_A^{NoTrade}$ to ξ_A^{Trade} , and unused allowances are sold to B with a profit per unit equal to $p - SW_{50}$. On the other hand, when $SW_{44} > p$, switching the T_4^{44} plants is not a profitable option. Thus, B reduces its switching effort from $\xi_B^{NoTrade}$ to ξ_B^{Trade} , and lacking allowances are bought from A with a discount per tonne of CO₂ equal to $p - SW_{44}$. In other words, there are mutually beneficial trading opportunities between A and B because of differences in the efficiency of their CCGTs.

Cost function for fuel switching with continuous and increasing marginal cost

A cost function with a continuous marginal cost curve is more convenient for optimization. Thus, in order to model the cost of switching of a firm i , we assume that the following cost function can be retained:

$$C_i(\xi_i) = \frac{1}{2} \xi_i^2 a_i G - \xi_i b C, \quad (2.2)$$

where C and G are fixed coal and gas prices⁵² and ξ_i is the switching effort of firm i (i.e. the quantity of CO₂ in tonnes, that is not emitted due to fuel switching). Finally, $a_i > 0$ and $b > 0$ are parameters that show how fuel prices influence the fuel switching cost.

51 Alternatively, the overall switching effort may be assigned to A and B so that $\xi_A^{NoTrade} > \xi_B^{NoTrade}$. This would lead to a better result for the collectivity, given that the total cost for Ξ (over A and B) would be lower in this case. However, this solution implies that the switching cost functions of A and B are known by authorities, which is very unlikely. Indeed, in practice, such information is costly. At the same time, firms have incentives for hiding private information about their cost functions (like firm A, in our example, who loses by revealing information about its true cost function). Thus, information about cost function should be very difficult to obtain for authorities and very costly.

52 Here again we consider a deterministic setting (i.e. fixed fuel prices).

Cost function **(2.2)** satisfies the properties we want to model. Indeed, when the switching effort (ξ_i) rises, for any given fuel prices, the marginal cost of switching ($\partial C_i(\xi_i)/\partial \xi_i$) increases and becomes more dependent on the gas price. Here, the way we introduce convexity allows us to have a marginal cost of switching which becomes more dependent on the gas price as the switching effort increases. On the contrary, we have a constant influence of the coal price on the marginal cost of switching, whatever the value of ξ_i . This reflects our assumption that each firm owns only one type of coal plants. With regard to parameters a_i and b , we see that a_i is a firm-specific parameter while b has the same value for all the firms. Parameter a_i measures the efficiency of a given firm i to abate CO₂ by fuel switching. The value of a_i depends on how efficient the CCGTs of firm i are. That is a firm with a profile of CCGTs which is globally weakly efficient (e.g. a profile where most of the CCGTs are around 45% of efficiency) has a high value for a_i , so that this firm is weakly efficient to abate CO₂. On the contrary, a firm with a profile of CCGTs which is globally strongly efficient (e.g. a profile where most of the CCGTs are around 55% of efficiency) has a low value for a_i , so that this firm is strongly efficient to abate CO₂. By contrast, parameter b has the same value for each firm. This means that the profile of coal plants is the same for each firm. In other words, not only does each firm have a profile of coal plants in which all the units have the same efficiency rate (and thus C has a constant influence on $\partial C_i(\xi_i)/\partial \xi_i$ whatever the value of ξ_i), but, in addition, there is a unique profile of coal plants for all the firms. For example, one can assume that all the firms own only coal plants of 38% of efficiency.

Let us now take our example with power producers A and B again. As before we assume that A has a profile of CCGTs which is more efficient than that of B (i.e. CCGTs of A are globally more efficient than the CCGTs of B). Moreover, there is a unique profile of coal plants for A and B in which units are all equally efficient: all the coal plants of A and B have the same efficiency rate of 38%. So, using **(2.2)** for cost functions of A and B, we get:

$$\begin{aligned}
- \quad C_A(\xi_A) &= \frac{1}{2} \xi_A^2 a_A G - \xi_A b C, \text{ for firm A,} \\
- \quad C_B(\xi_B) &= \frac{1}{2} \xi_B^2 a_B G - \xi_B b C, \text{ for firm B,}
\end{aligned}$$

where $a_A < a_B$, since A is more efficient than B to abate CO₂ by fuel switching (because A owns CCGTs that are globally more efficient). Accordingly, the slope of the marginal switching cost curve of B is steeper than that of A, and, therefore, A can abate more CO₂ emissions for any given

price of allowances (see Figure 38).

Figure 38: Continuous marginal switching cost curves of firms A and B. The curves are based on cost function (2.2) with fixed coal and gas prices.

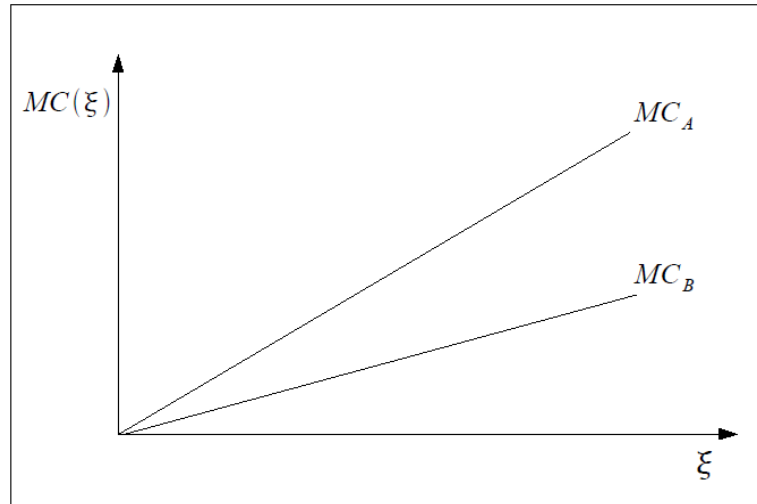
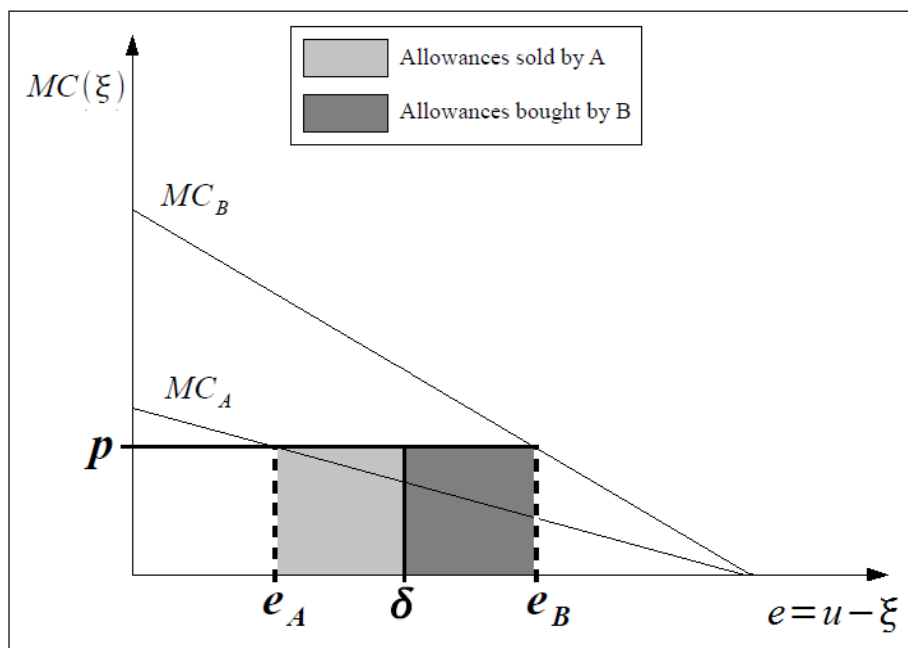


Figure 38 shows that A is more efficient than B in abating CO₂ emissions by fuel switching. Moreover, as in the case of a stepwise constant marginal switching cost, we can show that mutually beneficial trading opportunities exist between A and B, due to differences in their profiles of CCGTs. This is illustrated in Figure 39.

Figure 39: Mutually beneficial trading opportunities between firms A and B in the case of continuous marginal switching cost curves (as given by cost function (2.2))



We assume that A and B receive the same initial allocation of allowances for a given compliance period. We call this δ , and so the overall cap on CO₂ emissions is equal to 2δ . Moreover, we call e_i the level of CO₂ emissions (net of abatements) chosen by a firm i , where e_i is the difference between “uncontrolled”⁵³ emissions, u_i , and the switching effort, ξ_i , with $i = A, B$. As illustrated in Figure 39, A is more efficient than B in abating CO₂, and thus, for any given allowance price p , ξ_A is higher than ξ_B . On the one hand, it is advantageous for A to reduce its emissions, e_A , beyond the level prescribed by its initial endowment of allowances (i.e. A finds it beneficial to perform a higher level of switching effort), so as to sell unused allowances to B. This allows A to make profits by selling a volume of unused allowances equal to $\delta - e_A$ at a higher price than their switching costs. On the other hand, it is advantageous for B to increase its emissions, e_B , beyond the level prescribed by its initial endowment of allowances (i.e. B finds it beneficial to perform a lower level of switching effort), and buying to A the volume of lacking allowances equal to $\delta - e_B$. In fact, as long as the allowance price is below its marginal switching cost, B can reduce its compliance cost by buying allowances from A in order to increase its emissions. Here again, as in the case of a stepwise constant marginal switching cost, there are mutually beneficial trading opportunities between A and B because of differences in efficiency of their CCGTs.

53 “Uncontrolled” emissions correspond to “business-as-usual” emissions, i.e. CO₂ emissions before any effort of abatement.

4. The model

We consider a continuum of power producers whose carbon emissions are constrained by an emission trading scheme such as the EU ETS. Each firm, indexed by $i \in [0, 1]$, is assumed to be a price taker on the carbon market (i.e. the carbon market is competitive). In addition, we assume that each firm owns a fixed park of electricity generation plants⁵⁴ in which there are coal-fired plants, all of the same type, and different types of CCGTs (i.e. the CCGTs are not all equally energy efficient).

On the European carbon market, there are several years in a Phase. Theoretically, firms build a compliance strategy for each year, because at the end of each year they have to surrender a number of allowances equal to their carbon emissions recorded during the year in question. However, in practice, the EU ETS rule allowing permits to be borrowed from the following year for compliance in the current year,⁵⁵ enables firms in each year, to postpone the current emission constraint to the following year (for instance, it was possible at the end of 2008 to borrow from 2009 the number of permits necessary to cover the carbon emissions recorded in 2008). As a consequence, within a Phase, firms have the ability year by year to postpone the emission constraint of each year to the end of the last year of the Phase. So, carbon trading in a Phase works as if there were only one constraint per Phase.

We choose to set the time horizon considered by firms so that it corresponds to a Phase on the EU ETS where there are T periods, indexed by $t \in [1, \dots, T]$, in which firms make their decisions, and only one compliance constraint. At the end of period T , the authorities check that the number of allowances held by each firm is equivalent to its carbon emissions recorded throughout the Phase (i.e. during all the T periods). Therefore, at the end of period T , each firm will have to satisfy the following compliance constraint:

$$\sum_{j=1}^T u_{j,i} - \sum_{j=1}^T \xi_{j,i} = \delta_i + \sum_{j=1}^T \theta_{j,i},$$

where, for a firm i in a period t , $u_{t,i}$ stands for uncontrolled carbon emissions (i.e. carbon emissions before any abatement measures have been taken), $\xi_{t,i}$ is the number of tonnes of CO₂

⁵⁴ The number of power plants and the energy efficiency of each one cannot vary in the considered time interval.

⁵⁵ Within a Phase, permits can be borrowed from the next year only. For example, in 2005, permits could be borrowed from 2006, but not from 2007.

that have not been emitted thanks to fuel switching (the fuel switching effort) and $\theta_{t,i}$ represents the number of permits traded on the market (where $\theta_{t,i} > 0$ if permits are bought, and $\theta_{t,i} < 0$ if permits are sold). Finally, δ_i is the number of allowances allocated to a firm i for the whole Phase (known since the beginning of the first period). We assume that there is a single constraint on the total amount of emissions over the T time periods, and that all permits are issued at the beginning of first period. Therefore, firms can freely transfer permits across time periods, and thus, implicitly, banking and borrowing are allowed.⁵⁶

In each period t , in order to comply with the policy at the end of the Phase, firms can trade allowances on the secondary market (which is competitive) at a price p_t , or, alternatively, reduce their carbon emissions physically by switching from coal-fired plants to gas-fired plants. Accordingly, the overall compliance cost of a firm i in each period t is given by:

$$CT_i(\theta_{t,i}, \xi_{t,i}) = p_t \theta_{t,i} + C_i(\xi_{t,i}),$$

where $C_i(\xi_{t,i}) = \frac{1}{2} \xi_{t,i}^2 a_i G_t - \xi_{t,i} b C_t$ is the cost generated by the abatement of $\xi_{t,i}$ tonnes of CO₂ by means of fuel switching. Besides, in each time t , C_t is the coal price and G_t is the gas price. The cost function $C_i(\xi_{t,i})$ is given by equation (2.2). Thus, as explained in section 3 of this chapter, this corresponds to a situation where there is only one type of coal plants and different types of CCGTs. This assumption is justified because differences in the energy efficiency of power plants are much more important for CCGTs than for coal plants.⁵⁷ Accordingly, the coal price will have a constant influence on the marginal fuel switching cost, whatever the level of effort. By contrast, convexity in $C_i(\xi_{t,i})$ allows us to represent the rising dependence of the marginal cost of switching on the gas price, as the switching effort increases. Hence, the higher $\xi_{t,i}$ is, the higher the impact of G_t on the marginal cost of fuel switching is. Nevertheless, the influence of G_t on the marginal cost of fuel switching does not increase any more when $\xi_{t,i}$ is fixed.

In $C_i(\xi_{t,i})$, a_i is a firm-specific parameter measuring the efficiency of a given firm i to abate CO₂. The value of a_i depends on how efficient the CCGT plants of a given firm i are. That is a firm with a profile of CCGTs which is globally weakly efficient (e.g. a profile where most of the CCGTs are around 40% of efficiency) has a high value for a_i , so that this firm is weakly efficient to abate CO₂. On the contrary, a firm with a profile of CCGTs which is globally strongly efficient

⁵⁶ For a similar treatment, see Tietenberg [1985] and Slechten [2010].

⁵⁷ Note that Fehr and Hinz [2006] also assume one type of coal plants.

(e.g. a profile where most of the CCGTs are around 55% of efficiency) has a low value for a_i , so that this firm is strongly efficient to abate CO₂. Therefore, we assume that a_i can take any value between \underline{a} and \bar{a} (i.e. $a_i \in [\underline{a}, \bar{a}]$ where $i \in [0, 1]$ so that $\underline{a} \equiv a_0$ and $\bar{a} \equiv a_1$) with $\underline{a} < \bar{a}$. Note here that b has the same value in $C_i(\xi_{t,i})$, $\forall i$. This means that in addition to assuming that all the coal plants of each firm are all of the same type, we also assume that all the firms own the same type of coal plants.

Finally, in $C_i(\xi_{t,i})$, fuel prices are assumed to be exogenous variables. As a consequence, demand for fuels triggered by fuel switching is supposed to have no influence on fuel prices. Of course this hypothesis does not fully fit reality, but we think that it should be supported in some respects. First of all, the volume of carbon abatements that can be obtained by fuel switching is limited since, in each period, available gas capacities are limited too. This implies that fuel markets should not be very strongly affected by changes in demands for fuels created by the EU ETS. Secondly, European fuel markets are highly integrated into world markets since more than half of fuels consumed in European countries are imported from outside of Europe (see Hintermann [2010]). At the same time, demand for fuels of European power producers is relatively small compared to overall quantities consumed throughout the world. Therefore, variations in fuel demands for switching purposes should not be of great importance for world fuel prices and then for European fuel prices.

In each period t , the problem of a firm i is to choose $\xi_{t,i}$ and $\theta_{t,i}$ to minimize the cost of compliance in such a way that the firm will comply with the compliance constraint at the end of period T . At the beginning of each period t , a firm observes p_t , C_t , G_t , $u_{t,i}$, δ_i and D , the overall number of allowances allocated to all firms for the Phase. In addition, p_j , C_j , G_j , $\xi_{j,i}$, $\theta_{j,i}$ and $u_{j,i}$ are also known $\forall j \in \{1, \dots, t-1\}$. However, $p_{j'}$, $C_{j'}$, $G_{j'}$, $\xi_{j',i}$, $\theta_{j',i}$ and $u_{j',i}$ are unknown $\forall j' \in \{t+1, \dots, T\}$. In that case, these are stochastic variables whose exact values are known only at the beginning of the period j' in question. We will note them $\overline{p}_{j'}$, $\overline{C}_{j'}$, $\overline{G}_{j'}$, $\overline{\xi}_{j',i}$, $\overline{\theta}_{j',i}$ and $\overline{u}_{j',i}$.⁵⁸

Firms solve an optimization problem in each period t , where their decisions depend on the realizations of stochastic state variables that are uncontrolled carbon emissions and fuel prices. Moreover, they have to take into account the optimal decisions from the future and from the past. Therefore, they have to deal with a dynamic optimization problem, and we choose to solve it by

58 From a period $t-s$ ($\forall s > 0$) we will note \tilde{v}_t any random variable v_t whose realization is known at the beginning of t . Moreover, we will note $E_{t-s}[\tilde{v}_t] = \bar{v}_t$ the expected value of \tilde{v}_t in $t-s$.

backward induction.

4.1. Equilibrium strategies of firms

Given that the equilibrium solution will be obtained by backward induction, we have to begin the resolution with the last period of the Phase. In period T , each firm achieves its optimal strategy by solving the problem:

$$\begin{aligned} \min_{\theta_{T,i}, \xi_{T,i}} \quad & CT_i(\theta_{T,i}, \xi_{T,i}) = p_T \theta_{T,i} + C_i(\xi_{T,i}) \\ \text{s.t.} \quad & \sum_{j=1}^T u_{j,i} - \sum_{j=1}^T \xi_{j,i} = \delta_i + \sum_{j=1}^T \theta_{j,i} \end{aligned}$$

where $C_i(\xi_{T,i}) = \frac{1}{2} \xi_{T,i}^2 a_i G_T - \xi_{T,i} b C_T$ is the cost of abatement by fuel switching and $CT_i(\theta_{T,i}, \xi_{T,i})$ is the total cost of compliance.

Solving this problem, we get the *least cost solution* which yields the optimal effort condition,

$$\xi_{T,i} = \frac{p_T + b C_T}{a_i G_T}. \quad (2.3)$$

According to (2.3) the optimal effort is an increasing function of coal and permit prices, while it is a decreasing function of the gas price. These relations can be readily understood by considering that the switching effort is a substitute for coal consumption and the purchasing of permits, whereas it entails an increase in gas consumption. Moreover, we see that the optimal switching effort is a decreasing function of a_i . It means that firms with a higher efficiency to abate CO₂ make a higher switching effort for any given prices p_T , C_T and G_T .

Combining (2.3) and the compliance constraint, we derive the expression for the optimal demand of allowances in the last period,

$$\theta_{T,i} = \sum_{j=1}^T u_{j,i} - \sum_{j=1}^{T-1} \xi_{j,i} - \sum_{j=1}^{T-1} \theta_{j,i} - \delta_i - \frac{p_T + b C_T}{a_i G_T}. \quad (2.4)$$

Unsurprisingly, permit demand increases with the gas price and decreases with the coal price. The reason is that firms reduce their demand for coal when the coal price goes up relatively to the price

of gas. Therefore, as gas consumption increases, carbon emissions decline and demand for allowances falls off.

Now, we introduce the condition that the carbon market has to satisfy in order to be in equilibrium in each period. Such a market clearing condition states that at any period, a permit purchased by one firm has to be sold by another firm, so that the sum of all permits bought and sold will be equal to zero. So we have:

$$\int_0^1 \theta_{t,i} di = 0, \quad \forall t \in [1, \dots, T].^{59}$$

Integrating (2.4) on $[0,1]$ and applying the market clearing condition to each period, we get:

$$p_T = a G_T \left[\sum_{j=1}^T u_j - \sum_{j=1}^{T-1} \Xi_j - D \right] - b C_T, \quad (2.5)$$

where $D = \int_0^1 \delta_i di$, $u_t = \int_0^1 u_{t,i} di$, $\Xi_t = \int_0^1 \xi_{t,i} di$ and $a = \int_0^1 a_i di$.

In (2.5), u_j stands for aggregate uncontrolled carbon emissions recorded during a period j , D is the sum of the allocations of allowances for all firms for all the T periods (this is the aggregate cap on CO₂ emissions) and Ξ_j represents the aggregate fuel switching effort by firms for a period j .

We can now turn to period $T-1$. In this period, firms have to solve the following problem:

$$\begin{aligned} \min_{\theta_{T-1,i}, \xi_{T-1,i}} \quad & CT_i(\theta_{T-1,i}, \xi_{T-1,i}) = p_{T-1} \theta_{T-1,i} + C_i(\xi_{T-1,i}) + \beta E_{T-1} [\widetilde{p}_T \widetilde{\theta}_{T,i} + C_i(\widetilde{\xi}_{T,i})] \\ \text{s.t.} \quad & \sum_{j=1}^{T-1} u_{j,i} + \widetilde{u}_{T,i} - \sum_{j=1}^{T-1} \xi_{j,i} - \widetilde{\xi}_{T,i} = \delta_i + \sum_{j=1}^{T-1} \theta_{j,i} + \widetilde{\theta}_{T,i} \end{aligned}$$

where $C_i(\xi_{t,i}) = \frac{1}{2} \xi_{t,i}^2 a_i G_t - \xi_{t,i} b C_t$ with $t = T-1, T$ and $\beta = \left(\frac{1}{1+r} \right)$ is a discount factor (where r is a constant risk-less interest rate).

59 For proof of the existence of this intertemporal equilibrium, see Rubin [1996]. In addition, Rubin [1996] shows that this intertemporal equilibrium is efficient (i.e. it corresponds to the least cost solution).

We consider arbitrary price changes for allowances which are exogenous for firms. Then we assume that the percentage change in allowance prices per unit of time equals the interest rate: $(p_{t+1} - p_t)/p_t = r$ so that $p_t = \beta p_{t+1}$ (and so $p_t = \beta p_{t+1}^-$ with $E_t[p_{t+1}] = p_{t+1}^-$), $\forall t$, where $\beta = 1/(1+r)$ is a discount factor and r is a constant risk-less interest rate. As pointed out in Rubin [1996] (see also Kling and Rubin [1997]), assuming this kind of changes for allowance prices is equivalent to assuming that the firm buys or sells an intermediate number of allowances in each period (i.e. this is equivalent to assuming a non-bounded solution over the entire time horizon).⁶⁰ Without this assumption, it would be optimal to buy as many permits as possible if $p_t < \beta p_{t+1}^-$, or buy zero permits (and sell as many permits as possible) if $p_t > \beta p_{t+1}^-$. Thus, this assumption is a necessary technical requirement to avoid corner solutions.⁶¹

Combining (2.3) and the compliance constraint of $T-1$,⁶² we get the expression of the optimal value of $\widetilde{\theta}_{T,i}$ (the demand for allowances in T seen from $T-1$). Replacing this expression in $CT_i(\theta_{T-1,i}, \xi_{T-1,i})$ we can write:

$$CT_i(\theta_{T-1,i}, \xi_{T-1,i}) = \theta_{T-1,i}(p_{T-1} - \beta \bar{p}_T) - \beta \bar{p}_T \xi_{T-1,i} + C_i(\xi_{T-1,i}) \\ + \beta \bar{p}_T \left(\sum_{j=1}^{T-1} u_{j,i} + \widetilde{u}_{T,i} - \sum_{j=1}^{T-2} (\xi_{j,i} + \theta_{j,i}) - \delta_i \right) - \beta \bar{p}_T \frac{\bar{p}_T + b \bar{C}_T}{a_i \bar{G}_T} + \beta C_i(\xi_{T,i}) .$$

Minimizing, we obtain the *least cost solution*: $p_{T-1} = C'_i(\xi_{T-1,i})$. Then we deduce the optimal effort in $T-1$:

$$\xi_{T-1,i} = \frac{p_{T-1} + b C_{T-1}}{a_i G_{T-1}} . \quad (2.6)$$

Using (2.6) with the compliance constraint, we get the optimal demand for allowances in $T-1$:

$$\theta_{T-1,i} = \sum_{j=1}^{T-1} u_{j,i} + \widetilde{u}_{T,i} - \sum_{j=1}^{T-2} \theta_{j,i} - \widetilde{\theta}_{T,i} - \delta_i - \sum_{j=1}^{T-2} \xi_{j,i} - \frac{p_{T-1} + b C_{T-1}}{a_i G_{T-1}} - \frac{\bar{p}_T + b \bar{C}_T}{a_i \bar{G}_T} .$$

60 Without this assumption, it would be necessary to set bounds on the maximum number of permits that can be bought and sold in each time period, to avoid corner solutions (see section 2 of this Chapter). See Rubin [1996].

61 In a discrete-time setting, Tietenberg [1985] showed that the rate of increase in permit prices would be equal to the interest rate in order to achieve a competitive equilibrium which corresponds to the least-cost solution.

62 Note here that the compliance constraint is the same in each period, since we have only one compliance constraint for the Phase. The compliance constraint of any period $t < T$ ($T-1$ in the current case) is nothing else than the compliance constraint of T seen from t .

Integrating on $[0,1]$ and applying the market clearing condition to each period, we obtain:

$$\frac{p_{T-1} + bC_{T-1}}{aG_{T-1}} = \sum_{j=1}^{T-1} u_j + \bar{u}_T - D - \sum_{j=1}^{T-2} \Xi_j - \frac{\bar{p}_T + b\bar{C}_T}{a\bar{G}_T} . \quad (2.7)$$

If we assume that the carbon, coal and gas markets are efficient with respect to information, current prices fully incorporate all information concerning their future values. Therefore, in that context, we have the following three conditions: $p_{T-1} = \beta E_{T-1}[\bar{p}_T] = \beta \bar{p}_T$, $G_{T-1} = \beta E_{T-1}[\bar{G}_T] = \beta \bar{G}_T$ and $C_{T-1} = \beta E_{T-1}[\bar{C}_T] = \beta \bar{C}_T$.⁶³ Finally, taking the expectation of (2.7) and using the last three conditions, we get⁶⁴ :

$$p_{T-1} = \frac{1}{2} \cdot a G_{T-1} \left[\sum_{j=1}^{T-1} u_j + \bar{u}_T - \sum_{j=1}^{T-2} \Xi_j - D \right] - b C_{T-1} . \quad (2.8)$$

As expected, the permit price increases with the gas price and decreases with the coal price. This result is well documented in the literature and is explained by the fuel switching behavior of power producers. More interestingly, we see that the difference between uncontrolled carbon emissions (past, present and future) and the cap (D) influences the relation between the gas price and the price of allowances. Indeed in (2.8), the bracketted term (which determines the dependence of p_{T-1} on G_{T-1}) increases when uncontrolled emissions increase with respect to D . This evolution in the relation between the gas price and the allowance price is explained by the fact that firms substitute ever less efficient gas plants for previously used coal plants, as the fuel switching effort rises. This mechanism will be described more precisely later in Proposition 2.

Still in the bracketted term, the presence of $\sum_{j=1}^{T-2} \Xi_j$ shows that the higher the past switching efforts are, the smaller the impact of G_{T-1} on p_{T-1} is. The reason is that, all other things being equal, in order to attain the (expected) needed level of carbon abatement for the Phase (i.e. the level needed to comply with the cap-and-trade during the current Phase), efforts during present and future periods will be as low as efforts made in the past have been high. Consequently, if past efforts have been quite substantial, subsequent efforts are expected to be relatively small. That leads to diminished influence of the gas price on the price of allowances, because gas plants that will be used will be more efficient if switching efforts are lower.

63 For more details on the efficiency of markets, see Fama [1965] and Malkiel [2003].

64 For simplicity, we assume that all the random variables \bar{C}_t , \bar{G}_t , \bar{u}_t and \bar{p}_t are independent $\forall t$.

As for **(2.8)** in period $T-1$, we can find the backward induction solution of any period $t \in [1, \dots, T-1]$, given that we know the solutions of subsequent periods. Therefore, we decide to skip the chain of the solution and to consider directly the case of a period t that may be anywhere between the first period and $T-1$. In such a period, firms have to solve the problem:

$$\begin{aligned} \min_{\theta_{t,i}, \xi_{t,i}} \quad & CT_t(\theta_{t,i}, \xi_{t,i}) = p_t \theta_{t,i} + C_t(\xi_{t,i}) + \sum_{j=t+1}^T \beta^{j-t} E_t[\bar{p}_j \bar{\theta}_{j,i} + C_i(\bar{\xi}_{j,i})] \\ \text{s.t.} \quad & \sum_{j=1}^t u_{j,i} + \sum_{j=t+1}^T \bar{u}_{j,i} - \sum_{j=1}^t \xi_{j,i} - \sum_{j=t+1}^T \bar{\xi}_{j,i} = \delta_i + \sum_{j=1}^t \theta_{j,i} + \sum_{j=t+1}^T \bar{\theta}_{j,i} \end{aligned}$$

where $C_t(\xi_{t,i}) = \frac{1}{2} \xi_{t,i}^2 a_i G_t - \xi_{t,i} b C_t$ and $E_t[C_i(\bar{\xi}_{j,i})] = \frac{1}{2} \bar{\xi}_{j,i}^2 a_i \bar{G}_j - \bar{\xi}_{j,i} b \bar{C}_j$ with $j = t+1, \dots, T$ and $\beta = \left(\frac{1}{1+r} \right)$.

Following the same strategy as for the resolution in $T-1$, we get

$$\frac{p_t + b C_t}{a G_t} = \sum_{j=1}^t u_j + \sum_{j=t+1}^T \bar{u}_j - \sum_{j=1}^{t-1} \Xi_j - D - \frac{\sum_{j=t+1}^T \bar{p}_j + b \sum_{j=t+1}^T \bar{C}_j}{a \sum_{j=t+1}^T \bar{G}_j}, \quad (2.9)$$

which is analogous to **(2.7)** in $T-1$.

Again, we use the market efficiency argument by extending it to a context where there are more than two periods. Then, if the coal, gas and carbon markets are efficient with respect to information, we have the following conditions: $p_t = \beta^s E_t[\bar{p}_{t+s}] = \beta^s p_{t+s}^-$, $G_t = \beta^s E_t[\bar{G}_{t+s}] = \beta^s G_{t+s}^-$ and $C_t = \beta^s E_t[\bar{C}_{t+s}] = \beta^s C_{t+s}^-$, $\forall s > 0$. Hence, taking the expectation of **(2.9)** and using the last three conditions, we obtain:

$$p_t = \frac{1}{T-t+1} a G_t \left[\sum_{j=1}^t u_j + \sum_{j=t+1}^T \bar{u}_j - D - \sum_{j=1}^{t-1} \Xi_j \right] - b C_t, \quad (2.10)$$

which is the generalization of **(2.8)** for any period t such that $t \in [1, \dots, T-1]$. As before, the impact of the gas price on the price of allowances depends on the situation of uncontrolled emissions (past, present and future) with respect to the emission cap. It also depends on the past switching efforts.

Before going further in the resolution, let us present a first result which is reached by comparing (2.10) and (2.5). It is summarized in the following proposition:

PROPOSITION 1

Shocks that can affect the price of gas and uncontrolled carbon emissions have a stronger impact on the price of allowances if they occur in a period t which is closer to the last period (T).

Proof: the value of $\frac{1}{T-t+1}$ in (2.10) is an increasing function of t . \square

Previous studies have shown that the allowance price becomes more sensitive to shocks on uncontrolled carbon emissions when we move toward the last period of the Phase.⁶⁵ The result of Proposition 1 shows that the same pattern holds for the gas price influence.

As briefly explained for (2.8), the allowance price becomes more dependent on the gas price when uncontrolled emissions increase (since the fuel switching effort rises, and so dirtier gas plants are used). Proposition 1 also states that a positive shock on uncontrolled emissions will lead to an even greater dependence of the allowance price on the gas price if this shock occurs in a period which is close to T . The logic arises from the fact that the ability to adapt to a rise in uncontrolled emissions is smaller in periods that are close to the end of the Phase. Indeed, efforts that might be necessary between t and T are more difficult to postpone until later in the Phase when t is close to T . Therefore, the perspective of having to perform a major switching effort in this small time interval will make the abatement cost more sensitive to the gas price.

Likewise, we can also argue that if a shock appears in a period which is close to T , the probability that it will be neutralized by an opposite shock in a later period is smaller (because of a small time interval between t and T), and so it has a stronger impact. Consequently, in order to deal with such a positive shock, many firms will be willing to buy allowances at a higher price (higher than if they were in a period located sooner in the Phase). As a result, the market value of the switching effort will increase, leading to a gas rush for firms that can perform carbon abatements by switching fuels. That is why the allowance price will be more dependent on the gas price in this situation.⁶⁶

Note here that the gas price and the bracketted term in (2.10) have a weaker impact on the allowance price when the value of T increases. This is interesting because it shows consequences for

⁶⁵ See Seifert et al. [2008], and Hintermann [2010].

⁶⁶ Imagine that uncontrolled emissions increase suddenly and unexpectedly in the last period of the Phase. In such a situation, a lot of firms will want to buy permits before the end of the period. Therefore, the market value of the switching effort will rise, given that permits can be sold at a higher price. This will increase the attractiveness of gas and, finally, the dependence of the allowance price with respect to the gas price.

the model of the transition from the regime of relationships between Phase 1 and Phase 2 to the regime of relationships between Phase 2 and Phase 3. Whereas banking and borrowing were not allowed between Phase 1 and Phase 2, it is possible to bank allowances in Phase 2 to use them in Phase 3. Borrowing permits between Phase 2 and Phase 3 is still forbidden. However, an “implicit” (one-year-) borrowing of allowances may occur between two Phases (see Mansanet-Bataller and Pardo [2008a]).⁶⁷ Thus, firms could implicitly borrow allowances between Phase 2 and Phase 3. Therefore, one can consider that both banking and borrowing are possible between Phase 2 and Phase 3. Hence, Phase 2 and Phase 3 would be regarded as a single Phase, which corresponds to a higher value for T (i.e. single $T = T$ for Phase 2 + T for Phase 3). Therefore, the gas price and uncontrolled emissions have a weaker influence on the allowance price since carbon abatements can be smoothed on a larger time interval.

4.2. Equilibrium solution

In (2.10) some values are endogenous to the model. Therefore, in order to get an expression that depends on exogenous variables alone, we run an iterative algorithm that uses (2.10) by starting from the first period.

Applying (2.10) to the first two periods, we obtain two equations for p_1 and p_2 . Afterwards,

as $\Xi_t = \frac{p_t + b C_t}{a G_t}$, $\forall t \in [1, \dots, T]$, we can substitute p_1 in p_2 . We then get the full expression for

p_2 :

$$p_2 = a G_2 \left[\frac{1}{T} u_1 + \frac{1}{T-1} u_2 - \frac{1}{T(T-1)} \bar{u}_2 + \frac{1}{T} \sum_{j=3}^T \bar{u}_j - \frac{1}{T} D \right] - b C_2.$$

Continuing the same process for the following periods, we get a chain of equations

$\{p_1, p_2, \dots, p_{T-1}\}$ that enables us to deduce the full solution for any period t in the interval.⁶⁸ That

⁶⁷ According to Mansanet-Bataller and Pardo [2008a], the EU ETS rules (penalty with restitution) leads to the existence of implicit borrowing between two Phases. The “implicit borrowing” is produced if there is non-compliance at the end of the last year of a Phase. In this case, non-compliant firms have to surrender lacking allowances in the following year (in addition to paying penalties), which is in the next Phase. Thus, the only possibility is that the restitution of lacking allowances is done with allowances from the next Phase. Therefore, there may exist an implicit (one-year-) borrowing between two Phases.

⁶⁸ It is possible to show by recurrence that (2.11) stands for any period between $t=1$ and $T-1$. The proof is in Appendix A.

is:

$$p_t = a G_t \left[\sum_{j=1}^t \left(\frac{1}{T-j+1} u_j - \frac{j-1}{T(T-j+1)} \bar{u}_j \right) + \frac{1}{T} \sum_{j=t+1}^T \bar{u}_j - \frac{1}{T} D \right] - b C_t. \quad (2.11)$$

The remainder of this section will discuss the results that follow from (2.11). They are summarized in the next propositions.

PROPOSITION 2

In each period t , the influence of the price of gas on the price of allowances increases when the level of past, present and future uncontrolled emissions increases with respect to the cap on carbon emissions.

Proof: the bracketted term in (2.11) is increasing with respect to u_j , $\forall j \in [1, \dots, t]$, and \bar{u}_j , $\forall j \in [t+1, \dots, T]$, whereas it is a decreasing function of D . \square

The result in Proposition 2 contributes to the literature on carbon markets by showing that prices of fuels and uncontrolled carbon emissions can exert a combined influence on the price of allowances. Until now, some authors have shown that the allowance price is an increasing function of the gas price and a decreasing function of the coal price.⁶⁹ Others have found, in theoretical models, that the allowance price depends on the level of uncontrolled emissions.⁷⁰ However, to the best of our knowledge, no one has found that the gas price and uncontrolled carbon emissions can act together on the price of allowances, as in Proposition 2. This result is the consequence of the fuel switching behavior of power producers, in a context where gas plants do not all have the same energy efficiency. Indeed, the fuel switching process that we describe implies that ever less efficient gas plants are substituted for coal plants when the switching effort increases. In such circumstances, when uncontrolled emissions increase, the increased switching effort required will entail increased gas consumption to abate each tonne of CO₂. Accordingly, the cost of the gas consumption necessary to abate one tonne of CO₂ will increase with uncontrolled emissions (i.e. with the switching efforts made in response to rising uncontrolled emissions), leading to a greater sensitivity of the marginal cost of the switching effort with respect to the gas price. As a consequence, the price

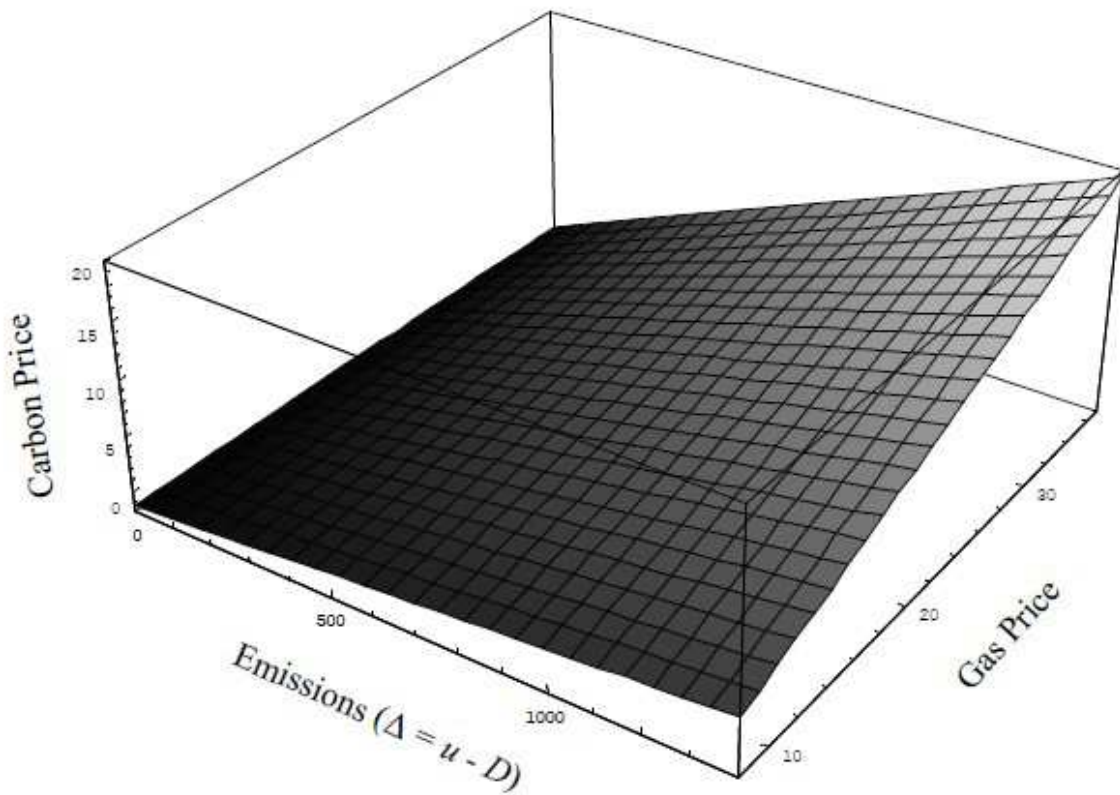
⁶⁹ For theoretical models, see Fehr and Hinz [2006] and Delarue et al. [2007]. Mansanet-Bataller et al. [2007] and Alberola et al. [2008] verified these relations in econometric studies for the EU ETS.

⁷⁰ See Maeda [2004], Seifert et al. [2008], and Hintermann [2010].

of allowances will depend more heavily on the gas price. In fact, Proposition 2 shows that the price of allowances increases with the level of uncontrolled emissions for two reasons: a reduced supply of permits (because the cap becomes more stringent) and a rising gas cost for switching efforts.

To illustrate Proposition 2, Figure 40 plots the carbon price, p_t , as a function of the gas price, G_t , and the total uncontrolled emissions over the Phase, u .

Figure 40: Surface representing the influence of the gas price on the carbon price depending on the level of past, present and future uncontrolled emissions. The graph is based on equation (2.11) taken in $t = 1$.



In Figure 40, we applied equation (2.11) in $t = 1$ in order to plot the solution.⁷¹ Thus, we obtained:

$$p_1 = a G_1 \left[\frac{1}{T} (u - D) \right] - b C_1,$$

where $u = u_1 + \sum_{j=2}^T \bar{u}_j$. Parameters were chosen so as to illustrate the position of the power sector

⁷¹ Applying the solution in $t = 1$ enables us to simplify the expression because, in this case, there are no ex post forecasting errors on uncontrolled carbon emissions. See Proposition 3 below.

in Phase 2 (see Table 12).

Table 12: Allocated allowances and verified emissions of the power sector in Phase 2 of the EU ETS. CITL data, available at <http://dataservice.eea.europa.eu/PivotApp/pivot.aspx?pivotid=473>.

	Allocated allowances ^a	Verified emissions ^{a,b}
2008	1199	1439
2009	1207	1319
2010	1222	1347
2011	1200	1345
2012	1200	1345
Total	$D = 6028$	$u = 6795$

^a We use verified emissions as a proxy for uncontrolled emissions.

^b Values for 2011 and 2012 are fixed arbitrarily so as to be approximately equal to values of 2010.

The value of T has been fixed at 5 to remind the five years in Phase 2.⁷² Moreover, we took 9.3 as value for the coal price.⁷³ Finally, using price data for coal (in Euros per thermal MWh), gas (in Euros per thermal MWh) and EUAs (in Euros per tonne of CO₂), from February 26, 2008 to October 30, 2009 (data are presented in Appendix B), with $\Delta = u - D = 767$ (see Table 12) and $T = 5$, we estimated parameters a and b (with the OLS and maximum likelihood methods). We obtained: $a = 0.002$ and $b = 0.13$.

In Figure 40, the dependence of the carbon price on the gas price appears in the slope of the G -directional characteristic curves (i.e. straight lines, in this case). Moving along the Δ -axis, when uncontrolled emissions increase, we observe an increasing G -directional steepness. In other words, the slope of the G -directional characteristic curves increases when uncontrolled carbon emissions increase. This reflects the fact that the influence of the gas price on the carbon price increases when the level of past, present and future uncontrolled emissions increases with respect to the cap on emissions (i.e. when $\Delta = u - D$ increases).

72 This means that each time period t corresponds to one year. Alternatively, one can consider that each t corresponds to a quarter ($T=15$), a month ($T=60$), etc. However, as data in Table 12 are yearly data, we chose to consider that $T=5$. Note that running the solution with $T=5$ and parameters a and b estimated with $T=5$ yields the same result as running the solution with $T=15$ (or any other T) and parameters a and b estimated with $T=15$ (or any other T).

73 We took $\bar{C} = 9.3$, which corresponds to the average coal price (in Euros per thermal MWh) between February 26, 2008 and October 30, 2009. See Appendix B for presentation of data.

Here, it is interesting to note that using another terminology, Proposition 2 can be seen as proof that we move higher in the *switching band* (i.e. we use dirtier gas plants with a higher *switching price*),⁷⁴ when uncontrolled carbon emissions increase. As a consequence, the allowance price becomes more dependent on the gas price.

Propositions 1 and 2 are of a great interest because together they show that in each period t , it is the intersection between the volume of uncontrolled carbon emissions (from the past, present and future) and the time of occurrence in the Phase of the current period (i.e. the temporal location of t in the Phase) that determines the sensitivity of the allowance price with respect to the gas price.

We have just seen that uncontrolled carbon emissions are of great importance for the allowance price. In the following proposition we go further in the description of the influence of carbon emissions.

PROPOSITION 3

In each period t , it is ex post forecasting errors concerning past and current uncontrolled carbon emissions that affect the allowance price, rather than their levels alone.

Proof: in (2.11), $\forall j \in [1, \dots, t]$, these are differences between u_j and \bar{u}_j which determine the influence of past and current uncontrolled emissions on the value of the bracketted term, and not only the u_j alone.⁷⁵ \square

Proposition 3 completes Proposition 2 by showing that for past and current periods, it is ex post forecasting errors on uncontrolled carbon emissions (and not only their observed values) that determine the sensitivity of the allowance price with respect to the gas price. Some authors have already shown that errors of forecasting concerning carbon emissions can influence, ex post, the allowance price.⁷⁶ We find, in addition, that this has an impact on the relation between the gas price and the price of allowances.

⁷⁴ As there is a switching price for any given pair of plants, the collection of all switching prices creates a *switching band*. For more details, see Delarue et al [2008].

⁷⁵ Let A and B be the terms in factor of, respectively, u_j and \bar{u}_j , $\forall j \in [1, \dots, t]$. We see that $A > B$, $\forall j \in [1, \dots, t]$, so that if we have $u_j \geq \bar{u}_j$, then necessarily $A u_j - B \bar{u}_j > 0$.

⁷⁶ See Maeda [2004] and Hintermann [2010] for theoretical models. For econometric studies on data from the EU ETS, see Mansanet-Bataller et al. [2007], Alberola et al. [2008] and Hintermann [2010].

The timing of the current period within the Phase may be important. However, for past uncontrolled emissions, the timing of the periods in which they occurred may also matter. This is described in the following proposition.

PROPOSITION 4

In each period t , the more recent a given past period is, the stronger the impact of the forecasting error on uncontrolled emissions that occurred in this period is.

Proof: in (2.11), values of the terms in factor of u_j and \bar{u}_j , $\forall j \in [1, \dots, t]$, increase when we consider a period j which is closer to period t .⁷⁷ \square

Proposition 4 indicates that past uncontrolled carbon emissions have a weaker influence on the price of allowances of period t (and on the relation between allowance and gas prices in this period) when they come from a distant past with respect to the current period. The reason is that when we consider a distant past period with respect to period t , the time interval between t and this past period is large enough to enable firms to smooth their carbon abatement efforts across periods. As a result, the proportion of the whole switching effort (to be made in response to uncontrolled emissions of the past period in question) will be smaller in period t , given that this effort has been spread out over a large number of periods. In other words, when we consider a distant past period firms have had a lot of time to adapt to uncontrolled emissions that occurred in that period. That is why these past uncontrolled emissions will not have a strong impact on the present.

The result of Proposition 4 can also be explained by the fact that the probability that a shock on a past u_j should be neutralized by an opposite shock on a subsequent $u_{j'}$ (where $j < j' \leq t$) is smaller when we consider a period j which is close to t (because of the small time interval between j and t). Accordingly, uncontrolled emissions of a recent past period will have a stronger impact on the present.

⁷⁷ As before we call A and B the terms in factor of, respectively, u_j and \bar{u}_j , $\forall j \in [1, \dots, t]$. So, $\partial A / \partial j > 0, \forall j$, and $\partial B / \partial j > 0, \forall j$ when $T \geq 1$.

5. Conclusion

In this Chapter, we have studied the implication of the fuel switching behavior of power producers for the relation between gas and allowance prices in a context where gas plants are not all equally efficient. In section 2, we have reviewed theoretical papers dealing with modeling of emission allowance markets. In section 3, we have introduced a cost function for fuel switching which exhibits the properties we discussed in Chapter 1 regarding the influence of efficiency of power plants. We have also demonstrated that mutually beneficial trading opportunities may exist among power producers that own different types of CCGTs.

In section 4, we have built a tractable equilibrium model which has enabled us to observe the impact of fuel switching in a context where CCGTs are not all equally efficient. Our main finding is that the influence of the gas price on the price of allowances depends on the level of uncontrolled carbon emissions from the past, the present and the future. This is because power producers tend to substitute, in the fuel switching process, less and less efficient gas plants for coal plants that were previously used, as the fuel switching effort increases. As a consequence, when the switching effort intensifies, more gas must be consumed to abate one tonne of CO₂ by fuel switching, which leads to having the gas price a greater influence on the marginal cost of fuel switching.

Other authors have already shown that uncontrolled carbon emissions and prices of fuels influence the price of allowances. However, our study goes further by showing that these variables can act together. Therefore, a rise in uncontrolled carbon emissions will affect the allowance price, not only because it makes the constraint on carbon emissions more stringent (since it reduces the number of allowances available on the market), but also because it induces a rising cost for the gas consumption needed to abate one tonne of CO₂ by switching fuels from coal to gas.

Beyond pure theoretical considerations, the results of this paper may have practical implications. Indeed, having ascertained that the correlation between fuel and carbon prices may vary over time depending on the level of uncontrolled carbon emissions, carbon market traders may want to take advantage of this either for hedging⁷⁸ or for speculative purposes.

⁷⁸ Power producers should want to hedge their businesses against the risk of a greater exposure of electricity and carbon markets with respect to the gas price in the event of an unexpected rise in carbon emissions. For a review on hedging in the power industry, see Unger [2002] and Reinaud [2007].

Chapter 3

Interactions between carbon and energy prices: theories and evidence in Phase 2 of the EU ETS

This chapter examines the interplay between energy markets and the European Union Emission Trading Scheme (EU ETS) during the first two years of Phase 2. We use an empirical methodology that enables us to study relationships between carbon, coal, gas and electricity prices. Estimating a Vector Error Correction Model (VECM), we investigate short- and long-run relationships between these prices. The analysis also includes Granger causality tests and impulse response functions. The results show evidence of both short- and long-run interactions with, notably, a significant link between carbon and gas prices in the equilibrium.

1. Introduction

In ratifying the Kyoto Protocol, the European Union committed itself to reducing its greenhouse gas emissions by 8% relative to the 1990 level in the first Kyoto commitment period (2008-2012). In January 2005, to meet this target in a cost-effective way, the European Union established the European Union Emission Trading Scheme (EU ETS), a cap-and-trade system for carbon emissions in the energy and industrial sectors. The power sector's strong influence on the EU ETS means carbon abatement decisions by European electricity producers are of major importance. In countries where electricity is mostly generated by burning fossil fuels (e.g. Germany, Spain, the UK, etc), the power sector is particularly influential due to massive carbon emissions and resulting high levels of allowance allocations.

Relationships between carbon, electricity and fuel markets have been investigated in several papers (see section 2 of Chapter 1 for an extensive literature review). Many of them have found empirical evidence showing that coal and gas prices are particularly relevant in explaining the carbon price fluctuations on the EU ETS (see Kanen [2006], Mansanet-Bataller et al. [2007], Alberola et al. [2008], Rickels et al. [2007], Hintermann [2010] and Rickels et al. [2010]). This is explained by power producers' ability to substitute (cleaner) gas-fired plants for (dirtier) coal-fired plants in power generation, thereby reducing carbon emissions (see Sijm et al. [2005], Kanen [2006], Delarue and D'haeseleer [2007] and Delarue et al. [2007]). This phenomenon is known as *fuel switching*. Econometric studies focusing on dynamic interactions between carbon, coal and gas prices have also been of growing interest in the last few years. Papers on this topic include Bunn and Fezzi [2007], Fell [2008], Mansanet-Bataller and Soriano [2009], Bonacina et al. [2009], Keppler and Mansanet-Bataller [2010], Nazifi and Milunovich [2010] and Creti et al. [2012]. By contrast, theoretical studies analysing these relationships are very scarce (see Delarue and D'haeseleer [2007], Fehr and Hinz [2006] and Bertrand [2010]).

Interactions between carbon and electricity prices have been one of the most investigated issues since the launching of the EU ETS. In particular, the impact of the carbon price on electricity prices has been a source of intense debates and controversy. Despite the free allocation of carbon allowances, the carbon cost can be considered as an opportunity cost (since otherwise allowances would be sold), and this opportunity cost has been passed through to wholesale electricity prices, leading to windfall profits for power producers (see Sijm et al. [2005], Sijm et al. [2006] and Neuhoff et al. [2006]). This is known as the cost *pass-through* of carbon allowances. On the other hand, some authors argue that selling allowances on the carbon market also induces an opportunity cost for power producers with market power on the electricity market (see Keppler [2010]). In renouncing to produce in order to sell allowances, these producers have to abandon their rent in the electricity market. Thus selling allowances also entails an opportunity cost that may be passed through to the carbon price. This is referred to as *short-term rent capture*. The issue of dynamic interactions between carbon and electricity prices is thus very important, and it has been examined in several econometric studies. Papers on this topic include Bunn and Fezzi [2007], Zachmann and von Hirschhausen [2007], Chemarin et al. [2008], Fell [2008], Keppler and Mansanet-Bataller [2010] and Nazifi and Milunovich [2010].

Links between electricity, fuel and carbon markets are obviously tenuous. Economic theory provides several ways to address these questions. Basically, relationships between fuel, electricity and carbon markets are described by three theories: *pass-through*, *short-term rent capture* and *fuel switching*. The first two concern the interplay between electricity and carbon markets, while the third is relevant in explaining relationships between fuel (coal and gas) and carbon prices.¹ The aim of this chapter is to explore these three theories, in examining their relevance through an empirical approach. We apply a Vector Error Correction Model (VECM) that enables us to analyze short-run and equilibrium relationships between carbon, coal, gas, and electricity prices. From this model, we investigate the dynamic of interactions between these prices through Granger causality tests and impulse response functions.

To date, a few papers have studied Phase 2 of the EU ETS from an econometric point of view. With regard to dynamic interactions between carbon and energy markets (using a VAR-VECM framework with Granger causality), Keppler and Mansanet-Bataller [2010] and Creti et al. [2012] are the only contributions. Like them, we rely on Granger causality techniques. As in Keppler and Mansanet-Bataller [2010], we focus on relationships between carbon and energy markets. Our work extends Keppler and Mansanet-Bataller [2010] by considering a single model involving all the variables on which we implement our analysis. In doing so, we look at simultaneous interactions among all the variables.² In addition, we test for cointegration and we compute impulse response functions. More recently, Creti et al. [2012] have investigated relationships between the carbon price and some energy and non-energy variables in Phase 2.³ Similarly to those authors, we test for cointegration and we estimate a VECM on which we implement our Granger causality tests. Unlike Creti et al. [2012], we include the electricity price in our analysis. Moreover, we include both the coal and gas prices, while Creti et al. [2012] use the

1 For a detailed presentation of each one of these theories, see section 2 of Chapter 1.

2 Keppler and Mansanet-Bataller [2010] were the first to examine the interdependency between energy and carbon markets in Phase 2, using a VAR framework. However, they work on several bi-variate VARs (on which they run pairwise Granger causality tests) rather than looking at simultaneous interactions between all the variables in a single VAR.

3 This paper has been developed in parallel to our work. Like us, they investigate cointegration and Granger causality in Phase 2. A difference is that we focus on relationships between carbon and energy markets based on the three theories presented in Chapter 1. Thus, Contrarily to Creti et al. [2012], we do not use a stock price index. By contrast, we include the price of electricity while this variable is not taken into account in Creti et al. [2012]. Besides, we include both the coal and gas prices, while Creti et al. [2012] use the switching price. We adopt this strategy in order to disentangle the effects of coal and gas in fuel switching. Finally, Creti et al. [2012] run estimations for Phase 1 in order to extend previous cointegration analysis which did not take into account the structural break of Spring 2006. By contrast, we focus on Phase 2 (as in Bonacina et al. [2009] and Rickels et al. [2010]) for sake of comparisons with previous studies analyzing interactions between carbon, coal, gas and electricity prices in Phase 1.

switching price.⁴ Finally, a last difference is that we compute impulse response functions in addition to Granger causality.

In summary, compared to the previous literature, our contribution is threefold. First, we present an extensive literature review on relationships between carbon and energy markets (see Chapter 1). The aim is to identify the main issues around this topic and give a wide view of previous related work. Second, we apply a full VAR (Vector Autoregression)-VECM approach⁵ to study interdependency between carbon, coal, gas and electricity prices in Phase 2. We compare our results with those of similar papers for Phase 1. Thus, in addition to testing the relevance of the aforementioned theories, we ask which of the results for Phase 1 can be extended to Phase 2. Third, we run an impulse response analysis to complete Granger causality. This allows us to account for more complicated interactions than with Granger causality.

Among our main results, we find that there is a significant link between carbon and gas prices in the equilibrium. We also find that coal and gas prices appear to be sensitive to the carbon price in the short-run. This last result could be explained by the crisis.

The remainder of this chapter is organized as follows. In section 2 we present the econometric methods that will be used in our empirical analysis. Section 3 displays some preliminary statistics and introduces econometric specification that will be estimated. We also present, in this section, estimation results, diagnostics, and additional investigations based on the estimated model. To conclude, section 4 summarizes the main results.

4 We follow the same strategy as a literature developed in Phase 1 to analyze relationships between carbon, fuel and electricity prices in a VAR-VECM framework (using Granger causality and impulse response functions). Those papers include Bunn and Fezzi [2007], Zachmann and von Hirschhausen [2007], Fell [2008], Chemarin et al. [2008] and Nazifi and Milunovich [2010]. Keppler and Mansanet-Bataller [2010] can also be added in this literature. However, to the best of our knowledge, no previous work has proposed a VECM to analyze the interplay between carbon, coal, gas, and electricity prices in Phase 2.

5 VAR models are Vector Autoregressive models, while VECMs are Vector Error Correction Models. See section 2 of this chapter.

2. Vector Autoregressive and Vector Error Correction Models

This section introduces the analysis of vector autoregressive models (VARs) and vector error correction models (VECMs).⁶ Granger causality tests and impulse response functions are also presented. Finally, we describe the methodologies for testing the presence of cointegration among several non-stationary variables.

2.1. Vector autoregressive models

The VAR approach is commonly used for analyzing the dynamic of relationships among variables over time. In VAR modeling, every endogenous variable⁷ is a function of the lagged values of all the endogenous variables in the system. Hence, a VAR is a multivariate system of regression models (i.e. there is more than one dependent variable) where each endogenous variable in the system depends on a combination of the previous k values of these endogenous variables.

A basic VAR model with a set of g variables and k lags (VAR(k)) has the form

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \dots + A_k Y_{t-k} + \varepsilon_t, \quad (3.1)$$

$$\text{where } Y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{g,t} \end{pmatrix}, A_0 = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_g \end{pmatrix}, A_k = \begin{pmatrix} a_{11,k} & a_{12,k} & \dots & a_{1g,k} \\ a_{21,k} & a_{22,k} & \dots & a_{2g,k} \\ \vdots & \vdots & \dots & \vdots \\ a_{g1,k} & a_{g2,k} & \dots & a_{gg,k} \end{pmatrix} \text{ and } \varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{g,t} \end{pmatrix}.$$

Y_t is a ($g \times 1$) vector with g endogenous variables, A_0, A_1, \dots, A_k are matrices of coefficients to be estimated (the A_1, \dots, A_k are ($g \times g$) matrices while A_0 is a ($g \times 1$) matrix of constants), and ε_t is a ($g \times 1$) vector of innovations with $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$ – where Σ_ε is the variance-covariance matrix – and $E(\varepsilon_t \varepsilon_s) = 0, \forall t \neq s$ (i.e. innovations may be contemporaneously correlated but are uncorrelated with their lagged values).⁸

6 For an extensive review about VARs and VECMs, see Bourbonnais [2005], Bourbonnais and Terraza [2008], Brooks [2008], Greene [2002], Lütkepohl and Krätzig [2004] and Lütkepohl [1991].

7 Endogenous variables are variables which impact the VAR and whose values are determined inside the VAR system. By contrast, exogenous variables are determined outside the VAR system, even though they impact the VAR (see below).

8 Note that simultaneity is not an issue for estimation of VARs, since only lagged values of the endogenous variables appear in the right-hand side of (3.1).

As usual in time-series modeling, data series used in a VAR model have to be stationary, since using non-stationary data can lead to spurious results. Thus, proper econometric analysis involves checking for non-stationarity in data through unit root tests.⁹ If series contain a unit root, they are first-difference stationary, while non-stationary in level. This means that they are affected by a linear stochastic trend.¹⁰ They are said to be I(1) or integrated of order 1 (while stationary series are said to be I(0)). Once series have been found to be I(1), they need to be rendered stationary by taking first differences (or second differences if they are I(2), etc).

A useful property of VAR models is the compactness which allows one to derive several notations for the same model. For an illustration, let us consider a simpler bi-variate version of **(3.1)** with two endogenous variables, $y_{1,t}$ and $y_{2,t}$. In this case, we can express **(3.1)** as follows:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \sum_{i=1}^k \begin{pmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{pmatrix} \begin{pmatrix} y_{1,t-i} \\ y_{2,t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix},$$

or, less compactly, it could be written as two individual equations,

$$\begin{cases} y_{1,t} = a_1 + \sum_{i=1}^k a_{11,i} y_{1,t-i} + \sum_{i=1}^k a_{12,i} y_{2,t-i} + \varepsilon_{1,t} \\ y_{2,t} = a_2 + \sum_{i=1}^k a_{21,i} y_{1,t-i} + \sum_{i=1}^k a_{22,i} y_{2,t-i} + \varepsilon_{2,t} \end{cases}.$$

One may want to extend model **(3.1)** in order to capture exogenous effects that may affect endogenous variables. This can be done by including a vector, X_t , of exogenous variables. So, model **(3.1)** is modified as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \dots + A_k Y_{t-k} + B X_t + \varepsilon_t, \quad (3.2)$$

where B is a matrix of coefficients. The components of X_t are known as exogenous variables because their values are determined outside the VAR. In other words, no component of X_t appears

⁹ For an extensive presentation of unit root tests, see Bourbonnais and Terraza [2008].

¹⁰ Non-stationary series can also be affected by non-linear stochastic trends. In that case, series contain more than one unit root. They are said to be integrated of order d (i.e. I(d)) with $d > 1$. However, such series are very scarce in economics and finance, where the great majority of series contain a single unit root.

in the left-hand side of (3.2), i.e. there is no equation in (3.2) with a variable of X_t as dependent variable. In model (3.2), the main purpose of the exogenous variables is to capture co-movements or interactions among endogenous variables that are caused by effects which are not determined in the model. In the case of interactions between carbon and energy markets, exogenous effects affecting endogenous variables (carbon, coal, gas and electricity prices in our case) can be temperatures – which are an important determinant of electricity and energy demand – and dummy variables reflecting days with particularly high or low temperatures.

The interconnectivity of the equations and the multiplicity of parameters and lags in a VAR model could render it difficult to interpret. With lagged variables that can have coefficients which are significant for some lags and not for others, it might be difficult to see whether a given variable has a persistent significant effect on another variable in the system. Besides, variables may have coefficients that change sign across the lags, which can render it difficult to see what effect a shock in a given variable would have upon future values of the variables in the system. Two very popular ways to overcome some of these difficulties are Granger causality tests and impulse response functions. Both are constructed on an estimated VAR model. These two methodologies are described below.

Granger causality tests (Granger [1969]) allow us to test the joint-significance of lagged value coefficients of a given variable – all other things being equal – in an individual equation of the VAR, with another variable as dependent variable. In doing so, Granger causality enables us to see whether a given variable has a persistent significant effect on another variable in the system (i.e. Granger causality enables us to investigate the dynamic significance of each variable in the system).

Granger causality tests seek to answer questions of the type: do past variations of a variable $y_{1,t}$ cause changes in subsequent values of another variable $y_{2,t}$? Or, equivalently, do past values of $y_{1,t}$ improve the forecast of $y_{2,t}$? If the answer is yes, the Granger causality between these variables is “uni-directional”, since $y_{1,t}$ “Granger-causes” $y_{2,t}$ while $y_{2,t}$ does not “Granger-cause” $y_{1,t}$. Granger causality can also be “bi-directional” if $y_{1,t}$ “Granger-causes” $y_{2,t}$ and vice versa (in this case there is a “feedback” effect between variables).

Formally speaking, it would be said that $y_{1,t}$ “does not Granger cause” $y_{2,t}$ if and only if $y_{2,t+h|\Omega_t} = y_{2,t+h|\Omega_t \setminus \{y_{1,s}|s \leq t\}}$, for $h=1,2,\dots$, where $y_{2,t+h|\Omega_t}$ is the optimal h -step forecast of $y_{2,t}$ at time t based on the set of all relevant information Ω_t , and $y_{2,t+h|\Omega_t \setminus \{y_{1,s}|s \leq t\}}$ is the same

value but based on $\Omega_t \setminus \{y_{1,s} | s \leq t\}$, the set of all elements of Ω_t not contained in the set $\{y_{1,s} | s \leq t\}$ (see Lütkepohl and Krätzig [2004]).

To illustrate how Granger causality tests can be conducted, let us consider again a simple bivariate version of (3.1) with two endogenous variables, $y_{1,t}$ and $y_{2,t}$:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \sum_{i=1}^k \begin{pmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{pmatrix} \begin{pmatrix} y_{1,t-i} \\ y_{2,t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix},$$

which could be written as two individual equations for causality tests,

$$\begin{cases} y_{1,t} = a_1 + \sum_{i=1}^k a_{11,i} y_{1,t-i} + \sum_{i=1}^k a_{12,i} y_{2,t-i} + \varepsilon_{1,t} \\ y_{2,t} = a_2 + \sum_{i=1}^k a_{21,i} y_{1,t-i} + \sum_{i=1}^k a_{22,i} y_{2,t-i} + \varepsilon_{2,t} \end{cases}.$$

Thereafter, testing for Granger causality running from $y_{1,t}$ to $y_{2,t}$ amounts to testing the following null hypothesis in the second equation: $a_{21,1} = a_{21,2} = \dots = a_{21,k} = 0$ (or $a_{21,i} = 0, \forall i = 1, \dots, k$). So, we can conclude that $y_{1,t}$ “Granger-causes” $y_{2,t}$ if H_0 is rejected. We can also test the null hypothesis $a_{12,1} = a_{12,2} = \dots = a_{12,k} = 0$ (or $a_{12,i} = 0, \forall i = 1, \dots, k$), in the first equation, in order to check if $y_{2,t}$ “Granger-causes” $y_{1,t}$. In the case of a simple VAR model where all the variables are stationary, the joint-hypotheses can be tested within the standard F -test framework.¹¹

Granger causality suggests which of the variables have a significant impact on subsequent values of the other variables in the model, all other things being equal. However, Granger causality is unable to explain the signs of the relationships, and it neglects interactions among variables in the system. To account for these complicated interactions, impulse response functions are constructed based on the moving average representation of the system.¹² They summarize dynamic interactions between variables by showing how a shock to innovations of one endogenous variable affects all

11 Note here that the procedure for testing Granger causality is more complex in the case of a VECM. See section 3.2.2 of this chapter.

12 According to the Wold representation theorem, any VAR(k) can be represented as a VMA(∞) – i.e. a vector moving average process with ∞ lags – (or, in the uni-variate case, any AR(k) can be represented as a MA(∞)). See Bourbonnais and Terraza [2008], Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

endogenous variables in the system.

A shock to one variable of the VAR not only directly affects this variable, but it is also transmitted to all other endogenous variables through time. Impulse response analysis consists in tracing out the effect of a one-time exogenous shock to one variable of the VAR. It summarizes the dynamic impact on the current and future values of all the endogenous variable in the VAR. Thus, for each equation in the VAR (i.e. for each endogenous variable), a unit shock can be applied to the errors in order to observe the effects on the other endogenous variables over time.¹³ The shape of the response (i.e. positive or negative) of a variable y_1 to a shock on a variable y_2 enables us to observe if the variable y_1 is a positive or negative function of the variable y_2 . This overcomes the difficulty of having coefficients that may change sign across the lags.

In practice, the impulse response functions are computed using the moving average representation (VMA for vector moving average) of a VAR. To illustrate how impulse responses operate, we consider a simple VAR(1) as follows¹⁴

$$Y_t = A_1 Y_{t-1} + \varepsilon_t \quad (3.3)$$

where Y_t , Y_{t-1} and ε_t are $(g \times 1)$ vectors and A_1 is a $(g \times g)$ matrix of coefficients. As a simplification, A_1 can be replaced by A (i.e. $A_1 \equiv A$) since it is the only matrix of coefficients in this case (VAR(1)). Expressing (3.3) as a VMA(∞) (i.e. a VMA with ∞ lags) yields

$$Y_t = \sum_{j=0}^{\infty} A^j \varepsilon_{t-j}, \quad (3.4)$$

or, more generally, when there is more than one lag, $Y_t = \sum_{j=0}^{\infty} \Phi_j \varepsilon_{t-j}$, where $\Phi_j = \sum_{i=1}^j \Phi_{j-i} A_i$

and A_i is the matrix of coefficients for Y_{t-i} (i.e. for the i^{th} lag).¹⁵ Besides, $\lim_{j \rightarrow \infty} A^j = 0$ (and

$\lim_{j \rightarrow \infty} \Phi_j = 0$).

13 Accordingly, if there are g variables in the system, a total of g^2 impulse responses can be generated.

14 The purpose here is not to give an extensive presentation of impulse response analysis, but rather to illustrate the principle in simple example. For a full presentation of impulse response functions in more complicated settings, see Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

15 The specification $Y_t = \sum_{j=0}^{\infty} \Phi_j \varepsilon_{t-j}$ with $\Phi_j = \sum_{i=1}^j \Phi_{j-i} A_i$ is useful only in the case of a VAR with more than one lag (VAR(k) with $k > 1$). In the case of a VAR(1), we can use the specification (3.4) (which is easier) because there is only one matrix of coefficients ($A_1 \equiv A$, whereas the matrices A_i do not exist $\forall i > 1$) and thus $\Phi_j = A^j$, $\forall j$. See Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

Using (3.4) it can be shown that (see proof below):

$$Y_{t+j} = \varepsilon_{t+j} + A Y_{t+j-1}, \text{ or equivalently, } Y_{t+j} = \sum_{s=0}^{t+j-1} A^s \varepsilon_{t+j-s} + A^{t+j} Y_t. \quad (3.5)$$

Proof: applying (3.4) to $t = 0, t = 1, t = 2$ and $t = 3$ yields

$$Y_0 = \sum_{j=0}^{\infty} A^j \varepsilon_{0-j} = \varepsilon_0 + A \varepsilon_{-1} + A^2 \varepsilon_{-2} + A^3 \varepsilon_{-3} + \cdots + A^{\infty-2} \varepsilon_{2-\infty} + A^{\infty-1} \varepsilon_{1-\infty} + A^{\infty} \varepsilon_{0-\infty},$$

$$Y_1 = \sum_{j=0}^{\infty} A^j \varepsilon_{1-j} = \varepsilon_1 + A \varepsilon_0 + A^2 \varepsilon_{-1} + A^3 \varepsilon_{-2} + \cdots + A^{\infty-2} \varepsilon_{3-\infty} + A^{\infty-1} \varepsilon_{2-\infty} + A^{\infty} \varepsilon_{1-\infty},$$

$$Y_2 = \sum_{j=0}^{\infty} A^j \varepsilon_{2-j} = \varepsilon_2 + A \varepsilon_1 + A^2 \varepsilon_0 + A^3 \varepsilon_{-1} + \cdots + A^{\infty-2} \varepsilon_{4-\infty} + A^{\infty-1} \varepsilon_{3-\infty} + A^{\infty} \varepsilon_{2-\infty},$$

$$\text{and } Y_3 = \sum_{j=0}^{\infty} A^j \varepsilon_{3-j} = \varepsilon_3 + A \varepsilon_2 + A^2 \varepsilon_1 + A^3 \varepsilon_0 + \cdots + A^{\infty-2} \varepsilon_{5-\infty} + A^{\infty-1} \varepsilon_{4-\infty} + A^{\infty} \varepsilon_{3-\infty}.$$

Since $\lim_{j \rightarrow \infty} A^j = 0$, the previous equations can be combined as follows: $Y_1 = \varepsilon_1 + A Y_0$,

$Y_2 = \varepsilon_2 + A Y_1 = \varepsilon_2 + A \varepsilon_1 + A^2 Y_0$, $Y_3 = \varepsilon_3 + A Y_2 = \varepsilon_3 + A \varepsilon_2 + A^2 \varepsilon_1 + A^3 Y_0$, and so on for higher value of t . Thus we deduce the value of any Y_{t+j} : $Y_{t+j} = \varepsilon_{t+j} + A Y_{t+j-1}$, or equivalently

$$Y_{t+j} = \sum_{s=0}^{t+j-1} A^s \varepsilon_{t+j-s} + A^{t+j} Y_t, \text{ which correspond to (3.5). } \square$$

Impulse response functions trace out the effects (i.e. the impulse responses) of a unit shock in one variable of the VAR at time t on the Y_{t+j} , $\forall j > 0$. Assuming that $Y_{t-j} = 0$ and $\varepsilon_{t+j} = 0$, $\forall j > 0$, and $Y_t = \varepsilon_t$, we can compute the impulse responses based on the VMA representation of the VAR given in (3.5). So, equations in (3.5)¹⁶ show the reaction of the VAR system after j periods (i.e. j periods after a shock at time t). For example, the effects of a unit shock at time $t = 0$ are given by:

$Y_0 = \varepsilon_0$, $Y_1 = A Y_0$, $Y_2 = A Y_1 = A^2 Y_0$, $Y_3 = A Y_2 = A^3 Y_0$, etc. As an illustration, let us assume the following bi-variate VAR(1)

¹⁶ Under the assumption $\varepsilon_{t+j} = 0$, $\forall j > 0$, the $Y_{t+j} = \varepsilon_{t+j} + A Y_{t+j-1}$ and $Y_{t+j} = \sum_{s=0}^{t+j-1} A^s \varepsilon_{t+j-s} + A^{t+j} Y_t$ correspond to $Y_{t+j} = A Y_{t+j-1}$ and $Y_{t+j} = A^{t+j} Y_t$.

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} 0.08 & -0.76 \\ -0.23 & 0.4 \end{pmatrix} \begin{pmatrix} y_{1,t-i} \\ y_{2,t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}. \quad (3.6)$$

We consider a unit shock to $y_{2,t}$ at time $t = 0$. So, under assumptions $Y_{0-j}=0$ and $\varepsilon_{0+j}=0$, $\forall j > 0$, and $Y_0 = \varepsilon_0$, we have:

$$Y_0 = \begin{pmatrix} y_{1,0} \\ y_{2,0} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1,0} \\ \varepsilon_{2,0} \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix},^{17}$$

and, applying (3.5) to (3.6),

$$Y_1 = AY_0 = \begin{pmatrix} 0.08 & -0.76 \\ -0.23 & 0.4 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} -0.76 \\ 0.4 \end{pmatrix},$$

$$Y_2 = AY_1 = \begin{pmatrix} 0.08 & -0.76 \\ -0.23 & 0.4 \end{pmatrix} \begin{pmatrix} -0.76 \\ 0.4 \end{pmatrix} = \begin{pmatrix} -0.36 \\ 0.33 \end{pmatrix} = A^2 Y_0 = \begin{pmatrix} 0.18 & -0.36 \\ -0.11 & 0.33 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} -0.36 \\ 0.33 \end{pmatrix},$$

$$Y_3 = AY_2 = \begin{pmatrix} 0.08 & -0.76 \\ -0.23 & 0.4 \end{pmatrix} \begin{pmatrix} -0.36 \\ 0.33 \end{pmatrix} = \begin{pmatrix} -0.28 \\ 0.21 \end{pmatrix} = A^3 Y_0 = \begin{pmatrix} 0.09 & -0.28 \\ -0.08 & 0.21 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} -0.28 \\ 0.21 \end{pmatrix},$$

and so on.

Continuing the same procedure for higher values of j , we get Y_{t+j} , $\forall j > 0$. The impulse responses are contained in the matrices A^j (which correspond to the matrices A^{t+j} of (3.5) in the case of a shock at time $t = 0$). In our example, we considered the impact of a shock to $y_{2,t}$ at time $t = 0$. Thus, we are interested in responses of $y_{1,t+j}$ to $y_{2,0}$ and of $y_{2,t+j}$ to $y_{2,0}$, $\forall j > 0$. The responses of $y_{1,t}$ to $y_{2,t}$ are given the coefficient a_{12} of the matrix A , while the responses of $y_{2,t}$ to $y_{2,t}$ are given the coefficient a_{22} of the matrix A . So, defining $a_{12}(j)$ ($a_{22}(j)$, respectively) as the response of $y_{1,t+j}$ to $y_{2,0}$ (of $y_{2,t+j}$ to $y_{2,0}$, respectively) after j periods,¹⁸ the impulse response functions are obtained as follows:

$$a_{12}(j) = \{a_{12}(1), a_{12}(2), a_{12}(3), \dots, a_{12}(\infty)\}, \quad (3.7)$$

¹⁷ Moreover, $\varepsilon_{1,0}$ is assumed to be zero.

¹⁸ In other words, $a_{12}(j)$ and $a_{22}(j)$ correspond to a_{12} and a_{22} in the matrix A^j .

and,

$$a_{22}(j) = [a_{22}(1), a_{22}(2), a_{22}(3), \dots, a_{22}(\infty)] , \quad (3.8)$$

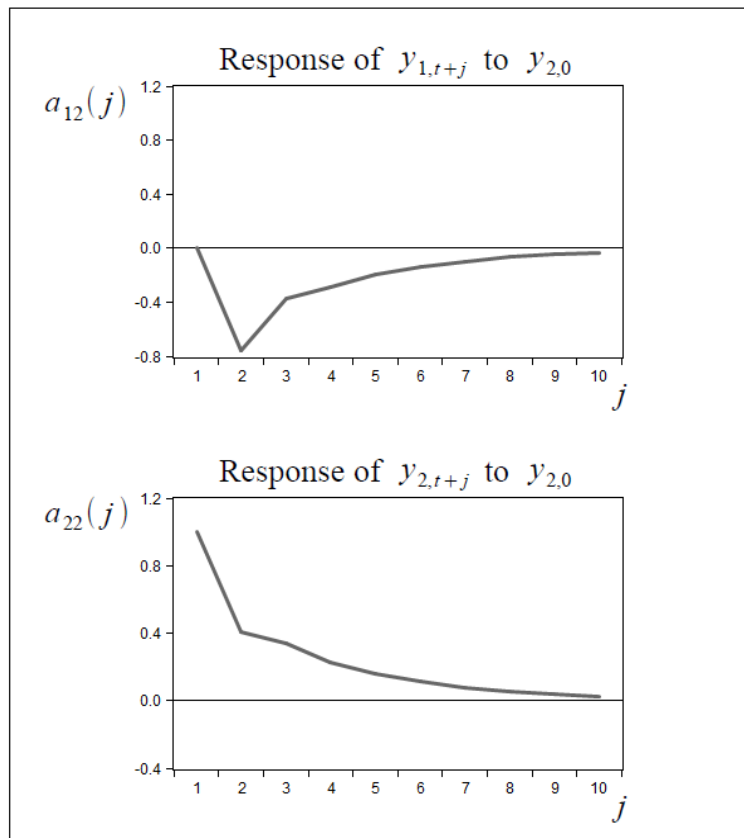
where (3.7) is the impulse response function that shows the response of $y_{1,t+j}$ to $y_{2,0}$, and (3.8) is the impulse response function that shows the response of $y_{2,t+j}$ to $y_{2,0}$.

Applying (3.7) and (3.8) to our example yields:

$$a_{12}(j) = [-0.76, -0.36, -0.28, \dots, 0] \text{ and } a_{22}(j) = [0.4, 0.33, 0.21, \dots, 0] ,$$

which can be represented graphically as in Figure 41.

Figure 41: Impulse response functions for a unit shock to $y_{2,t}$ at time $t = 0$



Looking at Figure 41, we see that the effects are transitory as the responses vanish over time. Indeed, according to (3.4) and (3.5), coefficients in the A^j decrease as j increases (and thus $a_{12}(j)$

and $a_{22}(j)$ decrease as j increases), and $\lim_{j \rightarrow \infty} A^j = 0$ (or $\lim_{j \rightarrow \infty} \Phi_j = 0$). This is explained by the fact that variables are all $I(0)$ in a VAR system (i.e. they are not affected by any trend). Note here that in the case of a VECM, a shock in one variable of the system may have some permanent effects given that the Φ_j do not necessarily converge to zero as j tends to infinity.¹⁹

Figure 41 gives other important information: when $y_{2,t}$ increases (because of the unit shock to $y_{2,t}$), the responses of $y_{1,t}$ are negative.²⁰ Therefore, we deduce that $y_{1,t}$ is a decreasing function of $y_{2,t}$. This illustrates how impulse response functions can help to deduce the shape of the relationship between two variables.

The impulse response refers to a unit shock to the errors of one equation in the system, assuming that the error terms of all other equations are held constant (equal to zero). This assumption might be unrealistic since the error terms might be instantaneously correlated across equations to some extent. Indeed, if the components of ε_t are correlated, a unit shock to $\varepsilon_{2,0}$ does not occur in isolation, and, accordingly, $\varepsilon_{1,0}$ cannot be held equal to zero. The components of ε_t are correlated if the residual variance-covariance matrix Σ_ε is not diagonal (i.e. if some or all of the covariances are non-zero). In order to overcome this problem, the standard procedure is to apply a transformation P to the innovations ε_t so that Σ_ε becomes diagonal, and thus the components of ε_t are no longer correlated. Hence, the resulting errors, v_t , are “orthogonalized” (i.e. all the instantaneous covariances are equal to zero): $v_t = P \varepsilon_t \sim N(0, \Sigma_v)$, where Σ_v is a diagonal variance-covariance matrix. The choice of P can be obtained through different orthogonalization procedures.²¹ Most of these orthogonalization procedures require us to specify an ordering of variables (i.e. which variables follow or precede movements in others variables), and results are sensitive to this ordering. Interestingly, the generalized impulse response function procedure (Pesaran and Shin [1998]) does not depend on the ordering of variables.²² Accordingly, we will use this orthogonalization procedure to compute impulse response functions in the econometric analysis of section 3 of this chapter.

19 This is explained by the fact there are $I(1)$ variables in a VECM, and therefore, a shock in one variable may enter into some trends followed by the $I(1)$ variables. See Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

20 This can also be observed in $a_{12}(j) = \{-0.76, -0.36, -0.28, \dots, 0\}$.

21 The program we use in our econometric works, Eviews, provides two options for orthogonalization: the Choleski decomposition of the variance-covariance matrix (see Lütkepohl [1991] and Lütkepohl and Krätzig [2004]) and the generalized impulse responses (see Pesaran and Shin [1998]).

22 Note here that when the residuals are almost uncorrelated, the results are not very sensitive to a change in the ordering of variables (see Lütkepohl [1991]).

2.2. Vector error correction models

Many economic time-series have a common equilibrium relationship. Examples may be the spot and futures prices for a given commodity/asset, related commodities (e.g. wheat and rice, gold and platinum, crude oil and gasoline, etc) or equities, prices of a same commodity in different markets, etc. Those series can move together over time around a common long-run equilibrium, even though deviations from the equilibrium are possible in the short-run. If deviations occur at a certain time, the series would return in the equilibrium later. In this way, a long-run equilibrium may be seen as a cointegration relationship, since cointegrated variables may deviate from their cointegration relationship in the short-run and gradually return in the long-run equilibrium during the subsequent time periods.

Formally speaking, two variables $y_{1,t}$ and $y_{2,t}$ are cointegrated of order (d, b) if two conditions are verified:

- (1) $y_{1,t}$ and $y_{2,t}$ are $I(d)$ ($y_{1,t} \sim I(d)$ and $y_{2,t} \sim I(d)$),
- (2) there is a linear combination of $y_{1,t}$ and $y_{2,t}$ which is $I(d-b)$, i.e. there is a (2×1) vector of coefficients β so that $\beta' Y_t \sim I(d-b)$ (or $\beta_1 y_{1,t} + \beta_2 y_{2,t} \sim I(d-b)$ if $\beta' = (\beta_1, \beta_2)$) where Y_t is a (2×1) vector whose $y_{1,t}$ and $y_{2,t}$ are the components and $d \geq b > 0$.

The usual notation to describe that the components of Y_t are cointegrated of order (d, b) is $Y_t \sim CI(d, b)$. In practice, most economic and financial variables are $I(1)$. In this case, it is possible that there is a linear combination of those variables that is stationary, i.e. $I(0)$. So, $d = b = 1$ and $Y_t \sim CI(1, 1)$, so that the components of Y_t are cointegrated if a linear combination of them is stationary. The stationary linear combination is called the cointegrating equation and can be interpreted as a long-run equilibrium relationship among the variables. Actually the $CI(1, 1)$ case is by far the most common in practice.²³ In our case, since all our econometric investigations (see section 3 of this chapter and sections 3 and 4 of Chapter 4) have been conducted with $I(1)$ series which have proved to be cointegrated of order $(1, 1)$, we restrict presentation in this section to the $CI(1, 1)$ case.

²³ Many econometric textbooks restrict analysis to the $CI(1, 1)$ case. For a more general presentation, see Lütkepohl [1991].

As we have already mentioned, economic time series often exhibit dynamic behavior consistent with I(1) processes. Not accounting for the non-stationarity of series can lead to spurious regression results (i.e. econometric modeling involving the levels of I(1) series can produce misleading results, showing significant relationships between unrelated series). Before the seminal work of Engle and Granger [1987], a usual response to this problem was to take the first-difference of each of the I(1) series – in order to convert them into stationary series – and use the first differenced series in subsequent econometric modeling. However, if series are cointegrated, removing non-stationarity by first differencing the I(1) series can delete the long-run (cointegrating) relationships. Engle and Granger [1987] have introduced a class of models that overcome these problems by using combinations of first differenced and lagged levels of I(1) cointegrated series. These models are known as Error Correction Models (ECMs). Engle and Granger [1987] have shown that each set of cointegrated series can be represented as an ECM (Granger representation theorem).

A common way of estimating an ECM is the Engle-Granger two-step method. It is conducted as follows.

- **Step 1:** Check that all the series are I(1) and then – if all the series are I(1) – estimate a cointegrating relationship using OLS. Once the relationship has been estimated, the residuals are tested (using unit root tests) to see if they are I(0). If they are I(0), an error-correction representation can be estimated, which corresponds to step 2. So, assuming that two I(1) variables, $y_{1,t}$ and $y_{2,t}$, are cointegrated, this means that a cointegrating relationship exists: $y_{1,t} = \beta_2 y_{2,t} + u_t$, where u_t is I(0) – i.e. $\beta_1 y_{1,t} - \beta_2 y_{2,t} \sim I(0)$ with $\beta_1 = 1$ – and β_2 is a cointegrating coefficient.
- **Step 2:** An ECM can be estimated with standard estimation methods such as OLS. The ECM is: $\Delta y_{1,t} = \delta u_{t-1} + \gamma_2 \Delta y_{2,t} + \varepsilon_{1,t}$ or $\Delta y_{1,t} = \delta (y_{1,t-1} - \beta_2 y_{2,t-1}) + \gamma_2 \Delta y_{2,t} + \varepsilon_{1,t}$,²⁴ where δ is an adjustment coefficient measuring the proportion of last period's equilibrium error that is corrected in time period t (it is sometimes referred to as the “speed of adjustment” toward the equilibrium), while γ_2 describes the short-run relationship between $\Delta y_{1,t}$ and $\Delta y_{2,t}$ (i.e. between changes in $y_{1,t}$ and changes in $y_{2,t}$). Note that $u_t = y_{1,t-1} - \beta_2 y_{2,t-1}$ is I(0), even though $y_{1,t-1}$ and $y_{2,t-1}$ are I(1). Thus, each part of the ECM is I(0) so that standard procedures for estimation and statistical inference can be applied.

24 It is possible to add an intercept to either the cointegrating equation or to the model or to both.

The notion of cointegration can be generalized for more than two variables. Assuming Y_t , a $(g \times 1)$ vector of variables (with $g \geq 2$), the components of Y_t are cointegrated of order $(1,1)$ if:

- (1) All the components of Y_t are $I(1)$,
- (2) there is at least one linear combination of the components of Y_t which is $I(0)$, i.e. there is a $(g \times 1)$ vector of coefficients, β , so that $\beta' Y_t \sim I(0)$.

The Engle-Granger two-step method can also be applied to estimate an ECM with more than two variables. For example, assuming a set of three $I(1)$ variables, $y_{1,t}$, $y_{2,t}$ and $y_{3,t}$, that are cointegrated, the Engle-Granger two-step method would be:

- **Step 1:** Find a cointegrating relationship: $y_{1,t} = \beta_2 y_{2,t} + \beta_3 y_{3,t} + u_t$, where u_t is $I(0)$ – i.e. $\beta_1 y_{1,t} - \beta_2 y_{2,t} - \beta_3 y_{3,t} \sim I(0)$ with $\beta_1 = 1$ – and β_2 and β_3 are cointegrating coefficients.
- **Step 2:** The ECM is $\Delta y_{1,t} = \delta (y_{1,t-1} - \beta_2 y_{2,t-1} - \beta_3 y_{3,t-1}) + \gamma_2 \Delta y_{2,t} + \gamma_3 \Delta y_{3,t} + \varepsilon_{1,t}$, where δ is an adjustment coefficient, and γ_2 and γ_3 describe the short-run interactions among the variables.

A problem with the Engle-Granger two-step method is that it enables us to test for only one cointegrating equation, no matter how many variables there are in the system. In the case of two variables, there can be at most one cointegrating relationship between the variables. However, in the case of g variables, there may be up to r independent cointegrating relationships (i.e. up to r linear combinations of the variables that are stationary), where $r \leq g - 1$. Hence, the Engle-Granger two-step method can be unappropriated. A solution to this problem has been introduced by Johansen [1991], who proposed a VAR-based cointegration test that allows to test for $r = 0, 1, \dots, g - 1$ cointegrating relationships. The Johansen's method consists in looking at the rank of the matrix of the long-run parameters in a VECM, where the rank of the matrix corresponds to the number of cointegrating relationships.²⁵ If the rank of the matrix is significantly different from zero, the series are cointegrated with r cointegrating relationships (where $r \in [1, \dots, g - 1]$).

²⁵ The rank of a matrix is equal to the number of its characteristic roots (the eigenvalues) that are different from zero. For simple illustrations on how to derive the eigenvalues of a matrix, see Brooks [2008]. See also Hayek and Leca [2001].

In order to apply the Johansen test, the VAR (3.1) needs to be turned into a VECM($k - 1$)²⁶ of the form:

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \dots + \Gamma_{k-1} \Delta Y_{t-k+1} + \varepsilon_t, \quad (3.9)$$

where $\Gamma_i = (\sum_{j=1}^i A_j) - I_g$ are ($g \times g$) matrices of short-run coefficients and $\Pi = \sum_{i=1}^k A_i - I_g = \delta \beta'$ is a matrix of long-run coefficients, with δ , a ($g \times r$) matrix of adjustment coefficients, and β is a ($g \times r$) matrix of cointegration coefficients.

The Johansen's method consists in estimating the unrestricted VECM (3.9) ((3.9) is said unrestricted because it is estimated without specifying the value of r) using maximum likelihood.²⁷ Thereafter, the Johansen tests are derived by looking at the rank of the estimated Π matrix, i.e. by identifying the number of its eigenvalues (characteristic roots) which are different from zero. Once the value of r is known, a restricted version of (3.9) can be estimated using maximum likelihood (or a VAR model such as (3.1) if $r = 0$).

After the unrestricted VECM (3.9) has been estimated, the variables are not cointegrated if we observe that the rank of Π is not significantly different from zero. So, no eigenvalue of Π is significantly different from zero: $\lambda_i \approx 0$, $\forall i = 1, \dots, g$, where λ_i is the i -th eigenvalue. Each eigenvalue is associated with a certain cointegrating vector. Thus, a significantly non-zero eigenvalue indicates a significant cointegrating vector.

Two statistics are used to test for cointegration under the Johansen approach: the Trace statistic and the Maximum Eigenvalue statistic.²⁸ They are formulated as follows:

$$\lambda_{trace}(r \setminus g) = -T \sum_{i=r+1}^g \ln(1 - \lambda_i),$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \lambda_{r+1}) = \lambda_{trace}(r \setminus g) - \lambda_{trace}(r+1 \setminus g),$$

where λ_{trace} is the Trace statistic and λ_{max} is the Maximum Eigenvalue statistic.²⁹ In λ_{trace} and λ_{max} , r is the number of cointegrating vectors under the null hypothesis and λ_i is the estimated value for the i -th eigenvalue from the Π matrix (i.e. from the Π matrix obtained by estimating the unrestricted VECM (3.9)). T is the number of observations.

26 For a detailed presentation on how to turn a VAR(k) in to a VECM($k - 1$), see Bourbonnais [2005].

27 Intercepts can be included either in the cointegrating vectors or in the VAR part of the VECM or in both. Eviews allows to specify all of these situations.

28 See Brooks [2008] and Bourbonnais [2005]. Note that these statistics are calculated by Eviews.

29 Both λ_{trace} and λ_{max} incorporate $\ln(1 - \lambda_i)$ rather than the λ_i themselves. Actually, the two specifications are equivalent because when $\lambda_i = 0$, $\ln(1 - \lambda_i) = 0$.

The λ_{trace} tests the null hypothesis of a number of cointegrating vectors which less than or equal to r ("at most r ") against the alternative that there are more than r cointegrating vectors. The λ_{trace} starts with $H_0 : r \leq 0$ against $H_1 : r > 0$; If H_0 is rejected, the next step is to test $H_0 : r \leq 1$ against $H_1 : r > 1$, and so on:

$$\begin{array}{lll}
 H_0 : r \leq 0 & \text{against} & H_1 : r > 0 \\
 H_0 : r \leq 1 & \text{against} & H_1 : r > 1 \\
 H_0 : r \leq 2 & \text{against} & H_1 : r > 2 \\
 \vdots & \vdots & \vdots \\
 H_0 : r \leq g & \text{against} & H_1 : r > g
 \end{array}$$

Thus, the value of r is continuously increased until the null hypothesis is no longer rejected. If H_0 is accepted for an r ranging from $r=1$ to $r=g-1$, we conclude that the variables are cointegrated with r independent cointegrating vectors.

The λ_{max} tests the null hypothesis of r cointegrating vectors against the alternative that there are $r+1$ or more cointegrating vectors. The λ_{max} starts with $H_0 : r=0$ against $H_1 : 0 < r \leq g$; If H_0 is rejected, the next step is to test $H_0 : r=1$ against $H_1 : 1 < r \leq g$, and so on:

$$\begin{array}{lll}
 H_0 : r=0 & \text{against} & H_1 : 0 < r \leq g \\
 H_0 : r=1 & \text{against} & H_1 : 1 < r \leq g \\
 H_0 : r=2 & \text{against} & H_1 : 2 < r \leq g \\
 \vdots & \vdots & \vdots \\
 H_0 : r=g-1 & \text{against} & H_1 : r=g
 \end{array}$$

As with the Trace statistic, the value of r is continuously increased until the null hypothesis is no longer rejected. If H_0 is accepted for an r ranging from $r=1$ to $r=g-1$, we conclude that the variables are cointegrated with r independent cointegrating vectors.

Once the rank of the Π matrix has been identified, the (restricted) VECM can be estimated using maximum likelihood. So, knowing the value of r , the Π matrix is defined as the product of the two matrices, δ and β , of dimension $(g \times r)$. For example, if $g=3$ (i.e. there are three endogenous variables in the system), the Π matrix can be written:

$$\Pi = \delta \beta' = \begin{pmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{pmatrix}.$$

So, if $r=1$, δ and β are (3×1) matrices and:

$$\Pi = \delta \beta' = \begin{pmatrix} \delta_{11} \\ \delta_{21} \\ \delta_{31} \end{pmatrix} \times (\beta_{11} \quad \beta_{21} \quad \beta_{31}) = \begin{pmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{pmatrix}.$$

If $r=2$, δ and β are (3×2) matrices and:

$$\Pi = \delta \beta' = \begin{pmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \\ \delta_{31} & \delta_{32} \end{pmatrix} \times \begin{pmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \end{pmatrix} = \begin{pmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{pmatrix},$$

and so on for higher values of r .

In many cases it is useful to normalize the cointegrating coefficients in β to set the value of one of them to unity. Such a normalization allows us to define one of the endogenous variables as the dependent variable in a cointegrating relationship, as would be the case in the Engle-Granger two-step approach. As an illustration we take again the example of two $I(1)$ variables, $y_{1,t}$ and $y_{2,t}$, cointegrated with a cointegrating relationship given by $y_{1,t} = \beta_2 y_{2,t} + u_t$. In this case, as $y_{1,t}$ is defined as the dependent variable of the cointegrating equation, the cointegrating vector $\beta = (\beta_1 \quad \beta_2)$ is normalized so that $\beta_1 = 1$. So, $\beta' \times (y_{1,t} \quad y_{2,t}) \sim I(0)$, with $\beta = (1 \quad -\beta_2)$.

As in the case of VAR models, it can be difficult to interpret a VECM due to the multiplicity of parameters and lags. Fortunately, Granger causality and impulse responses can also be investigated in the VECM framework.³⁰ Thus, these two methods can be used to answer questions of the type: Does a given variable have a persistent significant effect on another variable in the system? What is the effect of a shock to a given variable upon the future values of the variables in the system? What is the shape of the relationship between two variables? Positive or negative?

³⁰ Granger causality and impulse responses in the VECM framework will be further discussed in section 3 of this chapter.

3. Econometric analysis

The objective of this empirical work is to apply a full VAR-VECM approach to examine interdependency between carbon and energy prices in Phase 2 of the EU ETS. More precisely, we investigate the interactions between carbon, fuel and electricity prices during the first two years of Phase 2. In section 3.1, we first test for stationarity and cointegration. Based on the results, we choose which specification (VAR or VECM) is more appropriate for estimation. Next, in section 3.2, estimation results, Granger causality tests and impulse responses are presented.

3.1. Preliminary statistics

We use daily data for temperatures, fuel, carbon and electricity prices in Europe.³¹ Data series run from February 26, 2008 to October 30, 2009. This corresponds to the first two years of Phase 2 of the EU ETS. Our sample period begins on February 26, 2008 since data for the carbon spot price start on that day.

3.1.1. Stationarity tests

Proper econometric analysis involves checking for non-stationarity in data. In case all series contain a unit root (i.e. they are $I(1)$ or integrated of order 1), it is necessary to test for cointegration. If a long-run cointegrating relationship is found, analysis needs to be conducted through an error-correction model. However, when no cointegrating relationship is found whereas series are all $I(1)$, all series have to be converted into stationary series by taking first order differences.

To test for stationarity we apply three unit root tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Peron (PP) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The ADF and the PP tests assume non-stationary series under the null hypothesis, while the KPSS tests the null hypothesis that the series are stationary.

³¹ Data are presented in Appendix B.

Tables 13 and 14 present the results of the unit root tests. In each case tests are applied to log series in levels and in first differences.

Table 13: Unit root tests on level series (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Variables in (log) levels	ADF (t-Statistics)	PP (t-Statistics)	KPSS (LM-Statistics)
Carbon spot	-1.04	-1.04	1.87***
Carbon futures	-0.90	-1.01	1.92***
Coal	-0.70	-0.73	2.12***
Electricity	-0.93	-0.94	1.33***
Gas	-0.77	-0.76	2.25***
Temperature EU	-2.12	-1.94	0.34*
Temperature Ge	-2.47	-2.45	0.31
Temperature Sp	-2.40	-2.09	0.39*
Temperature UK	-3.03**	-3.35***	0.38*

Table 14: Unit root tests on difference series (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Variables in (log) differences	ADF (t-Statistics)	PP (t-Statistics)	KPSS (LM-Statistics)
Carbon spot	-11.32***	-18.51***	0.15
Carbon futures	-16.00***	-18.32***	0.15
Coal	-20.25***	-20.25***	0.20
Electricity	-19.66***	-19.62***	0.32
Gas	-25.84***	-26.29***	0.17
Temperature EU	-17.82***	-21.76***	0.11
Temperature Ge	-18.36***	-24.48***	0.09
Temperature Sp	-16.69***	-22.30***	0.08
Temperature UK	-19.04***	-37.31***	0.08

No matter which test specification is retained, all price series are always I(1), i.e. non-stationary in levels, but stationary in first differences. Temperatures tend to be sometimes stationary in levels, in particular for the UK. However, in most cases temperatures are also I(1).

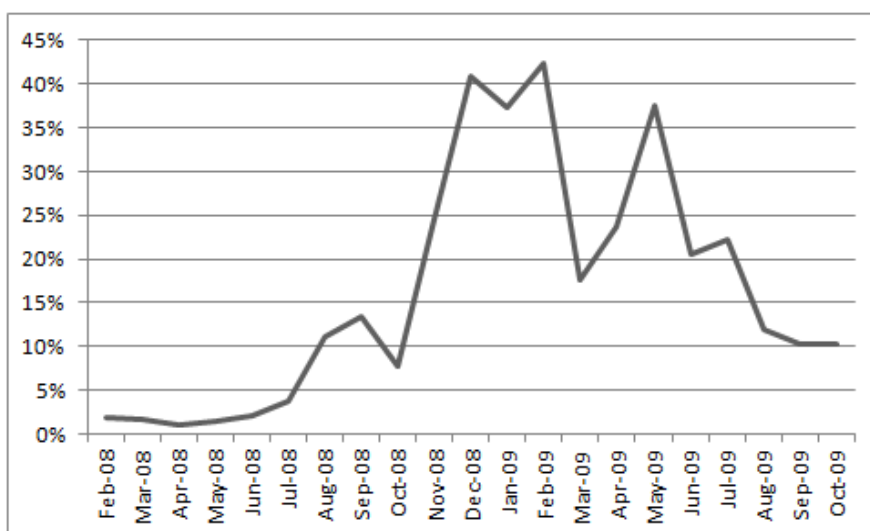
Before beginning our analysis of interactions between carbon and energy prices, we first want to know which EUA contract (spot or futures) better reflects information about the EU ETS. Accordingly we perform a first Granger causality test based on a bi-variate VAR between the EUA spot price and the EUA futures price.³² The results are presented in Table 15.

Table 15: Granger causality test results between spot and futures EUA prices, with three lags considered by the Schwarz information criterion (*, ** and *** denote statistical significance of Granger causalities at the 10, 5 and 1% levels, respectively)

Null Hypothesis	<i>p</i> -value
Spot price does not Granger cause Futures price	4.E-52***
Futures price does not Granger cause Spot price	0.1731

The results clearly show that the Granger causality runs from spot to futures prices, indicating that the carbon spot price is better at explaining the EU ETS fluctuations. Previous studies for Phase 1 found the opposite (see Uhrig-Homburg and Wagner [2007] and Keppler and Mansanet-Bataller [2010]) or bi-directional Granger causalities (see Milunovich and Joyeux [2007]), but none found that the spot price has driven the spot-future relationship.³³

Figure 42: Share of the spot market in the total traded volumes – spot (Bluenext) and futures (ECX, all contracts) – in 2008 and 2009. Data available on the Bluenext and ECX websites.



32 The same procedure is applied in Keppler and Mansanet-Bataller [2010].

33 Running the same tests for the sample period 1/02/2008-12/31/2008, Keppler and Mansanet-Bataller [2010] found that the spot-future relationship still runs from the futures price to the spot price as in Phase 1, but the results are less straightforward and the relationship is close to bi-directional.

One possible explanation of this reversal in the spot-futures relationship is that the spot market for EUAs has gained in importance in Phase 2 due to the credit crunch that came with the financial crisis (see Figure 42). Thanks to emission reductions, regulated firms were able to sell large amounts of unused allowances on the spot market in order to raise cash during the credit crunch. Moreover, to secure their future compliance with these financing strategies, some firms performed “time swaps” under which volumes of allowances that were sold on the spot market were offset by equal volumes of allowances bought for future delivery on the futures market.³⁴ That may explain why the spot price became the driver in the spot-futures relationship, and so why it better reflected information about the EU ETS. Accordingly, we decide to use the EUA spot price in our model.³⁵ Therefore, for the remainder of the chapter, when we refer to the “carbon price” we mean the spot price of EUAs.

3.1.2. Cointegration testing

As unit root tests reveal that series are all $I(1)$, we decide to test for cointegration between variables. To do this, the Johansen [1991] maximum likelihood estimation approach is used (see section 2 of this chapter). It consists in looking at the rank of the matrix of the long-run parameters in a VECM. If the rank of the matrix (which is equivalent to the number of cointegrating vectors) is significantly different from zero, the series are cointegrated. Thus, in order to test for cointegration we introduce a $VECM(k)$ specification that can be written:

$$\Delta P_t = \alpha + \delta \beta' P_{t-1} + \sum_{i=1}^k \Gamma_i \Delta P_{t-i} + \varepsilon_t, \quad (3.10)$$

where P_t is a (4×1) vector of endogenous variables that contains log price series of EUAs, electricity, coal and gas. The number of lags in the VECM is k , α is a (4×1) vector of parameters, and Γ_i are (4×4) matrices of parameters. The adjustment coefficients (that determine how the endogenous variables respond to any disequilibrium in the long-run relationship) appear in the $(4 \times r)$ vector denominated by δ , and β is the $(4 \times r)$ cointegrating vector, where r is the number of cointegrating relationships. Finally, ε_t is a (4×1) vector of un-modeled errors with $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$ where Σ_ε is the variance-covariance matrix.

34 See De Pertuis [2009], Sikorski [2009] and Charpin [2009].

35 We present in Appendix C the same econometric analysis as in Chapter 3, using the price of EUA futures contracts.

The number of lags to include in the VECM is chosen according to the Akaike information criterion, the Hannan-Quinn information criterion and the Final prediction error. The matrix of the long-run parameters to test in the Johansen approach is $\Pi = \delta \beta'$. Tables 16 and 17 present the results of the tests.

Table 16: Trace test for cointegration (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Null Hypothesis: Number of cointegrating vectors	Trace Statistic	Critical value (10% level)	p-value
$r \leq 0$	47.51116*	44.49359	0.0538*
$r \leq 1$	20.82399	27.06695	0.3687
$r \leq 2$	7.822208	13.42878	0.4846
$r \leq 3$	0.126021	2.705545	0.7226

Table 17: Maximum-Eigenvalue test for cointegration (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Null Hypothesis: Number of cointegrating vectors	Maximum-Eigenvalue Statistic	Critical value (10% level)	p-value
$r = 0$	26.68716*	25.12408	0.0648*
$r = 1$	13.00179	18.89282	0.4521
$r = 2$	7.696187	12.29652	0.4104
$r = 3$	0.126021	2.705545	0.7226

The results indicate the existence of a single long-run relationship between prices (i.e. $r = 1$), at the 10% level.³⁶ This suggests that a VECM approach is more appropriate than a VAR model. This confirms previous investigations which have reported significant cointegrating relationships between carbon and energy prices in Phase 1 (Bunn and Fezzi [2007], Zachmann and von Hirschhausen [2007], Fell [2008], Chemarin et al [2008] and Creti et al. [2012]) and in Phase 2 (Bonacina et al. [2009], Bredin and Muckley [2011] and Creti et al. [2012]).

³⁶ Remember that λ_{trace} tests $H_0 : r \leq j$ against $H_1 : r > j$, $\forall j \in [0, \dots, g]$, and λ_{max} tests $H_0 : r = j$ against $H_1 : j < r \leq g$, $\forall j \in [0, \dots, g-1]$ (see section 2 of this chapter). Accordingly, once H_0 has been accepted for a given j , H_1 is rejected for the same j and thus we deduce that r cannot be higher than j . That is why Tables 4 and 5 enable us to conclude that $r = 1$.

Note that temperature variables (series and dummies) have not been included in the tests. We decided to do so since we found no significant influence of these variables on prices in a preliminary regression analysis.³⁷ The fact that the influence of temperatures is not significant in Phase 2 whereas it was in Phase 1 (see Alberola et al. [2008] and Mansanet-Bataller et al. [2007]) should be explained by the economic recession that occurred in 2008 and 2009. Because of the recession, carbon emissions have declined and so the compliance constraints have been less binding. As a consequence, temperature variations were of less importance for allowance prices.³⁸

3.2. Econometric model and results

The first aim of this section is to find a proper representation for price series (carbon, electricity, coal and gas) and to estimate a long-run relationship. Once a satisfactory model has been estimated, we use it to investigate Granger causality and impulse response.

3.2.1. Estimation and diagnostic

Given the results we found for stationarity and cointegration tests, we have chosen a VECM specification. Thus we retain the model **(3.10)** for estimation. We estimate **(3.10)** with different options for the normalization of parameters in the cointegrating vector: Carbon normalization (= normalized value of 1 for the carbon price coefficient), Gas normalization (= normalized value of 1 for the gas price coefficient), Electricity normalization (= normalized value of 1 for the electricity price coefficient) and Coal normalization (= normalized value of 1 for the coal price coefficient).³⁹ For each specification, the lag order is chosen with the Akaike information criterion, the Hannan-Quinn information criterion and the Final Prediction Error. Accordingly we estimate **(3.10)** with three lags, using the maximum likelihood method. The estimation results for Carbon normalization are reported in Table 18.

37 Different combinations of temperature variables (temperatures in levels and dummy variables for hot and cold days, see Appendix B) of different countries (i.e. Germany, Spain, the UK, and the whole UE) have been tested. None has shown a significant influence on any of the prices (except for the electricity price which tends to be sensitive to cold temperatures).

38 The economic recession has an impact on three drivers of carbon emissions: the demand for electricity, the carbon price, and fuel prices (see Declercq et al. [2011]). Declercq et al. [2011] estimate an emission reduction of about 150 Mtonnes in the European power sector over the years 2008 and 2009. Note, however, that emission data from the CITL (Community Independent Transaction Log, that records emissions and trades in the European carbon market) has shown that the power sector was globally short of allowances during this period (see Trotignon [2010]).

39 See section 2 of this chapter.

Table 18: VECM (maximum likelihood) parameter estimations (*, ** and *** denote statistical significance of parameters at the 10, 5 and 1% levels, respectively). The t-statistics are given in square brackets.

VECM (short-run parameters)				
	Δ_t Carbon	Δ_t Coal	Δ_t Electricity	Δ_t Gas
EC_{t-1}	0.003849 [0.55646]	0.011195* [1.73579]	0.038986*** [3.99867]	0.041128*** [3.43285]
Δ_{t-1} Carbon	0.135772*** [2.72143]	0.235379*** [5.05930]	-0.015900 [-0.22607]	0.051469 [0.59554]
Δ_{t-2} Carbon	-0.137811*** [-2.67382]	0.021739 [0.45230]	-0.111515 [-1.53481]	-0.144024 [-1.61310]
Δ_{t-3} Carbon	0.144545*** [2.86196]	-0.035942 [-0.76312]	-0.108538 [-1.52445]	-0.100300 [-1.14642]
Δ_{t-1} Coal	-0.111205** [-2.08413]	0.020350 [0.40898]	-0.034638 [-0.46049]	0.163210* [1.76575]
Δ_{t-2} Coal	0.035301 [0.65991]	0.019681 [0.39453]	0.118179 [1.56717]	-0.076545 [-0.82604]
Δ_{t-3} Coal	0.071639 [1.38504]	0.011871 [0.24612]	-0.084245 [-1.15539]	-0.062547 [-0.69807]
Δ_{t-1} Electricity	0.070516* [1.94468]	0.034350 [1.01582]	0.019931 [0.38990]	0.202668*** [3.22645]
Δ_{t-2} Electricity	0.018677 [0.50858]	0.054210 [1.58293]	-0.041336 [-0.79845]	-0.076263 [-1.19879]
Δ_{t-3} Electricity	0.011599 [0.31723]	0.027743 [0.81367]	-0.013701 [-0.26582]	-0.016851 [-0.26605]
Δ_{t-1} Gas	-0.081337*** [-2.75937]	0.024071 [0.87568]	0.024902 [0.59927]	-0.289846*** [-5.67635]
Δ_{t-2} Gas	-0.069319** [-2.26419]	0.037597 [1.31689]	0.018270 [0.42332]	-0.087656* [-1.65281]
Δ_{t-3} Gas	-0.072435** [-2.45626]	0.006915 [0.25144]	-0.047938 [-1.15314]	-0.014495 [-0.28374]
Constant	-0.001086 [-0.84304]	-0.001121 [-0.93275]	0.000262 [0.14450]	-0.002356 [-1.05557]
Cointegrating vector (long-run parameters)				
Carbon	Coal	Electricity	Gas	Constant
1	-0.195509 [-0.96264]	0.078154 [0.37629]	-0.522261** [-2.39325]	-0.801713

In order to evaluate how appropriate the model is, we ran diagnostic tests to check for autocorrelation and non-normality in the residuals.⁴⁰ The Portmanteau (multivariate Box-Pierce/Ljung-Box) and LM (multivariate Lagrange Multiplier) tests, revealed no autocorrelation in the residuals. The tests were performed for several lags with a maximum of 15 lags included. The null of no autocorrelation was always clearly accepted. Although there is no autocorrelation in the residuals, the multivariate Jarque-Bera residual normality test shows evidence of non-normality. However, as shown in Gonzalo [1994], the maximum likelihood method in error correction models ensures that estimators are consistent and that hypothesis tests can be performed (with standard chi-squared tests), even when the errors are non-normal and/or heteroscedastic.

The estimation results, reported in Table 18, show that the gas price is the only variable which is significant in the cointegration equation. The sign is consistent with the fuel switching theory, with a positive relation between carbon and gas prices in the equilibrium.⁴¹ This is in line with the results of Bonacina et al. [2009] and Creti et al. [2012] for Phase 2, which indicate a significant influence of the switching price on the carbon price in the equilibrium, with the expected positive sign. Moreover, since estimations have been made with log-prices, the estimated coefficients can be interpreted as elasticities (Bunn and Fezzi [2007] make the same remark). Consequently, we can deduce that, in the long-run equilibrium, a gas price rise of 1% would be associated with a carbon price rise of about 0.5%.

As for short-run interactions, the main results show that the carbon price is influenced by the gas price lagged values and by its own lagged values. This confirms the results of Bunn and Fezzi [2007] about the influence of the gas price on the carbon price. Moreover, the gas price shows some evidence of dependence on its own lagged values and on those of the electricity price.

The results for the adjustment coefficients show that they are significant for all variables except for the carbon price. Thus the carbon price is *weakly exogenous for the cointegrating parameters* (i.e. the cointegration relation is not significant in the equation of this variable in the VECM, see Lütkepohl and Krätzig [2004]). This result was also found by Bunn and Fezzi [2007]. It

40 For a presentation of standard diagnostic tests, see Bourbonnais [2005], Lütkepohl and Krätzig [2004] and Brooks [2008].

41 Whatever the normalization (Carbon, Gas, Electricity or Coal normalization) the results are identical for short-run parameters. For the long-run parameters, the carbon price becomes the only significant variable in the cointegration equation when we choose the Gas normalization, while both gas and carbon prices are significant for the Electricity normalization and for the Coal normalization. This indicates that the link between carbon and gas prices is robust in the equilibrium.

may be explained by the influence of exogenous political forces that are difficult to model. For example, the carbon price could depend heavily on exogenous political decisions about the future of the EU ETS, the negotiations on a post-Kyoto agreement for climate policy or the future of the Kyoto mechanisms, etc.

3.2.2. Granger causality tests

Usually the Granger causality methodology applies to VAR models. However, Granger causality can also be investigated in the VECM framework (see Lütkepohl [1991], Mosconi and Giannini [1992] and Lütkepohl and Krätzig [2004]), as in the model (3.10). For an illustration, consider a simpler bi-variate version of (3.10) with two price variables $p_{1,t}$ and $p_{2,t}$:

$$\begin{pmatrix} \Delta p_{1,t} \\ \Delta p_{2,t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} \begin{pmatrix} \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} p_{1,t-1} \\ p_{2,t-1} \end{pmatrix} + \sum_{i=1}^k \begin{pmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{21,i} & \gamma_{22,i} \end{pmatrix} \begin{pmatrix} \Delta p_{1,t-i} \\ \Delta p_{2,t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix},$$

which could be written as two individual equations for causality tests,

$$\begin{cases} \Delta p_{1,t} = \alpha_1 + \delta_1(\beta_1 p_{1,t-1} + \beta_2 p_{2,t-1}) + \sum_{i=1}^k \gamma_{11,i} \Delta p_{1,t-i} + \sum_{i=1}^k \gamma_{12,i} \Delta p_{2,t-i} + \varepsilon_{1,t} \\ \Delta p_{2,t} = \alpha_2 + \delta_2(\beta_1 p_{1,t-1} + \beta_2 p_{2,t-1}) + \sum_{i=1}^k \gamma_{21,i} \Delta p_{1,t-i} + \sum_{i=1}^k \gamma_{22,i} \Delta p_{2,t-i} + \varepsilon_{2,t} \end{cases}$$

Thereafter, testing for Granger causality running from $p_{2,t}$ to $p_{1,t}$ amounts to testing $\delta_1 \beta_2 = 0$ and $\gamma_{12,i} = 0$ (with $i=1, \dots, k$) in the first equation, i.e. the following null hypothesis: $\delta_1 \beta_2 = \gamma_{12,i} = 0$, $i=1, \dots, k$ (see Mosconi and Giannini [1992] and Lütkepohl and Krätzig [2004]).⁴² So, we can conclude that $p_{2,t}$ “Granger-causes” $p_{1,t}$ if H_0 is rejected. We can also test the null hypothesis $\delta_2 \beta_1 = \gamma_{21,i} = 0$, $i=1, \dots, k$, in the second equation, in order to check if $p_{1,t}$ “Granger-causes” $p_{2,t}$. In each case, tests for coefficient restrictions are based on Wald tests. As pointed out in Lütkepohl and Krätzig [2004] the Wald test results may not be valid in the VECM framework due to the presence of I(1) variables. The cointegration may induce nonstandard asymptotic properties

⁴² Note that Eviews does not directly provide consistent results for Granger causality in the VECM framework. The correct specification of the tests have to be specified using the “Wald coefficient tests” option.

for the tests on the coefficients, leading to biased results. These difficulties can be removed by adding an extra lag in estimating parameters of the model. Then a $VECM(k+1)$ has to be estimated in place of a $VECM(k)$. However, the tests have to be performed on the first k lags of the $VECM(k+1)$ only.⁴³

The results for Granger causality tests using the estimation of (3.10) with four (i.e. $k+1$) lags (with Carbon normalization, as in Table 18)⁴⁴ are presented in Table 19.

Table 19: Granger causality test results with three lags considered (*, ** and *** denote statistical significance of Granger causalities at the 10, 5 and 1% levels, respectively).

	Dependent Variables							
	Carbon		Coal		Gas		Electricity	
	Chi-Sq	p-value	Chi-Sq	p-value	Chi-Sq	p-value	Chi-Sq	p-value
Carbon	-	-	20.05703	0.0005***	18.61797	0.0009***	8.553754	0.0733*
Coal	5.982611	0.2005	-	-	14.91859	0.0049***	10.25167	0.0364**
Gas	11.32722	0.0231**	2.521251	0.6408	-	-	8.619850	0.0713*
Electricity	4.201620	0.3764	5.126332	0.2746	37.67949	0.0000***	-	-

As for relationships between the carbon price and the fuel prices, we find significant Granger causalities that lend support to the fuel-switching theory. Notably, we identify a significant feedback effect between the gas and the carbon prices. Moreover, we find a significant impact of the carbon price on the coal price, while the reverse does not hold. Thus, our results suggest that interactions between the gas and the carbon prices exist in the short-run, as in the equilibrium. This confirms most of the previous investigations on this topic. The influence of the gas price on the carbon price was detected during Phase 1 through single-equation estimations (see Alberola et al. [2008] and Hintermann [2010])⁴⁵ and impulse response analyses (see Bunn and Fezzi [2007] and Fell [2008]). A significant impact of the coal price on the carbon price is also reported for Phase 1 by Mansanet-Bataller et al. [2007], Alberola et al. [2008] and Hintermann [2010] in single-equation estimations. Keppler and Mansanet-Bataller [2010] show that there is an indirect influence of coal and gas prices on the carbon price, through the spreads, during Phase 1 and during the first year of Phase 2. They also report a direct influence of the coal price on the carbon price in Phase 2. Finally,

43 For more details see Lütkepohl and Krätzig [2004].

44 Granger causality tests have also been performed with the other normalizations in the cointegrating vector. Results are unchanged.

45 See also Rickels et al. [2010] for Phase 2.

the results of Creti et al. [2012] indicate that the switching price Granger causes the carbon price in Phase 2.

As we have already mentioned, the influence of the fuel prices on the carbon price better reflects the fuel-switching theory. However, in addition to the influence of the fuel prices on the carbon price, we also find that the carbon price impacts both the gas and the coal prices. Keppler and Mansanet-Bataller [2010] report the same result for the beginning of Phase 2. They identify Granger causalities running from the carbon price to the coal and the gas prices.⁴⁶ For Phase 1, Nazifi and Milunovich [2010] are the only ones who find such a result, with a significant Granger causality running from the carbon price to the gas price.⁴⁷ As pointed out by Keppler and Mansanet-Bataller [2010], the most likely explanation for the influence of the carbon price on the fuel prices in Phase 2, is that the carbon market has processed relevant information about expected economic activity faster than fuel markets. As mentioned earlier, the use of the EU ETS as a short-term financial tool during the crisis (“time swaps”) may have turned the carbon spot market into a major place for information disclosures about economic activity, which may explain this result.⁴⁸ Note here that the influence of the carbon price is always significant for all the energy variables (see Table 19). Here again one may see these results as evidence of transmission of information from the carbon to the energy markets.

The results involving the carbon and the electricity prices suggest that the pass-through theory is valid, while the short-term rent capture is not verified. Indeed, while we find a significant impact of the carbon price on the price of electricity, we identify no Granger causality running from electricity to carbon. This lends support to the pass-through theory. Our results confirm most of the previous investigations for Phase 1, which have reported evidence of the carbon price influence on electricity (see Bunn and Fezzi [2007], Fell [2008], Zachmann and von Hirschhausen [2007] and Keppler and Mansanet-Bataller [2010]).⁴⁹ An exception here comes from Nazifi and Milunovich [2010] who do not validate this result for Phase 1, while they find a significant influence of the

46 Here it is interesting to mention the results of Creti et al. [2012] which show that the carbon price Granger causes the oil and stock prices in Phase 2. For those authors, this reflects an increasing role of the EU ETS in the economy.

47 Note that Bunn and Fezzi [2007] have found that a shock on the carbon price impacts the gas price in their impulse response analysis for Phase 1. However, the response is small in magnitude, and their results suggest that the opposite relationship is much more important.

48 Bonacina et al. [2009] have suggested an analogous interpretation to explain the lesser influence of the switching price after the crisis of 2008, while the carbon market was sensitive to stock prices. The authors interpret these results as the consequences of changing behaviors of market players because of the crisis and the credit crunch. With emission reductions, companies have been able to sell their unused allowances to raise cash during the credit crunch. These financing strategies were the main reasons for the volumes of trade at the end of 2008. The market players may also have traded allowances for speculative purposes.

49 See also Solier and Jouvét [2011] in a regression analysis.

electricity price on the carbon price. However, regarding Phase 2, the results of Keppler and Mansanet-Bataller [2010] validate the influence of the electricity price on the carbon price, but not the influence of the carbon price on the electricity price. Thus, they argue that the short-term rent capture theory prevails in Phase 2. By contrast, we find that the pass-through theory is better in explaining relationships between carbon and electricity markets in Phase 2. This latter result should be compared with estimations of Solier and Jouvet [2011], which indicate that the pass-through theory is significant in Phase 2, although it is more obvious in Phase 1. Interestingly, those authors report that the influence of the carbon price is stronger when the futures prices of off-peak electricity are used, as in our case. This suggests that the pass-through is more important in off-peak periods, due to a lesser scarcity of generation capacities.

3.2.3. Impulse response analysis

Granger causality suggests which of the variables have a significant impact on subsequent values of the other variables in the model, all other things being equal. However, Granger causality is unable to explain the signs of the relationships, and it neglects interactions among variables in the system. To account for these complicated interactions, impulse response functions are useful. As we saw in section 2 of this chapter, the impulse response functions are computed using the moving average representation (VMA) of a VAR. However, the Wold representation does not exist for VECMs. Hence, a VECM does not possess a VMA representation of the type discussed in section 2 of this chapter. Nevertheless, it is possible to derive the impulse response matrices Φ_j as defined in section 2 of this chapter.⁵⁰ In this case, the Φ_j may not converge to zero as j tends to infinity (see Lütkepohl [1991] and Lütkepohl and Krätzig [2004]), as is the case with a VAR (see section 2 of this chapter). Consequently, some shocks may have permanent effects.⁵¹

As we saw in section 2 of this chapter, among the orthogonalization procedures, the generalized impulse response function procedure (Pesaran and Shin [1998]) does not depend on the ordering of variables.⁵² Accordingly, we used this orthogonalization procedure to compute impulse

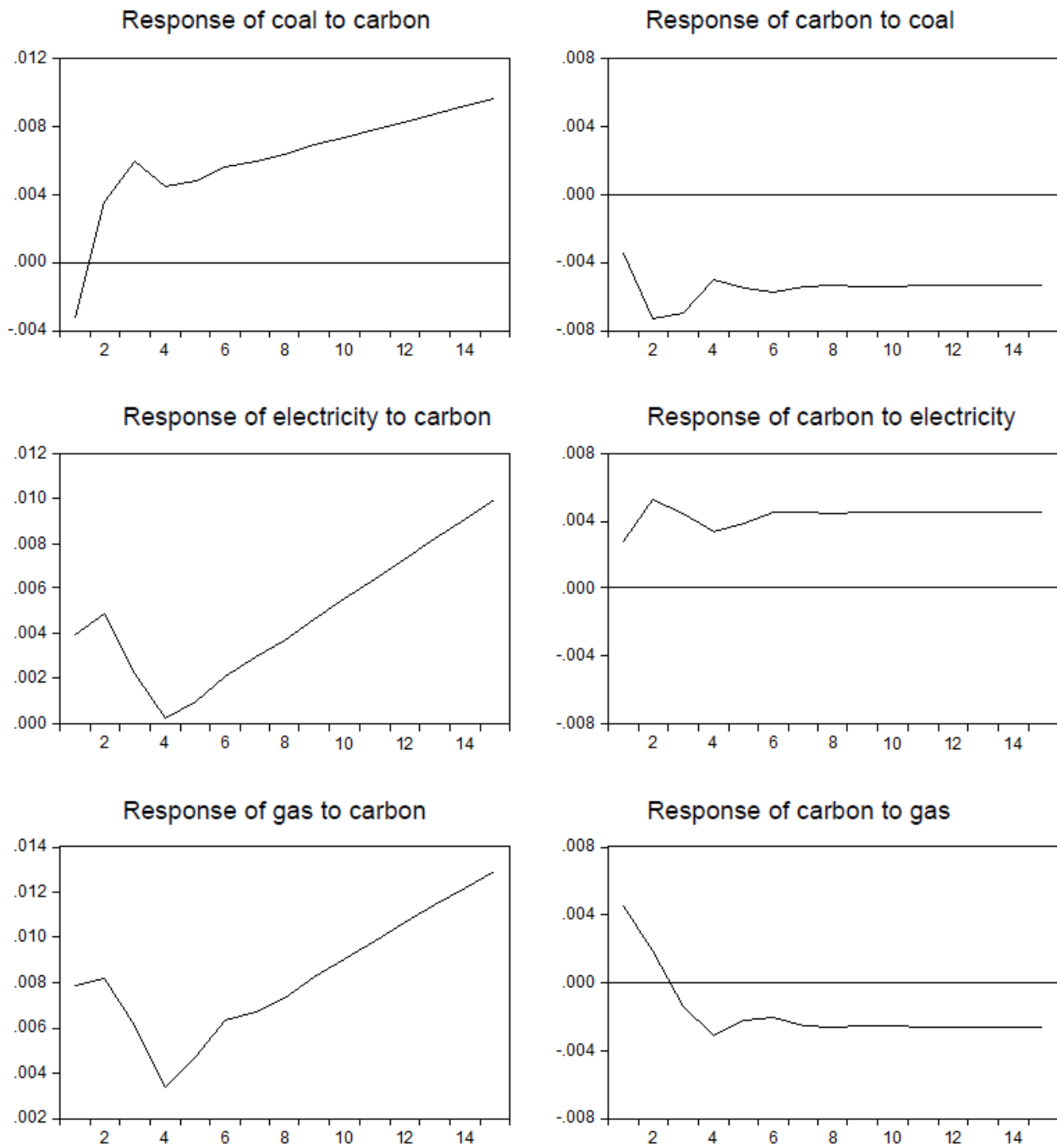
50 Fortunately, Eviews directly provides the impulse response functions for VECMs. Therefore, we do not include an extensive presentation of impulse responses in this case. For more details, the interested reader can refer to Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

51 Graphically it appears in the impulse response functions because they do not revert back to zero, as opposed to examples of Figure 41 in section 2 of this chapter. For illustrative examples, see Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

52 Note here that when the residuals are almost uncorrelated (as in our case), the results are not very sensitive to a change in the ordering of variables. See Lütkepohl [1991].

responses in our model. As our main interest is to determine how the carbon price reacts to energy prices and vice versa, we compute the impulse response functions of the energy prices for a shock to the carbon price, and the impulse response functions of the carbon price for shocks to each of the energy prices. The results are presented in Figure 43.

Figure 43: Generalized impulse response functions.



The signs of the impulse responses are consistent with the economic theories presented in section 2 of Chapter 1, except for the responses of carbon to gas and of coal to carbon. Under the fuel switching theory, the carbon price ought to increase when the gas price increases, and the coal price ought to decrease when the carbon price increases. In both cases Figure 43 shows reactions which are not consistent with fuel switching, except in the very first days after the shock.⁵³ Note that the positive response of coal to carbon could be explained by the transmission of information (relative to economic activity) from the carbon to the energy markets during the crisis. This may also explain the positive response of gas to carbon (in addition to fuel switching).

Figure 43 also shows that the magnitudes of the responses are all very small, especially for the responses of the carbon price to each of the energy prices. However, regarding the carbon price influence on the energy markets, the shape of the impulse response functions shows that effects are permanent (the responses do not revert to zero)⁵⁴ and that the responses increase over time. Therefore, the responses of electricity, coal and gas to a shock on the carbon price are not only higher in magnitudes (with respect to the responses of carbon to the energy prices), but they are also increasing and they produce permanent effects.

Several previous papers involving impulse response analysis found that the electricity price was sensitive to a shock on the carbon price in Phase 1 (see Bunn and Fezzi [2007], Fell [2008] and Zachmann and von Hirschhausen [2007]). Our results corroborate those previous analyses. However, only Bunn and Fezzi [2007] found that the gas price was affected by a shock on the carbon price.⁵⁵ Nevertheless, those same authors found a much more significant impact on the carbon price after a shock on the gas price, with a positive reaction according to the fuel-switching theory. This contrasts with our results which show that the response of the fuel markets to the carbon price is more significant than the reverse (i.e. the response of the carbon market to a shock on the gas price or on the coal price). These differences could be explained by our sample period. Whereas previous impulse response analyses were performed in Phase 1, we work in Phase 2. Thus, our result should be more fruitfully compared to Granger causality tests by Keppler and Mansanet-

53 According to the fuel switching theory, the coal price would have to decrease if the carbon price rose (negative response of coal to carbon), and the carbon price would have to increase if the gas prices increased (positive response of carbon to gas). However, as we can see in Figure 43, these reactions are observed only in the earliest days after the shock. Afterward, reactions are in contradiction with the fuel switching theory, with a positive response of coal to carbon and a negative response of carbon to gas.

54 As explained before, shocks may have permanent effects in an impulse response analysis based on a VECM. See Lütkepohl [1991] and Lütkepohl and Krätzig [2004].

55 Fell [2008] also reported that coal and gas prices react to a shock on the carbon price. However, he found that the reactions were slow and very small in magnitude.

Bataller [2010] and Creti et al. [2012], which concern Phase 2. As we have already mentioned, Keppler and Mansanet-Bataller [2010] find Granger causality running from the carbon price to the gas and coal prices, while Creti et al. [2012] show that the carbon price influences the oil price (and stock prices). Our impulse response analysis corroborates the results of those authors. In addition, we find that these relationships have positive signs, which is consistent with the hypothesis of the transmission of information – relative to economic activity – from the EU ETS to the energy markets during the crisis.

4. Conclusion

In this chapter we have examined interactions between carbon and energy markets during the first two years of Phase 2 of the EU ETS. We have used a VECM approach, with Granger causality tests and impulse response functions to investigate the dynamic of relationships between carbon, coal, gas, and electricity prices. We have found evidence of both short-run and long-run interactions.

In section 2, we first presented econometric tools we use in our empirical works. The econometric investigations and results are included in section 3. Our work extends previous literature in two directions essentially. We first generalized a previous contribution that analyzed relationships between carbon and energy markets in Phase 2 (Keppler and Mansanet-Battaler [2010]), by applying a full VAR-VECM approach to study interactions between carbon, coal, gas, and electricity prices in Phase 2. Our aim was to compare our results for Phase 2 with those of similar papers developed for Phase 1 (Bunn and Fezzi [2007], Zachmann and von Hirschhausen [2007], Fell [2008], Chemarin et al. [2008] and Nazifi and Milunovich [2010]), in addition to testing relevance of the theories presented in Chapter 1 (pass-through, short-term rent capture and fuel switching). Second, we computed impulse response functions to complete Granger causality. This allowed us to account for more complicated interactions than with Granger causality, and it extended the papers of Keppler and Mansanet-Battaler [2010] and Creti et al. [2012] for Phase 2.

The three most important results featured in this chapter can be summarized as follows. First, we find a significant impact of the gas price on the carbon price. The cointegration analysis shows that the gas price is a significant driver of the carbon price in the equilibrium, with a positive coefficient in line with fuel-switching. The results about the impact of fuel prices on the carbon price are more difficult to interpret in the short-run, with very small impulse responses and ambiguous signs. This suggests that fuel-switching stands in the equilibrium, while this is less obvious in the short-run.⁵⁶ One possible explanation may be that the fuel switching strategies are planned over time horizons which are beyond the very short-run, with likely wait-and-see behaviors. Second, our results indicate that the carbon price impacts the price of electricity, whereas the reverse effect is not significant. This can be seen as evidence of pass-through. Finally, for fuel prices, we obtained results which are more surprising and difficult to interpret at first glance. We find that the carbon price impacts the coal and gas prices (Granger causality and impulse response).

⁵⁶ See Rickels et al. [2010] for similar conclusions.

Fuel markets are expected to be little affected, if at all, by changes in demand for fuel created by the EU ETS. On the one hand, fuel demand triggered by fuel switching is limited due to the scarcity of gas capacities available for switching in each period. On the other hand, European fuel markets are integrated into world markets,⁵⁷ so that variations in fuel demand for switching purposes are very small with respect to world fuel markets. In that context, the most likely explanation of the short-term influence of the carbon price on the fuel prices is that the EU ETS was a driver for information disclosure about economic activity in Europe during the crisis, due to “time-swap” strategies. Thereafter, information about economic activity would have been passed on to fuel markets through the EU ETS.⁵⁸ This result must be a particular case caused by the crisis and the “de-coupling” of the European fuel markets with respect to the world fuel markets during this period, due to the continuing economic growth in the emerging countries while Europe was in recession.⁵⁹

57 Note here that the coal market is more global in essence than the gas market, since coal can easily be shipped all over the world whereas gas is largely distributed through pipelines as a regional commodity. However, the gas market is becoming increasingly global with progress in gas liquefaction creating more shipping opportunities.

58 This explanation is consistent with the positive sign we found in the impulse response of coal to carbon.

59 See Keppler and Mansanet-Bataller [2010].

Chapter 4

Cross-market price discovery in the European gas and CO₂ markets: an empirical analysis

Since the creation of the European Union Emission Trading Scheme (EU ETS), European power producers have monitored carbon emissions resulting from the composition of their production. According to fuel switching theory, gas and EUAs (European Union Allowances) can be considered substitutable inputs in electricity generation. They are thus related commodities, with cross-market dynamic of information running from the market which processes new information faster to the other. This chapter examines the cross-market price discovery process between the European carbon and gas markets. The aim is to evaluate the relative contribution of each market to the cross-market price discovery, in order to identify which one is the leader in this process. We use the Common Factor Weights approach introduced by Schwarz and Szakmary [1994]. We find that the carbon market is the leader.

1. Introduction

One indirect effect of the European Union Emission Trading Scheme (EU ETS) has been to change the value of using gas in electricity generation.¹ European power producers have been made more mindful of the carbon emissions resulting from the composition of their production, now that a price has been put on them. Generating power with natural gas produces about half the CO₂ emissions of generating power with coal. Accordingly, fuel switching, in this instance substituting gas-fired plants (CCGTs - Combined Cycle Gas Turbines) for carbon-intensive coal-fired plants, has become a way to achieve carbon abatements.

¹ Many authors argue that the EU ETS has strengthened the link between gas and power, with some unfavorable consequences such as gas price rises (Reinaud [2007]) or greater geopolitical risks (Bunn and Fezzi [2007] and Grubb and Newberry [2008]).

If the cost of carbon emissions is ignored, coal-fired plants are usually cheaper to run than gas-fired plants, because of their lower fuel cost. However, when a carbon price is introduced, generating electricity with gas-fired plants may become more attractive than using coal-fired plants. In fact, if the cost of increased carbon emissions with coal plants is higher than the additional fuel cost of gas plants, it is cheaper to produce with gas plants (and vice versa). Based on the comparison of these two costs, power producers can decide, for a given level of production,² either to increase the share of gas and thus reduce the number of EUAs (European Union Allowances, the carbon certificates from the European market), or, alternatively, to reduce the share of gas and increase the number of EUAs (because of increased emissions from burning more coal). Therefore, gas and EUAs can be considered substitutable inputs in electricity generation. Accordingly, they are related commodities,³ with cross-market dynamic of information running from the market that better records incremental information to the other. The aim of this chapter is to investigate this process.

Price discovery is the process by which markets record new information affecting prices. Information about related commodities/securities crosses linked markets with the result that incremental information affecting one market will also affect other markets latter. The question is which market captures information first? This is a significant question since the price of a market which processes new information faster than others, may be used, in many cases, to anticipate the price evolutions on related markets. Thus, it is useful evaluating the relative contribution of each market to the price discovery process.

Studying relationships between carbon and energy markets from a financial point of view has been of growing interest since the start of the EU ETS. This has been investigated in several econometric papers. Many of them concentrate on identifying the determinants of the carbon price in regressions. They find that coal and gas prices are particularly relevant in explaining the carbon price fluctuations (Mansanet-Bataller et al. [2007], Alberola et al. [2008] and Hintermann [2010]). Econometric studies focusing on cointegration and dynamic interactions between carbon and energy

2 We speak here of production levels in the “switching zone” of “intermediate load”, as defined in Chapter 1. This corresponds to off-peak load levels of production which are just higher than base load levels. On the one hand, fuel switching cannot occur in peak load, since, in this situation, all the power plants are already online and thus no CCGT is available. On the other hand, fuel switching is not a profitable option in base load, since base plants (i.e. power plants that run in base load) are cheaper to run than CCGTs and have near-zero carbon emissions (e.g. nuclear or hydroelectricity).

3 Here, we refer to EUAs as commodities since we consider they are inputs in electricity generation. However, as storage of EUAs (i.e. physical storage, neglecting the foregone interest) is costless or very cheap, they are often considered to be financial assets rather than pure commodities.

prices have also been of growing interest in the last few years. Papers on this topic include Bunn and Fezzi [2007], Bonacina et al. [2009], Fell [2008], Mansanet-Bataller and Soriano [2009], Keppler and Mansanet-Bataller [2010], Nazifi and Milunovich [2010], Bredin and Muckley [2011], Bertrand [2011a] and Creti et al. [2012].

However, to the best of our knowledge, no paper has investigated the cross-market price discovery process between carbon and energy markets. We fill this gap in the literature by focusing on the carbon and gas markets. Price discovery has been examined in various types of economic linkages among markets including related commodities/securities⁴ (e.g. Cortazar et al. [2008], Coppola [2008] and Chng [2010]), the spot-futures relationships (e.g. Garbade and Silber [1983], Schwarz and Szakmary [1994] and Theissen [2011]) and the different marketplaces for a same commodity/security (e.g. Goodwin [1991], Theissen [2002] and Thurlin [2009]). Where the EU ETS is concerned, price discovery has been examined in the spot-futures relationships for EUAs (Uhrig-Homburg and Wagner [2007] and Rittler [2009]) and for the futures prices of different exchanges (Benz and Klar [2008]). Focusing on the cross-market price discovery process between the carbon and gas markets, this paper aims to extend the aforementioned literature on relationships between carbon and energy markets.

To address the question of the cross-market price discovery process between carbon and gas markets, we use the common factor approach built on work by Schwarz and Szakmary [1994] and Gonzalo and Granger [1995]. The first step consists in estimating a vector error correction model (VECM) using the price series. Afterward, to quantify the relative contribution of each market to the cross-market price discovery, we compute the Common Factor Weights as defined by Schwarz and Szakmary [1994]. We find that the carbon market contributes more to the cross-market price discovery process.

The remainder of this chapter is organized as follows. In section 2 we present the logic of substitution between gas and EUAs. Section 3 describes the variables and sets out some preliminary statistics such as unit root tests and cointegration testing. Section 4 introduces the Common Factor Weights methodology, econometric specifications and displays estimation results. Section 5 concludes.

4 Examples are exchanges, screen-floor markets or regional/international markets.

2. Substitution between gas and carbon allowances

According to literature on the EU ETS, fuel prices are the most significant drivers of the carbon price in Europe, due to the ability of European power producers to reduce their carbon emissions by switching from coal to gas in electricity generation.⁵ This short-term abatement option is known as fuel switching. It happens in intermediate load (i.e. for intermediate levels of production that occur between 20% and 80% of the time, see Unger [2002]) between coal plants and CCGTs (Combined Cycle Gas Turbines).⁶

Fuel switching refers to the ability of power producers to reduce their carbon emissions by generating electricity with CCGTs where they previously used coal plants. It takes place in the short run, because it happens in a context where electricity generation facilities (the number of power plants) and their efficiencies (the energy efficiency of each power plant) are fixed. When power producers do not integrate the carbon cost into their decisions (“business-as-usual” scenario), they begin to produce with coal plants, whereas CCGTs are brought online for higher levels of load (i.e. when power demand increases), due to the lower fuel cost of coal. Alternatively, power producers may decide to use CCGTs first as substitutes for coal plants; this will allow them to reduce their CO₂ emissions compared with the “business-as-usual” scenario,⁷ but it will increase the fuel cost.

Fuel switching entails an increasing cost for fuel consumption. However, when the carbon cost is integrated into the cost of generating electricity, the handicap of coal because of its high carbon emissions has also to be taken into account. Indeed, if the carbon price is high enough, CCGTs may be preferable to coal plants, due to their lower carbon intensity. Therefore, up to a certain level for the carbon price (i.e. so long as the carbon price is higher than the additional fuel cost associated with the decision to produce first with gas in order to abate one tonne of CO₂), it is cheaper to use CCGTs first instead of coal plants. Conversely, if the carbon price is below the additional fuel cost associated with the decision to produce with gas, it is cheaper to use coal plants first and cover the increased carbon emissions with more permits. In other words, fuel switching

5 See Chapter 1 for an extensive review of econometric and theoretical papers on the interplay between carbon and energy markets.

6 In Europe, fuel switching can also occur with other plants for other levels of load. For example, switching can occur between oil plants and open cycle gas turbines, or also between hard-coal and lignite. However, as the quantities of carbon involved in switching between coal plants and CCGTs are much higher, this type of switching has been the main focus of power producers and researchers.

7 In this case, CCGTs run for longer periods because they are brought online first, whereas coal plants, that are brought online next (for higher levels of power demand), run for shorter periods. Therefore, as CCGTs generate a lower carbon output than coal plants, this switching enables power producers to reduce their carbon emissions.

occurs since with a high enough carbon price certain coal plants switch places with certain CCGTs in the merit order⁸ (see Sijm et al. [2005], Kanen [2006] and Delarue et al. [2008]). Consequently, at any time where fuel switching is possible (i.e. in intermediate load when some CCGTs are available for switching), power producers will have to choose between two options: increasing the proportion of CCGTs in power generation (i.e. physically reducing some of their carbon emissions by switching fuels) or buying more permits on the market to produce with coal plants. Therefore, gas and EUAs can be considered substitutable inputs in electricity generation, and they are subject to a trade-off which depends on the difference between the fuel switching cost (i.e. the additional fuel cost associated with the decision to produce first with CCGTs) and the cost of buying permits.

A widely used indicator of the cost of switching is the switching price (see Kanen [2006], Fehr and Hinz [2006] and Delarue and D'haeseleer [2007]). Let us take a short example in order to introduce the switching price. We define the marginal costs of producing one MWh of electricity (in Euros) with coal plants and with CCGTs, respectively, as: $MC_c^{BAU} = h_c COAL_t$ and $MC_g^{BAU} = h_g GAS_t$, in the BAU scenario, and $MC_c^{EU ETS} = h_c COAL_t + e_c EUA_t$ and $MC_g^{EU ETS} = h_g GAS_t + e_g EUA_t$ under the EU ETS. Here e_c and e_g are coefficients measuring the carbon emissions (in tonnes of CO₂ per MWh of electricity) from coal plants and CCGTs, respectively. h_c and h_g express how much fuel is consumed to generate one MWh of electricity with the same plants (where h_c is expressed in tonnes, and h_g in thermal MWh). $COAL_t$, GAS_t and EUA_t are the prices of coal (in Euros per tonne), gas (in Euros per thermal MWh) and CO₂ (in Euros per tonne) at time t .

Using these notations, the decision to switch fuels from coal to gas is made by comparing $MC_c^{EU ETS}$ with $MC_g^{EU ETS}$. Thus, it will be worth switching between the two technologies if $MC_c^{EU ETS}$ is higher than $MC_g^{EU ETS}$ (whereas MC_c^{BAU} could be lower than MC_g^{BAU}). More specifically, if the cost of increased carbon emissions with coal plants ($EUA_t(e_c - e_g)$, for each MWh of electricity) is higher than the additional fuel cost associated with the decision to produce first with CCGTs rather than with coal ($h_g GAS_t - h_c COAL_t$, for each MWh of electricity), it is cheaper to use CCGTs first instead of coal plants (and vice versa). Therefore, fuel switching should occur if and only if $EUA_t(e_c - e_g) > h_g GAS_t - h_c COAL_t$ (which corresponds to $MC_c^{EU ETS} > MC_g^{EU ETS}$). This last inequality allows us to derive the switching price, as define in Fehr and Hinz [2006] (see also Delarue and D'haeseleer [2007]):

⁸ The merit order is the ranking of all power plants of a given park by marginal cost of production. Technologies are stacked in order of increasing marginal cost of electricity production, so that power producers add more and more expensive plants to production as demand increases. For more details, see Unger [2002] and Kanen [2006].

$$SW_t = \frac{h_g GAS_t - h_c COAL_t}{e_c - e_g}, \quad (4.1)$$

so that fuel switching would (would not, respectively) occur at a period t if $EUA_t > SW_t$ ($EUA_t < SW_t$, respectively).⁹

In practice, there are numerous power plants with different rates of efficiency.¹⁰ So, taking into account these differences, we have one switching price for any given pair of coal and gas plants (see Chapter 1). Thus, for any given fuel prices, there are several switching prices associated with different pairings of coal and gas plants. However, as a simplification, it is very common to aggregate all the switching possibilities into one representative switching price. Assuming one representative type of CCGTs (i.e. one representative efficiency rate) and one representative type of coal plants, we follow the same strategy.¹¹ Thus, we have a representative switching price (given by equation (4.1)) which can be estimated and compared to the carbon price.

Following Tendances Carbone [2007] we assume that power plants have an efficiency rate of 40% for coal plants and 50% for CCGTs. So, using the calculation formulas introduced in Chapter 1 for heating and emission rates we get: $e_g = 0.4$, $h_g = 2$, $e_c = 0.85$, and $h_c = 0.36$. Thereafter, the representative switching price can be computed using equation (4.1), and it corresponds to SW_t^{50} of Chapter 1.¹²

9 Equation (4.1) is the same as equation (1.1) of Chapter 1.

10 These differences in the efficiency of plants may influence the cost of switching. See Chapter 2 for a theoretical justification. See also Sijm et al. [2005] and Delarue et al. [2008] for simulations of the switching cost with more or less efficient types of plant.

11 This assumption is clearly restrictive, even though it is quite common in the literature. In fact, to the best of our knowledge, all the econometric literature on fuel switching is built under the assumption of a single switching price. By contrast, some papers have investigated consequences of differences in efficiency of power plants in simulation analysis (e.g. Sijm et al. [2005] and Delarue et al. [2008])

12 In this chapter the switching prices are computed using the values of coefficients e_c and h_c associated with coal plants of 40% efficiency, whereas they were computed for coal plants of 38% efficiency in Chapter 1. Consequently, SW_t^{55} , SW_t^{50} and SW_t^{45} we use in this chapter are computed for coal plants of 40% efficiency. Note that we have also performed our estimations with switching prices (SW_t^{55} , SW_t^{50} and SW_t^{45}) associated with coal plants of 38% efficiency. We obtain identical results both regarding the cointegration analysis (section 3) and the estimated adjustment coefficients (magnitude and significance) in the VECMs (section 4).

3. Variables and preliminary statistics

In this section we first introduce variables that can be used to account for substitution between gas and carbon. Next, we test for stationarity and cointegration in the data.

3.1. Variables and data

As we saw in the previous section, the carbon price and the gas price should be compared to set the optimal composition of power generation due to substitution between gas and carbon allowances (see Chapter 1 for further details). Hence, there should be an arbitrage between the increased carbon cost with coal plants and the increased fuel cost with CCGTs. Different variables are used to account for this process.

According to the theory, the most natural way to study the arbitrage process is to compare the EUA price (i.e. the price of one tonne of carbon) with the switching price (i.e. the increased fuel cost to abate one tonne of carbon, as given by equation (4.1)). As explained in the previous section, following Tendances Carbone [2007] we assume a single representative switching price reflecting a situation where power plants have an efficiency rate of 40% for coal plants and 50% for CCGTs. Hence, we include SW_t^{50} as representative switching price used in our empirical investigations.¹³ Accordingly, from now on, when we refer to SW_t , we mean SW_t^{50} .

We also choose to include other variables for comparison with the carbon price. If the gas price rises relative to the coal price, the fuel switching cost rises. Therefore, the ratio between the gas price and the coal price can be used to represent the cost of switching. We call this variable *Ratio*, so that $Ratio_t = GAS_t / COAL_t$. Finally, we also use the gas price for direct comparison with the carbon price.

We use daily data for carbon, coal and gas prices in Europe.¹⁴ The data runs from February 26, 2008 to October 30, 2009, and it corresponds to the first two years of Phase 2 of the EU ETS. The carbon price is the daily closing price of EUA spot contracts of Bluenext.¹⁵ Bluenext was

13 Note that running estimations with different switching prices (i.e. with SW_t^{55} and SW_t^{45} , reflecting different pairings of coal and gas plants) does not modify results. See sections 3 and 4.

14 Data are presented in Appendix B.

15 We present in Appendix D the same econometric analysis as in Chapter 4, using the price of EUA futures contracts.

chosen because it is the most liquid spot market for EUAs (see Benz and Klar [2008] and Daskalakis et al. [2009]). The gas price, in Euros per thermal MWh, is the daily closing price of month ahead gas futures contracts negotiated on the Zeebrugge Hub. The coal price, in Euros per tonne, is the daily closing price of month ahead coal futures contracts, CIF ARA.

3.2. Preliminary statistics

For an error-correction representation to be valid, all series have to contain a unit root and have to be cointegrated. If series contain a unit root, they are first-difference stationary, while non-stationary in level. This means that they are affected by a linear stochastic trend. They are said to be $I(1)$ or integrated of order 1. Once series have been found to be $I(1)$, cointegration testing can be undertaken. If series are cointegrated, there exists a linear combination of series which is $I(0)$, i.e. stationary. Thus, there is a co-movement of the $I(1)$ series, which are stationary around a common stochastic trend.

3.2.1. Stationarity tests

To test for stationarity we apply three unit root tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Peron (PP) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The ADF and the PP assume non-stationary series under the null hypothesis, while the KPSS tests the null hypothesis that the series are stationary.

Tables 20 and 21 present the results of the unit root tests for series in level and in first difference.

Table 20: Unit root tests on level series (*, ** and *** denote statistical rejection of the null hypothesis at the 10, 5 and 1% levels, respectively)

Data series	ADF (t-Statistics)	PP (t-Statistics)	KPSS (LM-Statistics)
Carbon	-0.88	-0.86	1.97***
Coal	-1.15	-1.16	1.93***
Gas	-0.91	-0.92	2.17***

Table 21: Unit root tests on first difference series (*, ** and *** denote statistical rejection of the null hypothesis at the 10, 5 and 1% levels, respectively)

Data series	ADF (t-Statistics)	PP (t-Statistics)	KPSS (LM-Statistics)
Carbon	-16.04***	-19.14***	0.18
Coal	-20.77***	-20.77***	0.22
Gas	-24.73***	-25.14***	0.14

Results show that all series are non-stationary in level (see Table 20), while stationary in first difference (see Table 21). Accordingly we can conclude that they are all I(1), and, consequently, error-correction representations may be appropriate, depending on the cointegration analysis results.

3.2.2. Cointegration analysis

We test for cointegration between the carbon price and the switching price, the carbon price and the gas price, and the carbon price and the ratio. To conduct our cointegration tests, we apply the Engle-Granger [1987] two-step method, which can be used here since each of our tests involves two variables only.¹⁶

In the Engle-Granger two-step method, we estimate the cointegrating relationship (using OLS) to get the residuals of the cointegrating regression, and we test residuals to see if they are I(0). Next, if the residuals are I(0), an error-correction representation can be estimated. In our case, we consider the following cointegrating regressions (depending on the variable we use to represent the increased fuel cost of switching):

$$EUA_t = \beta_1 + \beta_2 SW_t + u_t^{SW}, \quad (4.2a)$$

$$EUA_t = \beta_1 + \beta_2 Ratio_t + u_t^{Ratio}, \quad (4.3a)$$

¹⁶ See Chapter 3.

$$EUA_t = \beta_1 + \beta_2 GAS_t + u_t^{GAS}, \quad (4.4a)$$

$$EUA_t = \beta_2 SW_t + u_t^{SW}, \quad (4.2b)$$

$$EUA_t = \beta_2 Ratio_t + u_t^{Ratio}, \quad (4.3b)$$

$$EUA_t = \beta_2 GAS_t + u_t^{GAS}, \quad (4.4b)$$

where u_t^{SW} , u_t^{Ratio} and u_t^{GAS} are the residuals to test.¹⁷

In order to consider more situations, we apply the two-step method to cointegrating equations with and without the constant β_1 . Accordingly, we refer to (4.2a), (4.3a) and (4.4a) when we include the constant, and (4.2b), (4.3b) and (4.4b) when we exclude the constant. Including a constant in our cointegrating equations enables us to account for factors other than fuel prices that affect the marginal cost of switching. They may be, for example, costs related to maintenance operations or unforeseen breakdowns of plants.¹⁸ Results for unit root tests are given in Tables 22 and 23.

Table 22: Unit root tests for equilibrium errors of cointegrating regressions (4.2a), (4.3a) and (4.4a) (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

Residuals	ADF (t-Statistics)	PP (t-Statistics)
u_t^{SW}	-1.09	-1.15
u_t^{Ratio}	-0.87	-0.85
u_t^{GAS}	-1.85*	-1.83*

¹⁷ We also conducted tests with SW_t^{55} and SW_t^{45} , but the results are identical.

¹⁸ Note that the influence of those factors is weak for fossil-fuel-based electricity, and especially for gas plants. In this case, the marginal cost depends mainly on fuel prices (Unger [2002]).

Table 23: Unit root tests for equilibrium errors of cointegrating regressions **(4.2b)**, **(4.3b)** and **(4.4b)** (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

Residuals	ADF (t-Statistics)	PP (t-Statistics)
u_t^{SW}	-1.75*	-1.74*
u_t^{Ratio}	-1.37	-1.41
u_t^{GAS}	-1.88*	-1.75*

As theory suggests that the carbon price should equal the switching price in the equilibrium, we also conduct the cointegration tests by pre-specifying the coefficient of the switching price rather than estimating it. We therefore continue the cointegration analysis (Engle-Granger two-step method) with the following cointegrating equation:

$$EUA_t = \beta_1 + SW_t + u_t^{SW}, \quad (4.5a)$$

$$EUA_t = SW_t + u_t^{SW}. \quad (4.5b)$$

As before, we refer to **(4.5a)** when we include the constant, and **(4.5b)** when we exclude the constant (in this case, we apply the unit root tests to the difference $EUA_t - SW_t = u_t^{SW}$). Results for unit root tests for **(4.5a)** and **(4.5b)** are given in Table 24.¹⁹

Table 24: Unit root tests for equilibrium errors of cointegrating relationships **(4.5a)** and **(4.5b)** (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

u_t^{SW}	ADF (t-Statistics)	PP (t-Statistics)
(5a)	-2.14**	-2.31**
(5b)	-2.03**	-2.15**

¹⁹ Here again, results are not modified by using SW_t^{55} or SW_t^{45} rather than SW_t^{50} .

Results from Tables 22 to 24 show that among tested cointegrating equations, equations **(4.2b)**, **(4.4a)**, **(4.4b)**, **(4.5a)** and **(4.5b)** can be retained for the VECM estimations since they have stationary errors. However, we exclude equations involving the ratio variable (see Tables 22 and 23). We will thus estimate, in the next section, several models involving the admissible equations. Our results confirm previous investigations which have reported significant cointegration between carbon and gas prices in Phase 1 (Bunn and Fezzi [2007] and Fell [2008]) and in Phase 2 (Bertrand [2011a]). Cointegration between the carbon price and the switching price has also been reported in Phase 2 (Bonacina et al. [2009] and Creti et al. [2012]).²⁰

²⁰ Bredin and Muckley [2011] also examine cointegration between carbon and fuel in Phases 1 and 2. They consider the clean dark spread (the electricity price minus the costs of coal and carbon) and the clean spark spread (the electricity price minus the costs of gas and carbon). Their results indicate significant cointegration in Phase 2.

4. Econometric analysis

In this section, we first present the methodology used for investigating the relative contribution of each market to the cross-market price discovery process. Then, the models we estimate and estimation results are given.

4.1. Methodology

In case of related commodities (e.g. wheat and rice, gold and platinum, crude oil and gasoline, etc), information that affects one market also affects other markets. Since some markets incorporate relevant information faster than others, prices of these markets are supposed to be used to anticipate price fluctuations on related markets. Measuring the contribution of each market to a cross-market price discovery process is thus an important issue.

Schwarz and Szakmary [1994] propose to quantify the contributions to the price discovery process using the estimated adjustment coefficients of a VECM. The adjustment coefficient, for a given variable in the VECM, indicates how this variable responds to deviations from the long-run equilibrium. The adjustment coefficients measure the effect on the system created by a deviation from the long-run equilibrium in one time period. Schwarz and Szakmary [1994] argue that the relative magnitude of each adjustment coefficient should be used to assess the intensity of the contribution of each market to the price discovery process. They call this measure the Common Factor Weights (CFWs), as an indicator of the weight of each variable in the common long-memory component.²¹

As an illustration, let us assume the following bi-variate VECM for EUA and gas prices:

$$\Delta P_t = \alpha + \delta \beta' P_{t-1} + \sum_{i=1}^k \Gamma_i \Delta P_{t-i} + \varepsilon_t \quad (4.6)$$

where P_t is a vector that contains price series for EUAs and gas (EUA_t and GAS_t). The number of lags in the VECM is k , α is a vector of constants, and Γ_i are matrices of parameters. ε_t is a

²¹ Gonzalo and Granger [1995] show how to decompose a system of cointegrated variables into transitory and common long-memory components. See Theissen [2002] for a simple presentation (see also Granger and Haldrup [1996] and Baillie et al. [2002]).

vector of errors with $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$ where Σ_ε is the variance-covariance matrix. The adjustment coefficients appear in the vector denominated by δ . They indicate how variables respond to deviations from the long-run equilibrium, in order to restore the equilibrium. Finally, β is the cointegrating vector.

Using the VECM (4.6) we can express the CFWs, as defined by Schwarz and Szakmary [1994], as below:²²

$$CFW^{EUA} = \frac{|\delta^{GAS}|}{|\delta^{EUA}| + |\delta^{GAS}|} \quad \text{and} \quad CFW^{GAS} = \frac{|\delta^{EUA}|}{|\delta^{EUA}| + |\delta^{GAS}|} \quad (4.7)$$

where δ^{EUA} and δ^{GAS} are the adjustment coefficients of EUA and gas prices, respectively. As the sum of the adjustment coefficients measures the total adjustment to a shock in one or both markets, the CFW of one market quantifies the share of the total effect which is recorded on this market.²³ Thus, if the cross-market price discovery occurs in the carbon market only, $CFW^{EUA} = 1$, and if it occurs in the gas market only, $CFW^{EUA} = 0$ (and then $CFW^{GAS} = 1$). In between, combinations such that $0 < CFW^{EUA} < 1$ and $0 < CFW^{GAS} < 1$ reflect situations where the cross-market price discovery occurs in both markets. So, if $CFW^{EUA} > CFW^{GAS}$ the contribution of the carbon market is higher than the gas market contribution (and vice versa).²⁴

4.2. Specifications and estimation results

In order to account for a wide spectrum of possible models, we choose to consider our basic VECM with and without constants in the model. Accordingly, with constants, the VECM (4.6) can be written:

²² The Common Factor Weight measure was developed on an intuitive basis by Schwarz and Szakmary [1994]. Theissen [2002] demonstrated that the weights with which variables enter the common long-memory component, as defined by Gonzalo and Granger [1995], are equal to the Common Factor Weights. See also Thurlin [2009].

²³ Another indicator measuring the contribution of each market to the price discovery process is the information share of Hasbrouck [1995]. As pointed out by Theissen [2002] the common factor weights and the information shares lead to similar conclusions. Theissen [2002] conclude that the common factor weights should be preferred to the information shares given that both measures lead to similar results and that the common factor weights are easy to calculate. Accordingly, we compute only the common factor weights in this work.

²⁴ Note that the market which adjusts less to deviations (i.e. the market which has a lower adjustment coefficient) has a higher CFW, meaning that it is the leader in the price discovery process. The reason is that, because this market is the first to record new information, it reacts less to these information in subsequent periods. By contrast, the market which adjusts more can be considered as a follower in the cross-market price discovery process.

$$\left\{ \begin{array}{l} \Delta EUA_t = \alpha^{EUA} + \delta^{EUA} u_{t-1}^{GAS} + \sum_{i=1}^k \gamma_{11,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{12,i} \Delta GAS_{t-i} + \varepsilon_t^{EUA} \\ \Delta GAS_t = \alpha^{GAS} + \delta^{GAS} u_{t-1}^{GAS} + \sum_{i=1}^k \gamma_{21,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{22,i} \Delta GAS_{t-i} + \varepsilon_t^{GAS} \end{array} \right. , \quad (4.8)$$

or, without constants,

$$\left\{ \begin{array}{l} \Delta EUA_t = \delta^{EUA} u_{t-1}^{GAS} + \sum_{i=1}^k \gamma_{11,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{12,i} \Delta GAS_{t-i} + \varepsilon_t^{EUA} \\ \Delta GAS_t = \delta^{GAS} u_{t-1}^{GAS} + \sum_{i=1}^k \gamma_{21,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{22,i} \Delta GAS_{t-i} + \varepsilon_t^{GAS} \end{array} \right. . \quad (4.9)$$

u_{t-1}^{GAS} is the equilibrium error of the cointegrating equation at hand. In this case (bi-variate VECM between EUA and gas prices), cointegrating equations (4.4a) and (4.4b) can be applied to models (4.8) and (4.9). Thus, we have four models to estimate: (4.8.4a), (4.8.4b), (4.9.4a) and (4.9.4b), where (4.8.4a) stands for model (4.8) with cointegrating equation (4.4a), and so on.

As we saw in section 3, cointegrating equations (4.2b), (4.5a) and (4.5b) can also be used. Accordingly we also estimate models similar to (4.8) and (4.9) by substituting variable SW_t for GAS_t (and so u_{t-1}^{SW} for u_{t-1}^{GAS}). Thus, we consider two more bi-variate versions of the VECM (4.6) – with and without constants in the VAR part of the model – between EUA_t and SW_t :

$$\left\{ \begin{array}{l} \Delta EUA_t = \alpha^{EUA} + \delta^{EUA} u_{t-1}^{SW} + \sum_{i=1}^k \gamma_{11,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{12,i} \Delta SW_{t-i} + \varepsilon_t^{EUA} \\ \Delta SW_t = \alpha^{SW} + \delta^{SW} u_{t-1}^{SW} + \sum_{i=1}^k \gamma_{21,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{22,i} \Delta SW_{t-i} + \varepsilon_t^{SW} \end{array} \right. , \quad (4.10)$$

or, without constants,

$$\left\{ \begin{array}{l} \Delta EUA_t = \delta^{EUA} u_{t-1}^{SW} + \sum_{i=1}^k \gamma_{11,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{12,i} \Delta SW_{t-i} + \varepsilon_t^{EUA} \\ \Delta SW_t = \delta^{SW} u_{t-1}^{SW} + \sum_{i=1}^k \gamma_{21,i} \Delta EUA_{t-i} + \sum_{i=1}^k \gamma_{22,i} \Delta SW_{t-i} + \varepsilon_t^{SW} \end{array} \right. \quad (4.11)$$

As before, u_{t-1}^{SW} is the equilibrium error of the cointegrating equation at hand. Therefore we have six more models to estimate (since cointegrating equations (4.2b), (4.5a) and (4.5b) can be applied to models (4.10) and (4.11)): (4.10.2b), (4.10.5a), (4.10.5b), (4.11.2b), (4.11.5a) and (4.11.5b), where (4.10.2b) stands for model (4.10) with cointegrating equation (4.2b), and so on.²⁵

Before making the estimation, let us discuss the adjustment coefficients further. As we mentioned, they determine the adjustment of each price series toward the long-run equilibrium, after a deviation from the long-run equilibrium. In our case, the adjustment process should be assured by substitution between carbon and gas. Accordingly, the signs of adjustment coefficients are expected to be negative, for the carbon price, and positive, for the other variable (reflecting the fuel cost of switching). Indeed, if we take cointegrating equation (4.4a) as an example (i.e. $EUA_t = \beta_1 + \beta_2 GAS_t + u_t^{GAS}$ and thus $u_{t-1}^{GAS} = EUA_{t-1} - \beta_1 - \beta_2 GAS_{t-1}$), when $EUA_{t-1} > \beta_1 + \beta_2 GAS_{t-1}$ (where $\beta_1 + \beta_2 GAS_{t-1}$ is an approximation of the cost of increasing the proportion of gas plants in the switching zone, see Chapter 1), one would expect a subsequent negative price change on the carbon market and/or a positive price change on the gas market, in order to restore the equilibrium.²⁶ Thus, this would result in a negative δ^{EUA} and a positive δ^{GAS} .

With regard to significance of adjustment coefficients, comparisons are also important for interpretation. Indeed, if one coefficient is significant while the other is not, one would expect one of the two markets (the one with a non-significant adjustment coefficient) to incorporate all the new information. For example, if the carbon market incorporated all the new information, δ^{EUA} should

25 We also applied the Johansen [1991] maximum likelihood approach, to check the validity of our cointegrating equations (identified in section 3) with models (4.8), (4.9), (4.10) and (4.11). Results of the Engle-Granger method are confirmed, except for the model (4.11.2b) (note, however, that cointegration is very close to being significant at the 10% level in this case).

26 If the carbon price exceeds the cost of switching, demand for carbon would decrease and demand for gas increase. Thus, the carbon price would decrease and the gas price would increase, until the equilibrium is restored.

be completely non-significant while δ^{GAS} would be significant.²⁷ By contrast, if both adjustment coefficients are significant, the CFWs are useful for assessing the relative contribution of each market to information discovery.

We can now turn to the estimation. We estimate our ten models using the maximum likelihood method.²⁸ For each specification, we choose the lag order using the Final Prediction Error and the Akaike, Schwarz and Hannan-Quinn information criteria. Accordingly, we include three lags for models **(4.8.4a)**, **(4.8.4b)**, **(4.9.4a)** and **(4.9.4b)**, and two lags for models **(4.10.2b)**, **(4.10.5a)**, **(4.10.5b)**, **(4.11.2b)**, **(4.11.5a)** and **(4.11.5b)**.

Residual analysis is conducted to evaluate how appropriate the models are. We run diagnostic tests to check for autocorrelation and non-normality in the residuals. Based on the Portmanteau test, tests for autocorrelation are performed with a maximum of 15 lags included in each model. Models **(4.10.2b)**, **(4.10.5a)**, **(4.10.5b)**, **(4.11.2b)**, **(4.11.5a)** and **(4.11.5b)** reject the null hypothesis of no autocorrelation, while results for **(4.8.4a)**, **(4.8.4b)**, **(4.9.4a)** and **(4.9.4b)** clearly suggest that there is no autocorrelation for these models. The multivariate Jarque-Bera residual normality test shows evidence of non-normality for all models. However, as shown in Gonzalo [1994], the maximum likelihood method in error correction models ensures that estimators are consistent and that hypothesis tests can be performed (with standard chi-squared tests), even when the errors are non-normal.

Diagnostic tests clearly show that models **(4.8.4a)**, **(4.8.4b)**, **(4.9.4a)** and **(4.9.4b)** are more appropriate since they reveal no autocorrelation in the residuals. Accordingly, these models are preferred, and we will focus on them for interpretations. Tables 25 and 26 present estimated adjustment coefficients and CFWs for the VECMs.²⁹

27 In other words, the leader (market) discovers all the new information and the follower adjusts.

28 In the case of error correction models, the maximum likelihood gives estimators with better properties than other estimation methods. See Gonzalo [1994].

29 Note that we have also performed estimations with SW_t^{55} and SW_t^{45} , in addition to $SW_t^{50} \equiv SW_t$. Results are identical both regarding significance and magnitude of estimated adjustment coefficients.

Table 25: Estimation results for adjustment coefficients (*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively)

	Dependent variable					
	EUA		GAS		SW	
	δ^{EUA}	t-Statistics	δ^{GAS}	t-Statistics	δ^{SW}	t-Statistics
(4.8.4a)	0.009842	1.562191	0.051899	3.793831***	-	-
(4.9.4a)	0.010346	1.759048*	0.051431	4.846395***	-	-
(4.8.4b)	0.008960	1.795965*	0.033068	2.553466**	-	-
(4.9.4b)	0.009231	2.017537**	0.033494	3.558777***	-	-
(4.10.2b)	0.002684	1.930188*	-	-	0.037523	2.473012**
(4.11.2b)	0.002769	2.124021**	-	-	0.037041	2.815277***
(4.10.5a)	0.002299	1.958535*	-	-	0.030862	2.371446**
(4.11.5a)	0.002367	2.172996**	-	-	0.030350	2.728435***
(4.10.5b)	0.002299	1.998332**	-	-	0.030863	2.573043**
(4.11.5b)	0.002283	2.235497**	-	-	0.028238	2.726110***

Table 26: Estimated Common Factor Weights (in percentages) using equations $CFW^{EUA} = \frac{|\delta^j|}{|\delta^{EUA}| + |\delta^j|}$ and $CFW^j = \frac{|\delta^{EUA}|}{|\delta^{EUA}| + |\delta^j|}$, where $j = GAS, SW$.

	CFW^{EUA}	CFW^{GAS}	CFW^{SW}
(4.8.4a)	84.06	15.94	-
(4.9.4a)	83.25	16.75	-
(4.8.4b)	78.68	21.32	-
(4.9.4b)	78.40	21.60	-
(4.10.2b)	93.33	-	6.67
(4.11.2b)	93.05	-	6.95
(4.10.5a)	93.07	-	6.63
(4.11.5a)	92.77	-	7.23
(4.10.5b)	93.07	-	6.93
(4.11.5b)	92.52	-	7.48

Results suggest that the carbon market contributes more to the cross-market price discovery process. This is particularly obvious for model **(4.8.4a)**, since δ^{EUA} is not significant while δ^{GAS} is highly significant. In this case we can conclude that the cross-market price discovery occurs only on the carbon market.³⁰ This means that all the new information is discovered on the carbon market,

³⁰ Previous studies have found that the adjustment coefficient of the carbon price was not significant in error correction

while only the gas market adjusts to deviations (created by new information) from the long-run equilibrium. One possible explanation might be that the carbon market may be more focused – in our sample period – on information about economic activity and recession or about some exogenous political decisions (e.g. decisions about the future of the EU ETS, the negotiations on a post-Kyoto agreement for climate policy or the future of the Kyoto mechanisms, etc.) rather than on the adjustment process towards the long-run equilibrium between carbon and gas prices.³¹

For other models, we still obtain two significant adjustment coefficients reflecting that both markets seem to contribute to the adjustment process. However, the δ^{EUA} do not have the expected sign. They are positive while, according to the substitution theory, they ought to be negative.³² Indeed, as mentioned earlier, when the EUA price is higher than the cost of increasing the proportion of gas in power generation, the EUA price needs to decline and/or the gas price needs to rise for the equilibrium to be restored. But, with two positive adjustment coefficients, this means that both prices increase. One possible explanation comes from values of adjustment coefficients for EUAs and gas. Because δ^{GAS} always has a higher positive value than δ^{EUA} (see Table 25), we deduce that the gas price rises more than the carbon price in order to adjust to deviations from the long-run equilibrium. Hence, the equilibrium can be restored because the gas price rises more than the EUA price. One could say that the carbon market moves in the wrong direction with respect to the substitution theory (it may be more focused on information about economic activity, exogenous political decisions, etc), but the gas market overcompensates for that.³³

With regard to the estimated CFWs, we clearly see that the carbon market contributes more to the adjustment process. As indicated in Table 26, the value of CFW^{EUA} is still around 80% (and so CFW^{GAS} is still around 20%), meaning that about 80% of information discovery occurs on the carbon market. Here again we conclude that the carbon market is the leader in the cross-market price discovery process.

models between carbon and energy prices (see Bunn and Fezzi [2007] and Bertrand [2011a]).

31 The carbon market may integrate some information about economic activity and transmit them to other energy markets. Interestingly, evidence of Granger causality running from carbon to coal and gas prices has been found in previous econometric papers for Phase 2 of the EU ETS (see Keppler and Mansanet-Bataller [2010] and Bertrand [2011a]), while the opposite was in general more significant for Phase 1 (see Chapters 1 and 3 for references). Still regarding Phase 2, Creti et al. [2012] have reported significant Granger causality running from the carbon price to oil and stock prices.

32 Note that the δ^{GAS} are still highly significant with positive signs as suggested by the substitution theory.

33 For an analogous explanation in the case of the EUA's spot-futures relationship, see Uhrig-Hombourg and Wagner [2007].

5. Conclusion

The EU ETS has increased the interest for gas in electricity generation. Due to the lower carbon intensity of gas plants, fuel switching can be a profitable option, depending on carbon and fuel prices. In this chapter we examined the economic link between EUA and gas markets due to fuel switching in electricity generation. We investigated how these markets contribute to the cross-market price discovery process, driven by substitution between carbon and gas, by comparing their relative adjustments to deviations from their long-run equilibrium. The market which adjusts more is thus considered as a follower in the cross-market price discovery process, and the market which adjusts less is considered as the leader (i.e. because this market is the first to record new information, it adjusts less to these information in subsequent periods), meaning that it records incremental information faster.

We estimated different VECM models involving EUA and gas prices, and we calculated the Common Factor Weights (Schwarz and Szakmary [1994]) to assess the relative contribution of each market to the cross-market price discovery process. The results indicate that the gas market adjusts more than the carbon market to deviations from the equilibrium. Hence, we conclude that the carbon market is the leader in the cross-market price discovery process between gas and EUAs. This finding might be of practical importance for market participants, which are expected to use, in many cases, prices of the most efficient markets to anticipate the price evolutions on other related markets.

Our results suggest that the carbon market dominate the price discovery process. However, one may expect the opposite to be more consistent. Indeed, fuel markets are usually supposed to be little affected, if at all, by changes in demand for fuel created by the EU ETS, since fuel demand triggered by fuel switching is limited due to scarcity of gas capacities available for switching in each period. Moreover, European fuel markets are integrated into world markets, so that variations in fuel demands for switching purposes in Europe are very small with respect to world fuel markets.³⁴ In that context, our results may reflect a particular situation caused by the economic and financial crisis and the “de-coupling” of the European fuel markets with respect to the world markets during the period we analyzed.³⁵ Because of emission reductions in the recession, firms

³⁴ See Chapters 1 and 2.

³⁵ During the years 2008-2009, there was a period of “de-coupling” between the European and world fuel markets. Market participants had different expectations about the European and world markets, due to the continuing economic growth in emerging countries while Europe was in recession. Thus, once the “de-coupling” was effective, European fuel markets were more focused on the European situation, rather than on world markets (Keppler and

covered by the EU ETS were able to sell large amount of unused allowances in order to raise cash during the credit crunch.³⁶ Therefore, due to these financing strategies, the carbon market may have processed relevant information about economic activity faster than other European markets.³⁷ That might explain why the carbon market seems to have become a driver for information disclosure during this period. Thus, the fact that the carbon market is the leader in the cross-market price discovery process might be explained by our sample period.³⁸ Consequently, our results should be considered carefully and it would be interesting to undertake the same analysis in a more “normal” sample period in order to see whether results are modified. This may be a subject for future research.

Mansanet-Bataller [2010]).

36 Note that a lower influence of the gas price in a context of recession (and thus lower uncontrolled carbon emissions) is in line with Proposition 2 of the theoretical model in Chapter 2.

37 See Chapter 3.

38 The gas market also discovers large amounts of information about energy markets and other factor that might permanently affect the cost of fuel switching. For example, the gas market is expected to record first information about technological progresses in the extraction of non-conventional gases, gas liquefaction or pipeline projects such as Nabucco. Accordingly, outside of a recession period, the gas market should take a more important place in the process of information discovery in the carbon-gas relationship (more than the 15-20% we found in Table 26), and even probably dominate.

Appendix A

Proof by recurrence of equation (2.11) of Chapter 2

We show that (2.11) is verified for all t . The demonstration is made by recurrence in three steps as follows.

Step 1: check that (2.11) is right in $t = 1$

Solving the intertemporal problem in the case of two periods ($T = 2$), we get

$$p_1 = a G_1 \left[\frac{1}{2} u_1 + \frac{1}{2} \bar{u}_2 - \frac{1}{2} D \right] - b C_1. \quad (\text{A.1})$$

Now, applying (2.11) in $t = 1$, we obtain

$$p_1 = a G_1 \left[\frac{1}{T} u_1 + \frac{1}{T} \sum_{j=2}^T \bar{e}_j - \frac{1}{T} D \right] - b C_1,$$

which is equivalent to (A.1) when $T = 2$. We conclude that (2.11) is right in $t = 1$. \square

Step 2: recurrence hypothesis

We assume that (2.11) is right in $t - 1$. We then get:

$$p_{t-1} = a G_{t-1} \left[\sum_{j=1}^{t-1} \left(\frac{1}{T-j+1} u_j - \frac{j-1}{T(T-j+1)} \bar{u}_j \right) + \frac{1}{T} \sum_{j=t}^T \bar{u}_j - \frac{1}{T} D \right] - b C_{t-1}. \quad (\text{A.2})$$

Step 3: show that (2.11) is verified in t using the recurrence hypothesis

For any t and $t - 1$, when (2.11) is right in $t - 1$, we have:

$$p_t = a G_t \left[\frac{p_{t-1} + b C_{t-1}}{a G_{t-1}} + \frac{1}{T-t+1} u_t - \frac{t-1}{T(T-t+1)} \bar{u}_t - \frac{1}{T} \bar{u}_t \right] - b C_t. \quad (\text{A.3})$$

Substituting (A.2) (the recurrence hypothesis) into (A.3), we get

$$p_t = a G_t \left[\sum_{j=1}^t \left(\frac{1}{T-j+1} u_j - \frac{j-1}{T(T-j+1)} \bar{u}_j \right) + \frac{1}{T} \sum_{j=t+1}^T \bar{u}_j - \frac{1}{T} D \right] - b C_t,$$

that is (2.11) in period t . So, (2.11) is verified for all t , by recurrence. \square

Appendix B

Data description

We use daily data for temperatures, coal, gas, carbon and electricity prices in Europe.¹ Data series run from February 26, 2008 to October 30, 2009. This corresponds to the first two years of Phase 2 of the EU ETS. Our sample period begins on February 26, 2008 since data for the carbon spot price start on that day.

Temperatures

Temperatures affect demand for power because they determine needs for heating (in winter periods) or cooling (in summer periods). As a consequence, temperatures influence uncontrolled carbon emissions. In particular, it is expected that uncontrolled carbon emissions will depend heavily on extreme temperatures (i.e. extremely hot and cold temperatures).²

We consider the European temperature index of Tendances Carbone (published by the CDC Climat Research). This is a weighted average of temperatures for France, Spain, Germany and the UK, where weights are proportional to the size of countries' NAPs. We also use country specific temperatures for Germany, Spain and the UK. Here data are those of the BlueNext Weather index which is constructed as the average of regional temperatures within a country, weighted by the populations of those regions.³

The effect of temperature on energy demand (and thus on carbon emissions) is known to be non-linear since energy is used for both cooling and heating purposes. To take into account this non-linearity, the usual way is to identify thresholds reflecting cold and hot temperatures. In order to identify days with particularly high or low temperatures, we compute the quintiles of each temperature series. Thereafter, we define a day as extremely hot if the temperatures of this day are in the last quintile. If temperatures of a day are in the first quintile, the day is considered as extremely cold. Next, quintile series are used to construct dummy variables accounting for extremely hot and cold days (see Figures 44 and 45).

¹ We thank May Armstrong of the CDC Climat Research for making these data available to us.

² Several papers have shown that extreme temperatures are the most important weather variables influencing the EU ETS (see Alberola et al. [2008] and Mansanet-Bataller et al. [2007]).

³ Note that the BlueNext Weather indices are used as values for national temperatures in calculating the European temperature index of Tendances Carbone.

Figure 44: Dummy variables for hot temperatures.

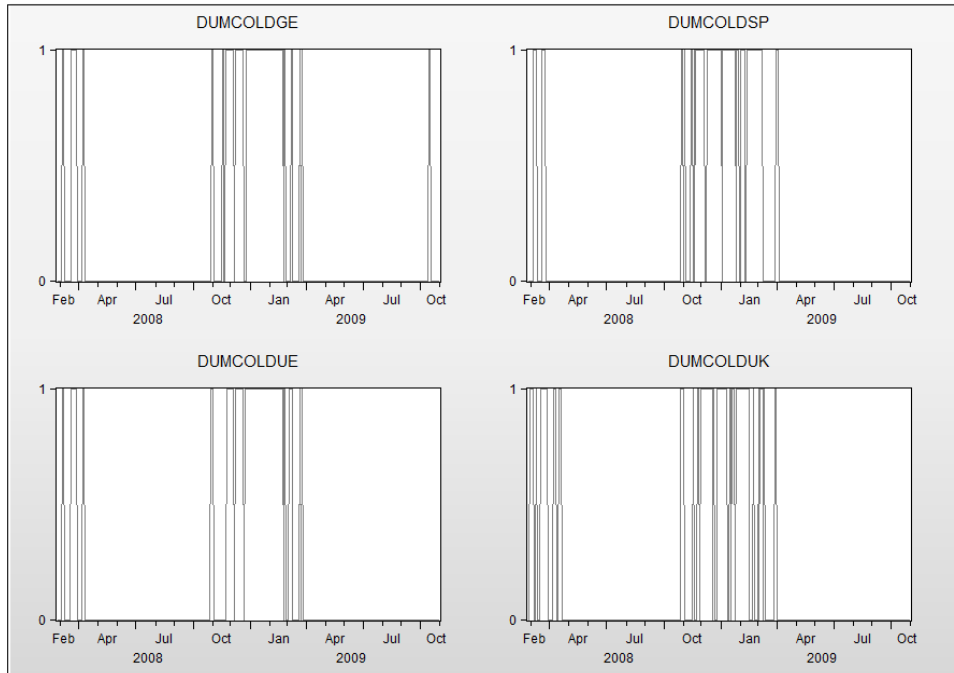
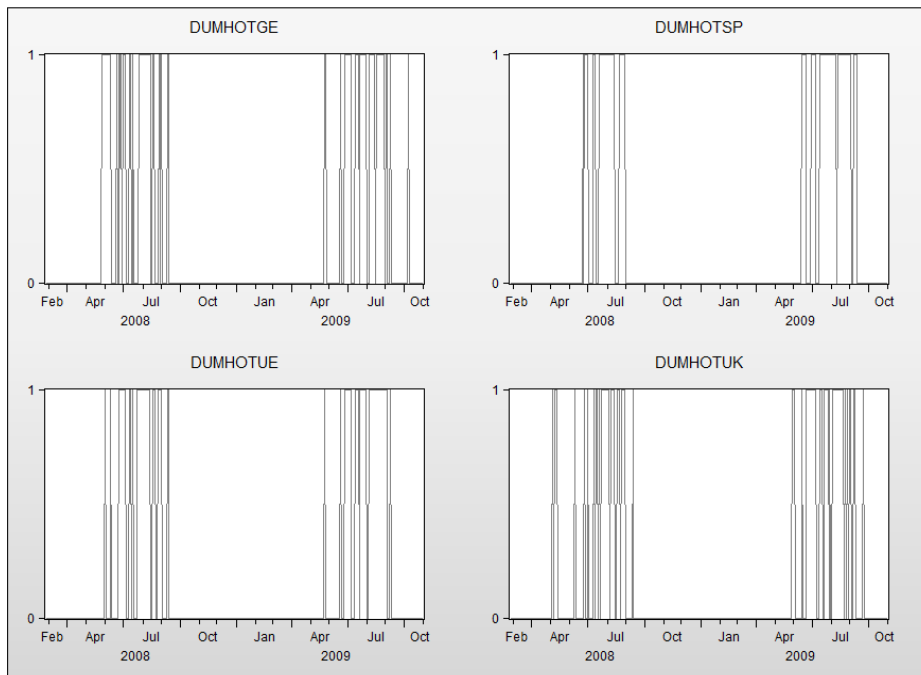


Figure 45: Dummy variables for cold temperatures.

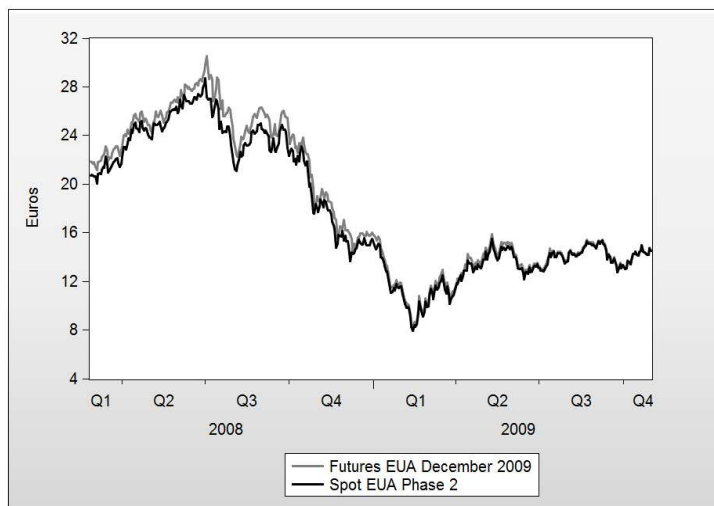


Carbon prices

The data collection for the carbon prices is made up of the daily closing prices of EUA (European Union Allowance, the carbon allowances from the EU ETS) spot and futures contracts. Prices for

spot and futures contracts are those of BlueNext and European Climate Exchange (ECX), respectively, since BlueNext is the most liquid spot market and ECX is the most liquid market for futures contracts (see Benz and Klar [2008] and Daskalakis et al. [2009]). Futures prices are those of contracts with delivery in December 2009.

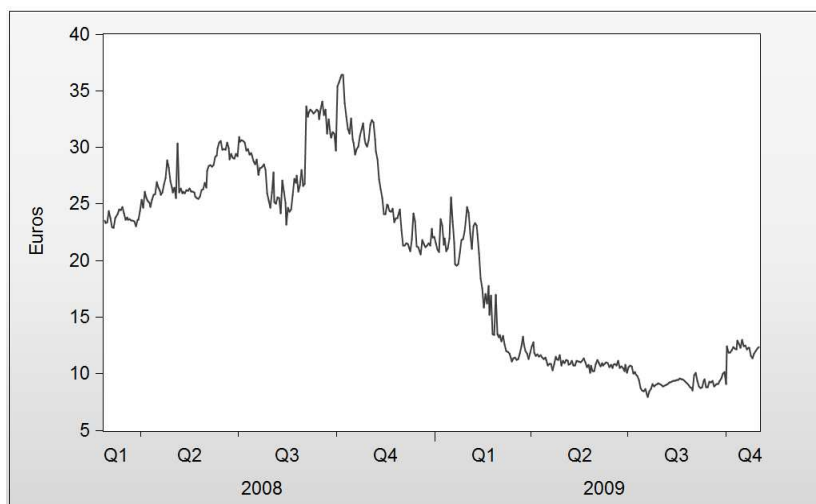
Figure 46: Spot and futures EUA prices.



Energy prices

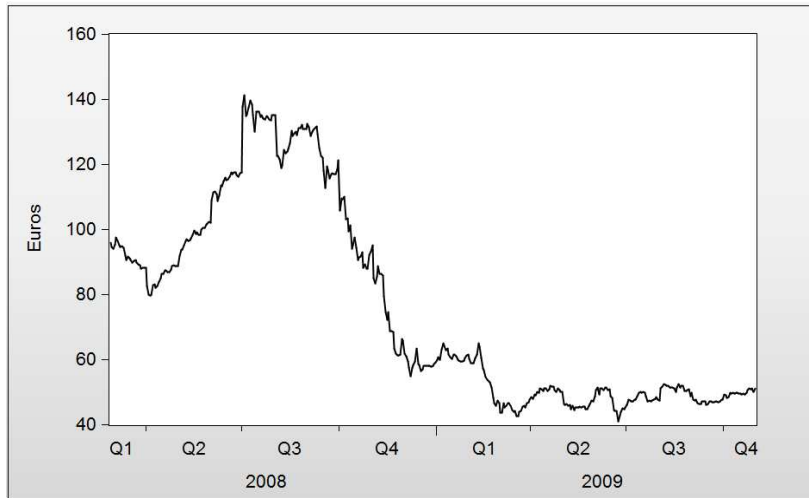
The gas price, in Euros per thermal MWh, is the daily closing price of month ahead gas futures contracts negotiated on the Zeebrugge Hub (Belgium). The coal price, in Euros per tonne, is the daily closing price of month ahead coal futures contracts, CIF ARA.⁴

Figure 47: Natural gas prices (Zeebrugge, Belgium).



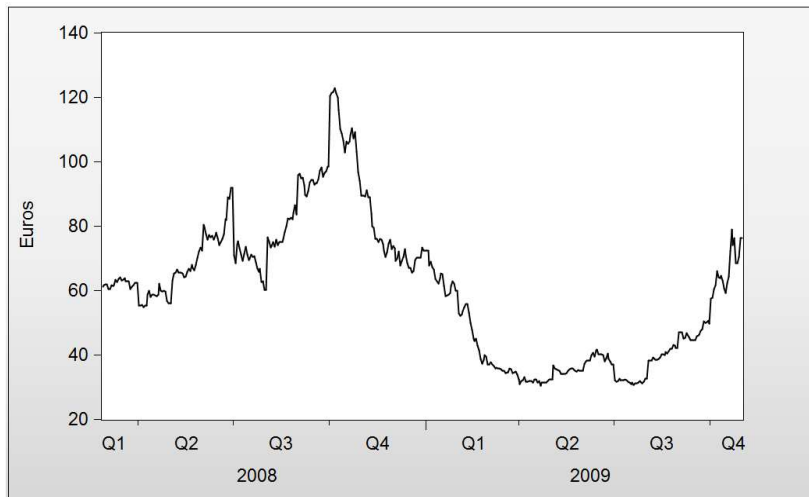
⁴ CIF ARA defines the price of coal inclusive of freight and insurance (Cost, Insurance and Freight) delivered to Amsterdam, Rotterdam or Antwerp (ARA).

Figure 48: Coal prices (CIF ARA).



For electricity prices, we include data from Powernext, the French power market. Prices are daily closing prices, in Euros per MWh of electricity, of month ahead futures contracts for base load.

Figure 49: Electricity prices (Powernext, France).



Appendix C

Results of Chapter 3 using the futures prices of EUAs

In the econometric analysis of Chapter 3, we used the price of EUA spot contracts, according to the results of the Granger causality test between spot and futures EUA prices we performed in section 3.1 of Chapter 3 (see Table 15). To complete this work, we present here the same analysis as in sections 3 of Chapter 4, using the price of EUA futures contracts. We obtain similar conclusions.

Cointegration testing

We apply Johansen [1991] maximum likelihood estimation approach to test for cointegration between carbon, coal, gas and electricity prices. The results are given in Tables 27 and 28.

Table 27: Trace test for cointegration (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Null Hypothesis: Number of cointegrating vectors	Trace Statistic	Critical value (5% level)	p-value
$r \leq 0$	47.87117**	47.85613	0.0498**
$r \leq 1$	21.12448	29.79707	0.3499
$r \leq 2$	8.587611	15.49471	0.4049
$r \leq 3$	0.097653	3.841466	0.7547

Table 28: Maximum-Eigenvalue test for cointegration (*, ** and *** denote statistical rejection of the null at the 10, 5 and 1% levels, respectively)

Null Hypothesis: Number of cointegrating vectors	Maximum-Eigenvalue Statistic	Critical value (10% level)	p-value
$r = 0$	26.74669*	25.12408	0.0637*
$r = 1$	12.53687	18.89282	0.4956
$r = 2$	8.489958	12.29652	0.3311
$r = 3$	0.097653	2.705545	0.7547

As when we used the spot price of EUAs, the results indicate the existence of a single long-run relationship between prices. Therefore, we estimate a VECM. The results are in Table 29.

Table 29: VECM (maximum likelihood) parameter estimations (*, ** and *** denote statistical significance of parameters at the 10, 5 and 1% levels, respectively). The t-statistics are given in square brackets.

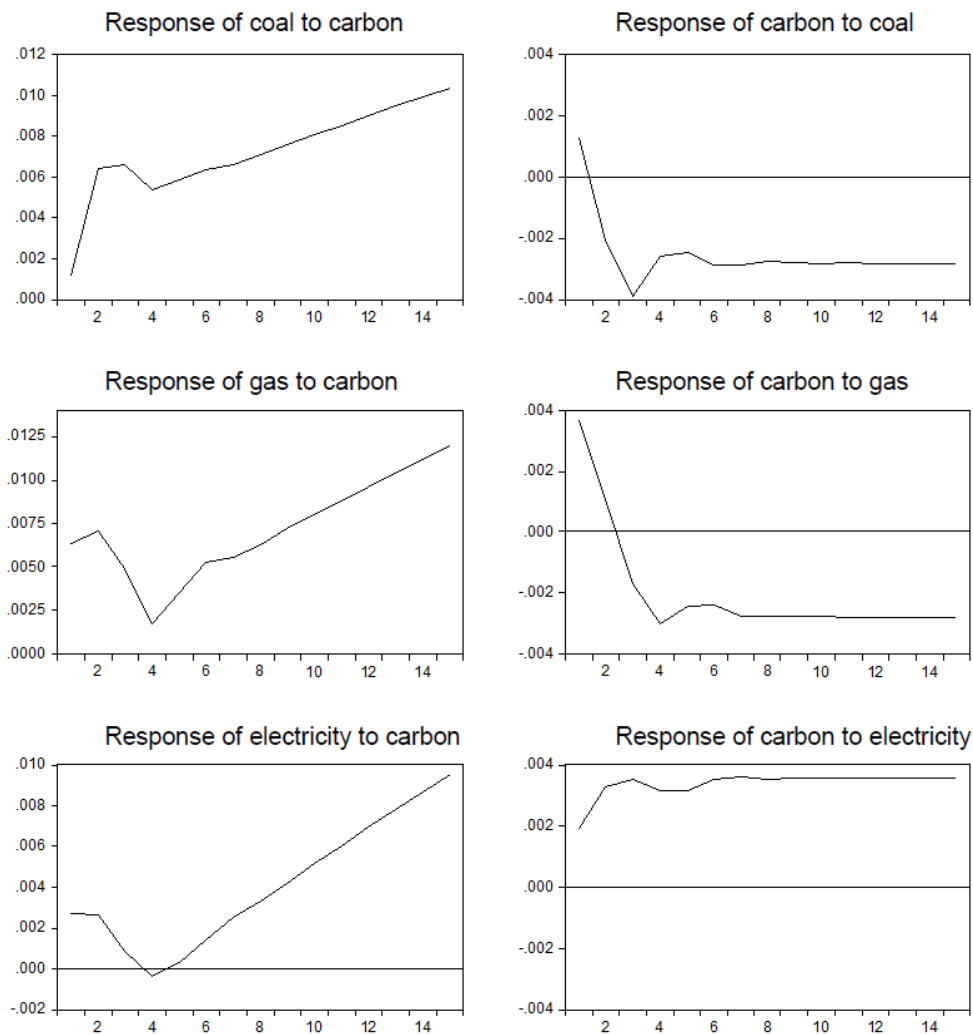
VECM (short-run parameters)				
	Δ_t Carbon	Δ_t Coal	Δ_t Electricity	Δ_t Gas
EC_{t-1}	0.005076 [0.73552]	0.011198* [1.70606]	0.038826*** [3.97622]	0.042306*** [3.53290]
Δ_{t-1} Carbon	0.156684*** [3.16802]	0.172894*** [3.67530]	-0.042720 [-0.61044]	0.030144 [0.35123]
Δ_{t-2} Carbon	-0.133485*** [-2.65838]	-0.044744 [0.93685]	-0.093016 [-1.30916]	-0.108833 [-1.24905]
Δ_{t-3} Carbon	0.118527*** [2.39408]	-0.023267 [-0.49410]	-0.074417 [-1.06229]	-0.124322 [-1.44711]
Δ_{t-1} Coal	-0.122691*** [-2.36562]	-0.006347 [0.12866]	-0.050910 [-0.69372]	0.16323 [1.40360]
Δ_{t-2} Coal	-0.024857 [-0.47878]	-0.00032 [-0.00649]	0.116982 [1.59243]	-0.062715 [-0.69613]
Δ_{t-3} Coal	0.039581 [0.77517]	0.028211 [0.58085]	-0.060228 [-0.83359]	-0.027270 [-0.30777]
Δ_{t-1} Electricity	0.039506 [1.09153]	0.037723 [1.09578]	0.019016 [0.37131]	0.198020*** [3.15293]
Δ_{t-2} Electricity	0.037021 [1.01213]	0.063285* [1.81902]	-0.041953 [-0.81059]	-0.075638 [-1.19167]
Δ_{t-3} Electricity	0.019260 [0.52790]	0.030418 [0.87654]	-0.014159 [-0.27428]	-0.018915 [-0.29878]
Δ_{t-1} Gas	-0.070635*** [-2.41637]	0.036954 [1.32928]	0.029912 [0.72326]	-0.284434*** [-5.60815]
Δ_{t-2} Gas	-0.058362* [-1.91698]	0.0424532 [1.46601]	0.015086 [0.35019]	-0.090439* [-1.71189]
Δ_{t-3} Gas	-0.052218* [-1.77922]	0.000202 [0.00723]	-0.053019 [-1.27670]	-0.013708 [-0.26917]
Constant	-0.001277 [-0.99305]	-0.001240 [-1.01413]	0.000271 [0.14902]	-0.002359 [-1.05708]
Cointegrating vector (long-run parameters)				
Carbon	Coal	Electricity	Gas	Constant
1	-0.204385 [-1.00599]	0.089518 [0.43248]	-0.558123** [-2.55908]	-0.738613

Based on this model, we investigate Granger causality and we compute impulse response functions. The results are given in Table 30 and in Figure 50.

Table 30: Granger causality test results with three lags considered (*, ** and *** denote statistical significance of Granger causalities at the 10, 5 and 1% levels, respectively).

	Dependent Variables							
	Carbon		Coal		Gas		Electricity	
	Chi-Sq	p-value	Chi-Sq	p-value	Chi-Sq	p-value	Chi-Sq	p-value
Carbon	-	-	10.00383	0.0404**	17.83800	0.0013***	8.348203	0.0796*
Coal	5.856146	0.2102	-	-	16.45800	0.0025***	10.16313	0.0378**
Gas	8.200564	0.0845*	3.201275	0.5247	-	-	9.340479	0.0531*
Electricity	3.419144	0.4903	4.875092	0.3004	36.63098	0.0000***	-	-

Figure 50: Generalized impulse response functions.



We obtain similar conclusions as when we used the EUA spot price.

Appendix D

Results of Chapter 4 using the futures prices of EUAs

The econometric analysis of Chapter 4 is also based on the price of EUA spot contracts. Therefore, to complete this work, we present here the same analysis as in sections 3 and 4 of Chapter 4, using the price of EUA futures contracts. We obtain similar conclusions.

Cointegration analysis

We apply the Engle-Granger [1987] two-steps method to test for cointegration the carbon price and the switching price, the carbon price and the gas price, and the carbon price and the ratio.¹ We use the same cointegrating regression as presented in section 3 of Chapter 4. The results for the unit root tests of those cointegrating regressions are given in Tables 31, 32 and 33.

Table 31: Unit root tests for equilibrium errors of cointegrating regressions (4.2a), (4.3a) and (4.4a) (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

Residuals	ADF (t-Statistics)	PP (t-Statistics)
u_t^{SW}	-1.22	-1.21
u_t^{Ratio}	-0.79	-0.81
u_t^{GAS}	-2.04**	-1.99**

Table 32: Unit root tests for equilibrium errors of cointegrating regressions (4.2b), (4.3b) and (4.4b) (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

Residuals	ADF (t-Statistics)	PP (t-Statistics)
u_t^{SW}	-1.85*	-1.81*
u_t^{Ratio}	-1.43	-1.44
u_t^{GAS}	-2.10**	-1.84*

¹ As in Chapter 4, we report only the results involving SW_t^{50} for estimations using the switching price. Estimations have also been performed using SW_t^{55} and SW_t^{45} . The results are the same as with SW_t^{50} .

Table 33: Unit root tests for equilibrium errors of cointegrating relationships **(4.5a)** and **(4.5b)** (*, ** and *** denote statistical rejection of the null hypothesis – non-stationarity – at the 10, 5 and 1% levels, respectively)

u_t^{SW}	ADF (t-Statistics)	PP (t-Statistics)
(5a)	-2.20**	-2.34**
(5b)	-2.10**	-2.22**

Results show that among tested cointegrating equations, equations **(4.2b)**, **(4.4a)**, **(4.4b)**, **(4.5a)** and **(4.5b)** can be retained for the VECM estimations since they have stationary errors. However, we exclude equations involving the ratio variable. Therefore, as in section 4 of Chapter 4, we estimate several models involving the admissible cointegrating equations. These are presented in what follows.

Estimation results

Tables 34 and 35 present estimated adjustment coefficients and CFWs for the VECMs.

Table 34: Estimation results for adjustment coefficients (*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively)

	Dependent variable					
	<i>EUA</i>		<i>GAS</i>		<i>SW</i>	
	δ^{EUA}	t-Statistics	δ^{GAS}	t-Statistics	δ^{SW}	t-Statistics
(4.8.4a)	0.008434	1.430363	0.051867	4.012605***	-	-
(4.9.4a)	0.009069	1.640103	0.051283	4.881687***	-	-
(4.8.4b)	0.008352	1.7255117*	0.034500	2.752008***	-	-
(4.9.4b)	0.008658	1.928827*	0.034827	3.673800***	-	-
(4.10.2b)	0.002373	1.866971*	-	-	0.009362	3.127210***
(4.11.2b)	0.002477	2.077137**	-	-	0.034637	2.921621***
(4.10.5a)	0.002116	1.894191*	-	-	0.030216	2.524245**
(4.11.5a)	0.002110	1.934189*	-	-	0.030197	2.710628***
(4.10.5b)	0.002116	1.894191*	-	-	0.030216	2.524252**
(4.11.5b)	0.002168	2.169440**	-	-	0.028015	2.821047***

Table 35: Estimated Common Factor Weights (in percentages) using equations $CFW^{EUA} = \frac{|\delta^j|}{|\delta^{EUA}| + |\delta^j|}$ and $CFW^j = \frac{|\delta^{EUA}|}{|\delta^{EUA}| + |\delta^j|}$, where $j = GAS, SW$.

	CFW^{EUA}	CFW^{GAS}	CFW^{SW}
(4.8.4a)	86.01	13.99	-
(4.9.4a)	84.97	15.03	-
(4.8.4b)	80.51	19.49	-
(4.9.4b)	80.09	19.91	-
(4.10.2b)	79.78	-	20.22
(4.11.2b)	93.33	-	6.67
(4.10.5a)	93.46	-	6.54
(4.11.5a)	93.47	-	6.53
(4.10.5b)	93.46	-	6.54
(4.11.5b)	92.82	-	7.18

We obtain similar conclusions as when we used the EUA spot price.

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