The *Real* Option to Fuel Switch in the presence of *Expected* Windfall Profits under the EU ETS*

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Abstract

This paper develops a simple model to evaluate the value and the activation frequencies of a generation system consisting of coal-fired and a gas-fired power plants using a real options approach, and the notions of clean-spark and clean-dark spreads. Under a cap-and-trade scheme, the use of emission permits represents an opportunity cost. In the energy industry different generation technologies produce different levels of CO_2 emissions and, therefore, different opportunity costs. Addressing the question of how *expected* windfall profits affect the profitability of a generation plant and its activation frequencies, the paper shows that conventional findings are reversed. When the opportunity cost is internalized, the rate of activation of the gas plant decreases while that of the coal plant increases.

Keywords: Activation frequency, Dark-spread, Emission permits, Generation Mix, Spark-spread.

JEL Classifications: C13, C15, Q40.

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1 Introduction

In a pollution-constrained economy where polluting companies are subject to environmental regulations that cap their noxious emissions, each firm faces a basic choice of two main abatement alternatives: modifying the production process which generates the emissions as a by-product or trading marketable permits.[1] The latter option, also referred to as emissions trading, is a market-based measure which is currently very popular among policy makers. In a system of marketable permits, such as the European Emission Trading Scheme (EU ETS), relevant companies exchange permits on the theory that trading creates economic incentives that encourage firms to minimize the costs of pollution control to society. The chief appeal of economic incentives as the regulatory device for achieving environmental standards is the potentially large cost-saving that they promise.[2] The source of these savings is the capacity of economic instruments to take advantage of large differential abatement costs across polluters. Based on such an idea, Montgomery (1972) provides a rigorous theoretical justification of how a market-based approach leads to the efficient allocation of abatement costs across various pollution sources. Necessary and sufficient conditions for market equilibrium and efficiency are derived, given the setting of multiple profit-maximizing firms who attempt to minimize total compliance costs. Theoretical aspects that Montgomery (1972) does not discuss have been addressed by several studies, as reported in Taschini (2009).

Based on the substitution principle between emission permits and abatement technology, Tietenberg (1985) and Rubin (1996) proved that, in the stylized model of Montgomery (1972), the price of emission permits corresponds to the marginal cost of the cheapest abatement alternative. In the context of EU ETS, which encompass CO_2 emissions in the European Union, the cheapest abatement technology that can be easily implemented in the short to medium term is the so-called fuel-switching.[3] Switching from "cheap-but-dirty" coal to "expensive-but-cleaner" gas is, in fact, a *real* option for fuel-burning energy producers in Europe. In particular, gas has a lower relative carbon intensity, i.e. CO_2 emission per MWh produced. Therefore, gas-fired electricity production emits less CO_2 per MWh of electricity produced than coal-fired power generation. So, fuel-switching from coal to gas yields a reduction of CO_2 emissions per MWh of electricity and implies less emissions to be covered by permits. Moreover, one would expect that the higher the price of emission permits, the larger the shift toward gas-fired generation for a fixed gas price. Our findings are in line with this expectation and with European policy makers' expectations. However, this calculation ignores the presence of windfall profits in the market (see Sijm et al. (2006), Bunn and Fezzi (2007), and Zachmann and von Hirschhausen (2008)). We show that when one internalizes the opportunity cost of CO_2 emission permits this result is reversed.

[1]Niemeyer (1990) gives a more detailed list of abatement alternatives.

[2]We refer to Baumol and Oates (1988) for a complete discussion on market-based policy measures.

[3]Alberola et al. (2008) discuss the market mechanisms that regulate EU ETS, Fehr and Hinz (2006), Carmona et al. (2009) and Chesney and Taschini (2008) model the permit price formation in the EU ETS framework in both the presence and absence of existing abatement alternatives.

As a consequence of the introduction of EU ETS, the structure of the business profitability of this industry and the decision process about the power-generation mix have changed. Today, fuel-burning operators in Europe decide their power generation mix incorporating market price interactions among natural gas, coal, electricity, and CO_2 permits.[4] The first aim of this paper is to develop a simple model to evaluate the value of a generation system consisting of a coal-fired and a gas-fired power plants using a real options approach, and the notions of clean-spark and clean-dark spreads. Our objective is to quantify how often the system operator relies on gas and on coal over a fixed-time horizon. Second, we extend the initial set-up and model the presence of *expected* windfall profits. In particular, we investigate the impact of the opportunity to pass a fraction λ of the CO_2 permit cost on the market-price of electricity assessing its likely magnitude on the profitability of each generation unit and, consequently, on the corresponding activation frequency.

The implementation of dark and spark-spreads in the real options contest has been adopted by Hsu (1998), Hlouskova et al. (2005), and Laurikka (2006), among others. Dark and spark-spread concepts have been introduced in the energy markets as market spreads between, on the one hand, coal and electricity prices, and natural gas and electricity prices, on the other. Defining operating profits as the difference between the fuel price per unit of electricity and the revenues from selling that unit at the market price, the dark-spread measures the net operating profits of a coal-fired generation unit; the spark-spread measures the net operating profits of a gas-fired generation unit. Option contracts on these spreads have been initially implemented as financial instruments with the scope to mitigate exposure to energy price risks. Successively, these spreads have been proposed as evaluation instruments: computing dark and spark-spreads helps in determining the economic value of the generation assets that are used to transform coal or natural gas into electricity. Considering a specific fuel-burning generation unit, a profit maximizer operator activates the plant and consumes a specific unit of fuels only if the revenue of selling one electricity unit is higher than its corresponding production cost. The opportunity of turning both plants on and off, based on the market prices of fuels, emission permits and electricity, is a *real* option which measures the flexibility that characterizes this type of industry. In the recent past, numerous authors relied on real-options theory for assessing the magnitude of this flexibility and its impact on the decision process of the electricity production. For instance, Fiorenzani (2006) investigates the operational flexibilities and constraints of the refinery industry; Laurikka (2006) explores the impact of the presence of a market for emission permits on investments in integrated gasification combined cycle plants; Abadie and Chamorro (2009) evaluate a natural gas investment by means

[4] In this paper we model a pure profit maximizer energy company not subject to supply or demand constraints, or any other type of production commitment.

of Monte Carlo simulations.

Considering an electricity generation system consisting of coal and gas-fired power plants, we operationalize the most natural decision criteria: the system operator runs the most profitable plant based on the price of input (gas, coal, and CO_2) and output factors (electricity). Assuming a frictionless system where inactive costs are negligible, we show by means of Monte Carlo simulations that the efficiency and carbon intensity of a plant are key components for the system evaluation. Efficiency is represented by the so-called heat rate (Hr). The lower the heat rate the more efficient the plant. Whether one internalizes the *expected* windfall profits or not, we show that the lower the Hr of a specific plant, the higher the frequency of its activation. When the system operator has an opportunity to pass a fraction λ of the CO_2 permit cost on to the market-price of electricity, conventional findings and expectations are reversed. Not surprisingly, the higher λ (the higher the CO_2 price level), the higher the value of the generating system. However, when we model explicitly the impact of windfall profits on electricity price and account for different CO_2 emission factors (coal has a higher emission factor than gas), we obtain a different rate of activation frequencies. In particular, the operator relies more often on the most expensive and polluting option: coal-generation. This is possible because passing on the opportunity costs of a certain carbon intensity to the market-price of electricity can facilitate the operator in undertaking the most expensive (and profitable) coal-burning option.

Section 2 introduces the structure of the model. In particular, we specify the stochastic processes describing the evolution of prices of the underlying factors (coal, gas, electricity and emission permits). Section 3 details the calibration techniques we use to fit the model to market data. Section 4 discusses the results we obtain using Monte Carlo simulations over a twenty-year horizon. In this section we also investigate the economic implications of the presence of *expected* windfall profits. Section 5 concludes.

2 Problem formulation

In this section we describe the structure of the model that build extensively on chapter 19 of Fusai and Roncoroni (2008). Then, we introduce the methodology we employ to assess the economic value and the activation frequency of a generation asset consisting of a coal-fired and a gas-fired plants that transform coal or natural gas into electricity using the most profitable process. Such a *structured* electricity generation system is nothing but a compound option, i.e. an option (to produce or not) on an option (to use coal or gas for electricity production). In particular, the exercise payoff of this compound option involves the value of clean-dark and clean-spark options, and an adjustment of the definition of Market Heat rate given in Hsu (1998).

The operator of the generation system is a profit maximizer and a price taker on the input (coal, gas and emission permits) and output (electricity) markets. As it is not the objective of our research to solve an optimal investment-timing problem, we can assume that both coal and gas plants are already in place. Furthermore, we assume that the costs associated with the inactivity state of both units are negligible.[5] The system operator should run a generation plant only if it is profitable to do so. This condition is satisfied when operating profits (revenues minus costs) are positive. As a consequence of the introduction of EU ETS, operating profits should be adjusted to include the cost of the CO_2 emitted per MWh, obtaining the so-called clean-dark and clean-spark spreads (see Alberola et al. (2008) and references therein). Each plant possesses a specific emission factor which depends on fuel-type and is measured in tons of CO_2 emitted per MWh of electricity produced. CO_2 emission factors are default values provided by several governmental and international institutions. We use the values provided by the European Environmental Protection Agency. As in Laurikka (2006), we analytically define clean-dark and clean-spark spreads as:

$$\pi_{cd} = (p_e - p_c \cdot \mathrm{Hr}_c - p_{\mathrm{CO}_2} \cdot e_c)^+ \quad \text{and} \quad \pi_{cs} = (p_e - p_g \cdot \mathrm{Hr}_g - p_{\mathrm{CO}_2} \cdot e_g)^+ ,$$

where p_e and p_c (p_g) are the electricity and the coal (gas) price, respectively; Hr_c (Hr_g) is the heat rate of coal (gas); p_{CO_2} is the price of European CO_2 emission permits and e_c (e_g) is the emission factor of an average coal-fired (gas-fired) plant; and $(\cdot)^+$ stands for $\max(\cdot, 0)$. When π_{cd} (π_{cs}) is positive, the operator should run the coal-fired (gas-fired) plant, otherwise he should shut it down. We assume that there are no costs entailed in turning a plant on and off. The inclusion of constant values representing costs for operating, activating and deactivating the plant is straightforward in the current set-up and not considered here.

The heat rate measures the efficiency of the plant and determines how much fuel is required to produce one unit (MWh) of electricity. The lower the heat rate, the more efficient the power plant. Typically, modern power plants are more efficient and are characterized by low heat rates. This implies that such plants can generate more electricity while burning the same unit of fuel. Heat rates are defined as the number of British Thermal Units (Btu) required to produce one kWh of electricity. The most efficient coal plants achieve Hr_c as low as 7,000 Btu/kWh, whereas existing installations have Hr_c equal to 11,000 Btu/kWh. The most efficient gas plants achieve Hr_g as low as 6,000 Btu/kWh, whereas old installations have Hr_g exceeding 12,000 Btu/kWh. For an easier interpretation of our results, both Hr_c and Hr_g range in our analysis, from 6,000 to

[5] An implementation of technical constraints, like rump-up times, or minimum-supply commitments would not change our main conclusions. Letting the gas plant be more flexible than a coal plant, would shift unambiguously upwards the likelihood magnitude of the frequency of activation of the gas plant. However, this would not reverse the direction of the impact of *expected* windfall profits on the rate of activation. In any case, this type of modeling should be addressed using more appropriate stochastic optimal control tools.

11,000 Btu/kWh. Throughout the paper we express the price of electricity p_e in €/MWh, the price of coal p_c in €/MMBtu, the price of gas p_g in €/MMBtu, and the price of emission permits $p_{\mathrm{CO_2}}$ in €/ton$_{\mathrm{co_2}}$. Heat rates are expressed in MMBtu/MWh. Emission factors are expressed in terms of ton$_{\mathrm{co_2}}$/MWh. For a fixed MHr$_c$ (MHr$_c$) and a fixed quantity of electricity produced, the amounts of coal (gas) burned and CO_2 emitted are constant. Accordingly, expressing the electricity generation costs in terms of fuel use and corresponding CO_2 emissions is straightforward. Therefore, we write π_{cd} and π_{cs} in terms of an adjusted version of the Market Heat rate (MHr^a). The MHr$_c^a$ (MHr$_g^a$) is defined as the ratio between the market prices of electricity and CO_2-adjusted coal (CO_2-adjusted gas):

$$\mathrm{MHr}_c^a = \frac{p_e}{p_c(p_c, p_{\mathrm{CO_2}})} \quad \text{and} \quad \mathrm{MHr}_g^a = \frac{p_e}{p_g(p_g, p_{\mathrm{CO_2}})},$$

where $p_c(p_c, p_{\mathrm{CO_2}}) = (p_c \cdot \mathrm{Hr}_c + p_{\mathrm{CO_2}} \cdot e_c)$ is the so-called adjusted coal price, and $p_g(p_g, p_{\mathrm{CO_2}}) = (p_g \cdot \mathrm{Hr}_g + p_{\mathrm{CO_2}} \cdot e_g)$ is the so-called adjusted natural gas price. We refer to Guessow (2009) for further discussion on fuel transformation rules. Based on the adjusted-MHr definition, equations π_{cd} and π_{cs} can be written as:

$$\pi_{cd} = \left((\mathrm{MHr}_c^a - 1) \cdot p_c(p_c, p_{\mathrm{CO_2}})\right)^+ \quad \text{and} \quad \pi_{cs} = \left(\left(\mathrm{MHr}_g^a - 1\right) \cdot p_g(p_g, p_{\mathrm{CO_2}})\right)^+ .$$

Adjusted market heat rates now represent the underlying assets. When the adjusted market heat rate of a plant is above 1, this generation unit is in-the-money. In particular, when MHr$_c^a > 1$ (MHr$_g^a > 1$) the operator should run the coal-plant (gas-plant) or, using financial terminology, he should exercise his clean-dark spread (or clean-spark spread) option. Because we are considering a frictionless electricity generation system consisting of two distinct generating units, the operator is interested in running the most profitable plant when both spread options are in-the-money. This extra flexibility-layer is properly described using the definition of a compound option. Evaluating the generation system as a compound option, we capture the simultaneous opportunity to use coal or gas when both the clean-dark spread and the clean-spark spread are positive. In our framework, the compound option π_g is:

$$\pi_g(p_c, p_g, p_{\mathrm{CO_2}}) = \max\left[\left((\mathrm{MHr}_c^a - 1) \cdot p_c(p_c, p_{\mathrm{CO_2}})\right)^+, \left(\left(\mathrm{MHr}_g^a - 1\right) \cdot p_g(p_g, p_{\mathrm{CO_2}})\right)^+\right], \tag{1}$$

Relying on the definition of operating profits given above, the clean-dark (clean-spark) spread measures the net operating profits of a coal-fired (gas-fired) generation unit where fuel prices are CO_2-adjusted. This definition will be relevant in the next section where we discuss model results.

Relying on the methodology used by Fiorenzani (2006), an evaluation of a generation system can be decomposed into an evaluation of a strip of European clean-dark and clean-spark spreads options. In particular, a coal-plant (gas-plant) corresponds to a portfolio of European call options written on coal (natural gas) and electricity spot prices. This contingent-claim approach allow us to match the value of a generation system over a fixed time horizon, with a finite sum of expected discounted payoffs. The payoff at each instant $t, t \in [0, T]$ is described by equation (1). Such an evaluation requires one to specify the stochastic dynamics of underlying price processes, i.e. adjusted coal price, adjusted natural gas price, and electricity price. Figure 1 shows the non-CO_2-adjusted (upper diagram) and CO_2-adjusted (lower diagram) log-prices of the API-2 coal forward contracts (balance of the month) and the Zeebrugge gas price (day ahead contract) from October 2005 to June 2009.[6]

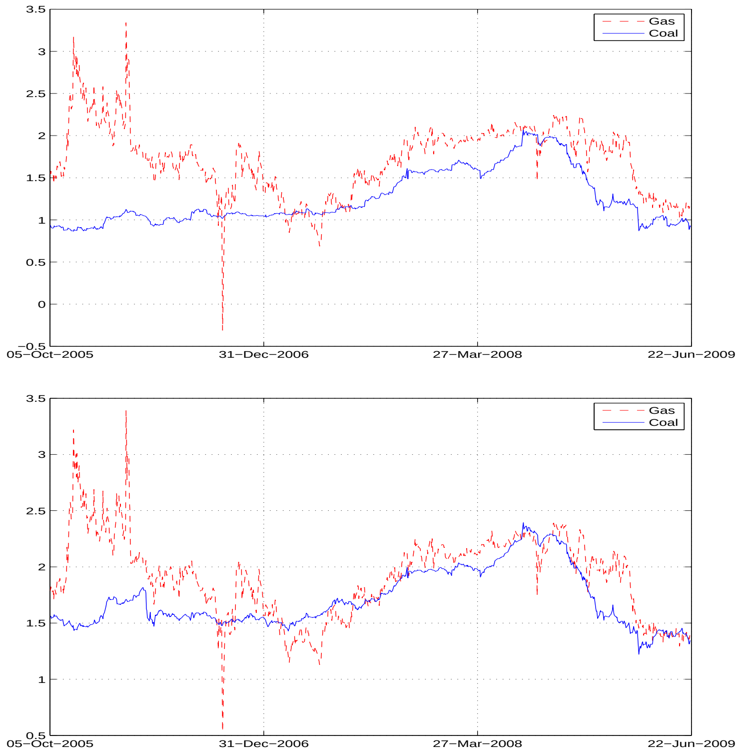

Figure 1: The daily log-price of API-2 coal and Zeebrugge gas during the period October 2005 - June 2009. Upper diagram reports non-CO_2-adjusted log-prices; lower diagram reports CO_2-adjusted log-prices.

Following standard literature in commodity modeling, we assume that coal and natural gas log-prices follow two distinct mean reverting processes with a linear trend and a constant volatility

[6]The data base on API-2, Zeebrugge gas and French electricity from Essent Trading - Geneva (CH) is gratefully acknowledged. The data set includes daily prices.

term.[7] In particular, the log-price of coal follows:

$$dp_c(t) = \theta^c(\mu^c(t) - p_c(t))dt + \sigma^c dW^c(t), \quad \text{where} \quad \mu^c(t) = \alpha^c + \beta^c t \tag{2}$$

and the log-price of gas follows

$$dp_g(t) = \theta^g(\mu^g(t) - p_g(t))dt + \sigma^g dW^g(t), \quad \text{where} \quad \mu^g(t) = \alpha^g + \beta^g t. \tag{3}$$

$p_c(t)$ and $p_g(t)$ are the log-prices of coal and gas at time t, respectively; θ measures the speed of adjustment to the linear trend $\mu(t)$; and σ is the instantaneous and constant volatility parameter.

Following Geman and Roncoroni (2006), we assume the log-price of electricity follows a Markov jump-diffusion process.[8] This model is able to capture most of the stylized features of electricity prices: mean reversion towards a seasonal trend and presence of spikes. Figure 2 shows the log-price (average of day ahead electricity hourly prices) of French electricity from October 2005 to June 2009.

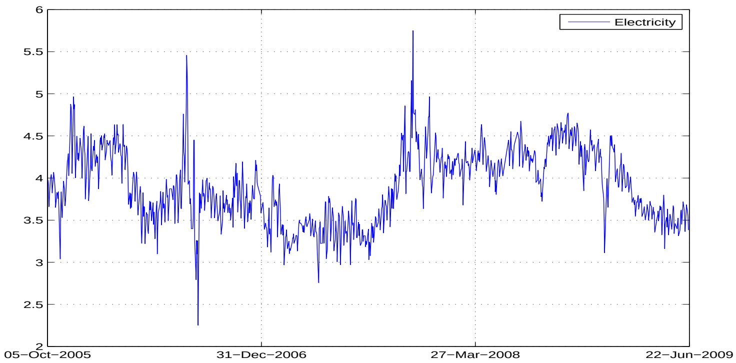

Figure 2: The log-price of day ahead French electricity from October 2005 to June 2009.

The dynamics of the log-price of French electricity are then described by the following stochastic differential equation:

$$dp_e(t) = [\mu^e(t)' + \vartheta_1(\mu^e(t) - p_e(t^-))]dt + \sigma^e dW^e(t) + h(p_e(t^-))dJ(t) \tag{4}$$

where μ^e represents the seasonal trend and $\mu^e(t)' = \partial\mu^e(t)/\partial t$; ϑ_1 is the mean reversion speed; and σ^e is the constant instantaneous volatility parameter. The trend μ^e combines a linear

[7] As reported in Geman (2005), mean-reverting processes (or Ornstein Uhlenbeck processes) have been employed for modeling standard commodities, such as oil, copper and gold. We refer to Abadie and Chamorro (2008) and Cartea and Williams (2008) for further discussions about model selection for coal and gas.

[8] For a comprehensive analysis about alternative methods for electricity price modeling, we refer to Weron (2006) and Benth et al. (2008).

trend and an annual and semi-annual seasonality component:

$$\mu^e(t) = \alpha + \beta t + \gamma \cos(\epsilon + 2\pi t) + \delta \cos(\zeta + 4\pi t)$$

where α is a constant coefficient; βt is the linear trend; and the last two terms represent a yearly and six-month periodic component with possible different magnitudes. The second component represents the diffusion part of the process. The last component accounts for the presence of spikes in the log-price path of electricity. In particular, the counting process $N(t)$ and the compound Poisson process $J(t) = \sum_{i=1}^{N(t)} J_i$ define jumps occurrence. An intensity function

$$\iota(t) = \vartheta_2 \cdot \left[\frac{2}{1 + |\sin[\pi(t-\tau)/k]|} - 1 \right]$$

steers the jump occurrence once a year ($k = 1$) with a peak during summertime ($\tau = 0.5$).[9] ϑ_2 represents the expected maximum number of jumps per year. Jump sizes are modeled by a sequence of i.i.d. truncated exponential variables with density:

$$p(J_i \in dx; \vartheta_3, \psi) = \frac{\vartheta_3 e^{-\vartheta_3 x}}{1 - e^{-\vartheta_3 \psi}}$$

where $0 \leqslant x \leqslant \psi$ and ψ represent the maximum size of absolute price changes in the logarithmic scale. Finally, the function h defines a switch for the jump direction:

$$h(p_e(t^-)) = \begin{cases} +1 & \text{if} \quad p_e(t) \leqslant \mu^e(t) + \Delta \\ -1 & \text{if} \quad p_e(t) > \mu^e(t) + \Delta \end{cases}$$

This means that if the electricity price is above a threshold Δ then the next jump will be in a downward direction and vice-versa.

Based on the specification of the stochastic dynamics of the underlying log-price processes, we can evaluate the value of the generation asset at time s as the sum of a finite number of compound options:

$$V_s(\pi_g(t)) = \sum_{t=s}^{T} \mathbb{E}_s \left[e^{r_t \cdot t} \pi_g(t)(p_c(t), p_g(t), p_{\mathrm{CO}_2}(t)) \right] = \sum_{t=s}^{T} \mathbb{E}_s \left[e^{r_t \cdot t} \pi_g(t) \right] \tag{5}$$

Time spans 20 years, 250 days per year. We use a daily time-unit, this implies $T = 5,000$ days. We assume the term structure of the discount rate r_t is a strictly increasing function of time. In particular, r_t starts from an arbitrary 5.05 percent and reaches 5.45 percent after 20 years. The

[9] This is a desirable feature when one models the U.S. electricity market, as in Geman and Roncoroni (2006), but maybe this is not the most realistic model for European electricity markets. However, our main objective is the analysis of the impact of *expected* windfall profits on the activation of the generation system, and not the identification of the model which best fits our electricity data. Therefore, we do not investigate alternative models here.

use of different values would not affect our results. We also assume, for the sake of simplicity, that the discount factor r_t and the underlying processes are statistically independent.[10] We account for the presence of correlation between the underlying fuel processes and the electricity process. However, we neglect correlation between coal and natural gas.[11] Let ϵ_e, ϵ_c, and ϵ_g be three independent standard normal random variables and let $\rho_{e,c}$ ($\rho_{e,g}$) be the constant correlation coefficient between electricity and coal (gas). We then employ the Cholesky decomposition to specify the Brownian increments in equations (2), (3) and (4) as:

$$\begin{cases} \sigma^e dW^e(t) = \sigma^e \epsilon_e(t)\sqrt{dt} \\ \sigma^c dW^c(t) = \sigma^c \left(\rho_{e,c} \cdot \epsilon_e(t) + \sqrt{1-\rho_{e,c}^2}\epsilon_c(t)\right) \cdot \sqrt{dt} \\ \sigma^g dW^g(t) = \sigma^g \left(\rho_{e,g} \cdot \epsilon_e(t) + \sqrt{1-\rho_{e,g}^2}\epsilon_g(t)\right) \cdot \sqrt{dt} \end{cases}$$

Sijm et al. (2006), Bunn and Fezzi (2007), and Zachmann and von Hirschhausen (2008), among others, find empirical evidence of cost pass-through of CO_2 emission permits prices on the electricity price in several European markets.[12] This phenomenon has been identified as windfall profits. By definition, windfall profits occur when an entrepreneur enjoys profits in excess of what he expected, usually as the result of a drastic change in market conditions. Because the use of emission permits represents an opportunity cost for the operator of the generation system, the pass-through of a fraction λ of the price of CO_2 permits is not totally unexpected.[13] In order to internalize the opportunity cost in the evaluation methodology, we enrich the dynamics of the log-price of electricity as follows:

$$dp_e(t) = [\mu^e(t)' + \vartheta_1(\mu^e(t) - p_e(t^-))]dt + \sigma^e dW^e(t) + h(p_e(t^-))dJ(t) + \gamma dp_{\mathrm{CO}_2}(t) \tag{6}$$

where the first three components are already specified in equation (4). The last component accounts for the opportunity to pass the costs of emission permits through to the electricity market. Figure 3 shows the log-price of CO_2 futures emission permits with maturity December 2009 from October 2005 to June 2009.[14]

[10] In the standard real options approach to investment under uncertainty, agents formulate optimal policies under the assumptions of risk neutrality or complete financial markets. Similarly, we assume that the market is complete and account for agents risk aversion using a weighted average cost of capital as discount factor r_t, see Dixit and Pindyck (1994).

[11] As it is not the objective of our research to predict optimal activation times by analyzing the statistical relationships of the input factors, we do not account for the presence of correlation between coal and gas.

[12] Current literature still provides ambiguous results on this issue. For instance, Nazifi and Milunovich (2009) suggest that the dynamics of energy prices are rather independent from the price of carbon emissions permits.

[13] This holds regardless of the allocation criteria of the emission permits (grandfathering, auction, etc.)

[14] The choice of this type of contract is justifiable by the fact that emission permits are a so-called non-standard commodity. Fuel burning utilities, for example, do not physically need the emission-right to produce and, therefore, to pollute on a daily base. Also, transaction volumes of CO_2 futures contracts are fairly larger than CO_2 spot contracts.

Figure 3: The daily log-price of futures emission permits with maturity December 2009, from October 2005 to June 2009.

We assume the log-price of emission permits follows a geometric Brownian motion:

$$dp_{\mathrm{CO}_2}(t) = \mu_{\mathrm{CO}_2} dt + \sigma^{\mathrm{CO}_2} dW^{\mathrm{CO}_2}(t) \tag{7}$$

where μ_{CO_2} and σ^{CO_2} are respectively the constant instantaneous drift term and the volatility parameter. By incorporating explicitly the CO_2 permit price, we extend the previous valuation of the generation asset and investigate the impact of *expected* windfall profits on the operator's activation decision. In order to do that, we also specify the Brownian increments in equations (7) as:

$$\sigma^{\mathrm{CO}_2} dW^{\mathrm{CO}_2}(t) = \sigma^{\mathrm{CO}_2} \left(\rho_{e,\mathrm{CO}_2} \cdot \epsilon_e(t) + \sqrt{1 - \rho^2_{e,\mathrm{CO}_2}} \epsilon_{\mathrm{CO}_2}(t) \right) \cdot \sqrt{dt}$$

where ϵ_{CO_2} is a standard normal random variable independent from the previous standard normal random variables; and ρ_{e,CO_2} is the constant correlation coefficient between electricity and the CO_2 price of emission permits. The evaluation of the operator's activation decisions based on equation (5) is in section 4.

3 Data and Parametrization techniques

Our data set contains coal, gas, electricity and emission permits daily prices. For coal we used the API#2 balance of the month coal forward contract quoted in \$/ton and which we converted to €/MMBtu. For the gas price we took the Zeebrugge spot series which are quoted in pence/th and converted to €/MMBtu. We adjusted the gas and coal prices for the emission permits price using default IPCC emission factors from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. For electricity we use French power spot prices which are quoted in €/MWh. The ECX-traded EUA futures with maturity 2009 are quoted in €/ton CO_2. All data series span the time interval from October 5, 2005 to June 19, 2009 (excluding week-ends and holidays).

The parameters of the mean reverting processes (2) and (3), and of the geometric Brownian motion (7) are calibrated by maximum likelihood. Table 1 reports parameters' estimation.

	Gas	Coal	EUA
α	2.01	1.57	
β	-0.06	0.07	
θ	6.11	0.50	
σ^2	1.80	0.09	0.24
$\rho_{e,\cdot}$	0.18	-0.002	0.01
μ			2.99

Table 1: Estimated parameters for the coal and natural gas price processes. ρ is the constant correlation coefficient between prices of electricity and $\cdot = \{\text{coal}, \text{gas}, \text{CO}_2\text{permits}\}$.

The estimation of (4) is based on Geman and Roncoroni (2006). We first filtered out all prices that exceed a threshold determined by the 90-percentile of the sample price distribution. We then estimated the parameters of the trend and the seasonal components (two sinusoids with a yearly and a 6-month periodicity) by OLS. The jump part is disentangled by the rest identifying a threshold Γ. We calibrated the model with different values for the threshold Γ and selected the set of parameters that delivers the best moment-matching. As in Fusai and Roncoroni (2008), instead of assuming that volatility is constant, we let it be time-dependent with $\sigma^2(t) = \sigma_0^2 + a\ \cos^2(\pi t + b)$. The mean reversion parameter ϑ_1, the jump size parameter ϑ_3 and the parameters σ_0^2, a and b are estimated by maximum likelihood. We refer to Geman and Roncoroni (2006) for a comprehensive description of estimation procedures. Table 2 reports the estimated parameters for the electricity log-price process.

Before estimating the correlation parameters ρ between the de-trended electricity and fuel prices, we filtered out the electricity price variations that are above the threshold Γ. Also, the discount factor used in (8) has a linear increasing structure. In particular, we assume it goes from from 0.0505 to 0.0543 over a twenty-year period.

		Without $dp_{CO_2}(t)$	with $dp_{CO_2}(t)$
α	Average level	3.84	1.41
β	Long-run linear trend	0.04	0.1
γ	Magnitude of yearly trend	-0.20	-0.27
ϵ	Phase of yearly trend	2.19	1.93
δ	6-months magnitude	0.07	0.06
ζ	6-months phase	3.32	3.02
η	Regression coefficient		0.78
K	Jump periodicity	1	1
τ	Jump time shift	0.5	0.5
θ_2	Mean expected number of jumps	10.59	10.59
θ_3	1/average jump size	0.3	0.3
ψ	Max. jump size	1.57	1.57
Δ	Threshold	1.75	1.75
Γ	Jump size threshold	0.51	0.51
	Average jumps per year	12.47	12.47
	Mean jump size	0.72	0.72
σ^2	Constant volatility	7.52	7.69
a	Magnitude of periodic variance	7.77	9.7
b	Phase of periodic variance	0.24	0.23
θ_1	Mean reversion speed	40.88	1.07

Table 2: Parameters for the electricity spot price process.

4 Model Results

In this section we investigate the operator's activation decision based on the profitability of each plant that constitutes the generation system. By simulating 5.000 price-paths for CO_2-adjusted coal, CO_2 adjusted gas, and electricity, we first evaluate the coal-plant value, the gas-plant value, and their frequency of activation using equation (5) in the absence of CO_2 cost pass-through. In this framework, Monte Carlo simulations are based on equations (2), (3) and (4). Table 3 reports the value of the generating system $V_0(\pi_g(t))$, the gas plant $V_0(\pi_{cs}(t))$, and the coal plant $V_0(\pi_{cd}(t))$. The last two values correspond to a situation where the operator runs just one type of generation unit. As anticipated in section 2, the compound option π_g measures the extra flexibility layer of the generation system, i.e. $V_0(\pi_g(t)) \geq \{V_0(\pi_{cd}(t)), V_0(\pi_{cs}(t))\}$. As Figure 4 also shows, the lower the heat rates, the higher the value of the generation system. This result is in line with our expectations.

Table 4 reports the corresponding frequencies of activation (FA) of the generation system, the gas plant and the coal plant. As expected, the less efficient the plant, the lower the activation frequency. Moreover, in absence of *expected* windfall profits, the system operator relies more on the gas plant than on the coal plant.

Heat Rate Gas	Heat Rate Coal	System value	Gas plant	Coal plant
6	6	115,460	112,960	61,269
6	11	113,200	112,980	25,523
11	6	97,220	85,839	61,572
11	11	88,416	86,066	25,925

Table 3: Value of a generation asset consisting of a coal and a gas fired plants (System value); Value of a stand alone gas plant; and value of a stand alone coal plant under varying heat rates.

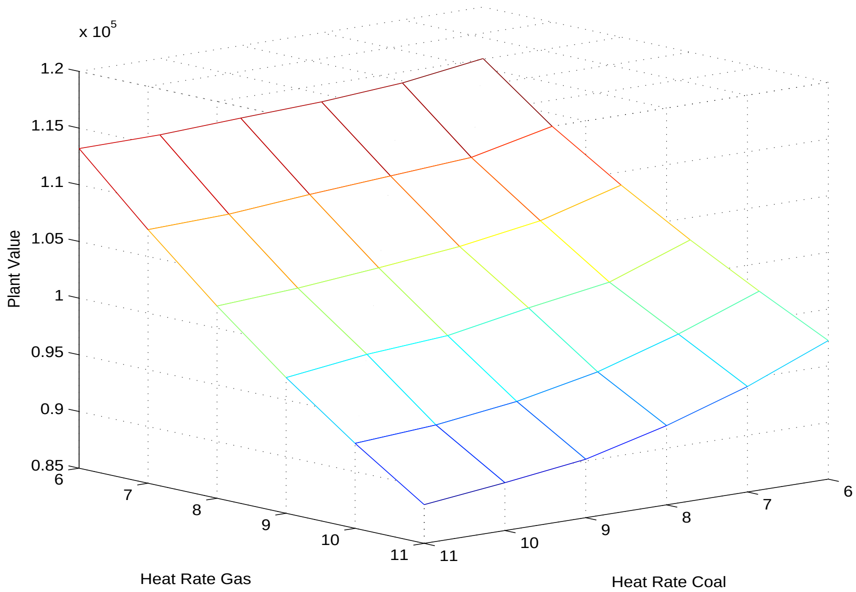

Figure 4: Value of a generation asset under varying heat rates.

Heat Rate Gas	Heat Rate Coal	FA plant	FA Gas	FA Coal
6	6	0.493	0.44	0.05
6	11	0.487	0.48	0.004
11	6	0.473	0.34	0.13
11	11	0.441	0.40	0.03

Table 4: Frequency of activation (FA) of a generation system (plant), a gas plant, and a coal plant under varying heat rates.

As discussed in section 2, utilities can pass through a fraction λ of the opportunity costs of CO_2 emission permits in the electricity market. In order to investigate how *expected* windfall profits affect the operator's activation decision, we compute the expected value in equation (5), running Monte Carlo simulations based on equations (2), (3) and (6), but where the parameters of the electricity price are the those in the fourth column of Table 2. The results we obtain are consistent with our expectations. Fixing the price of CO_2 emission permits, the higher λ, the higher also is the value of the generation system. Similarly, fixing the level of λ, the higher the price of CO_2 emission permits, the higher is the value of the generation system. These results are reported in Table 5 and shown in Figure 5. Again, the compound option π_g measures the extra flexibility layer of the generation system, and $V_0(\pi_g(t)) \geq \{V_0(\pi_{cd}(t)), V_0(\pi_{cs}(t))\}$.

λ	CO_2 permit price	System value	Gas plant	Coal plant
0	5	21,601	21,484	3,150
0	25	21,680	21,560	3,182
0	65	21,679	21,562	3,220
0	85	21,548	21,437	3,126
0.25	5	24,930	24,516	4,928
0.25	25	27,232	26,793	6,498
0.25	65	29,113	28,423	7,935
0.25	85	29,702	28,916	8,213
0.75	5	33,128	31,534	10,597
0.75	25	45,166	41,616	23,171
0.75	65	56,592	48,858	35,331
0.75	85	60,171	50,796	39,142
1	5	38,427	35,651	15,033
1	25	59,334	50,803	38,937
1	65	83,054	63,129	64,442
1	85	90,689	66,431	72,958

Table 5: Value of a generation asset consisting of a coal and a gas fired plants (System value), a stand alone gas plant, and a stand alone coal plant under varying λ and CO_2 emission permits price. We assume coal and gas heat rates are both equal to 8 MMBtu/MWh.

Now we can answer the question about how the pass-through of the opportunity cost of the CO_2 emission permits affects the operator's activation decision and, therefore, the profitability of each generation unit. Table 6 reports the frequency of activation of the generation system, the coal plan and the gas plant. Fixing the price of CO_2 emission permits, the higher λ, the higher (lower) the activation frequency of the coal (gas) plant. Similarly, fixing the level of λ, the higher the price of CO_2 emission permits, the higher (lower) the activation frequency of the coal (gas) plant. This result is consistent with the fact that different generation technologies produce different levels of CO_2 emissions, and therefore the opportunity cost of CO_2 emissions per MWh differ as well. Figure 6 shows that for $\lambda > \lambda^*(CO_2)$, where $\lambda^*(CO_2)$ is a threshold level for a

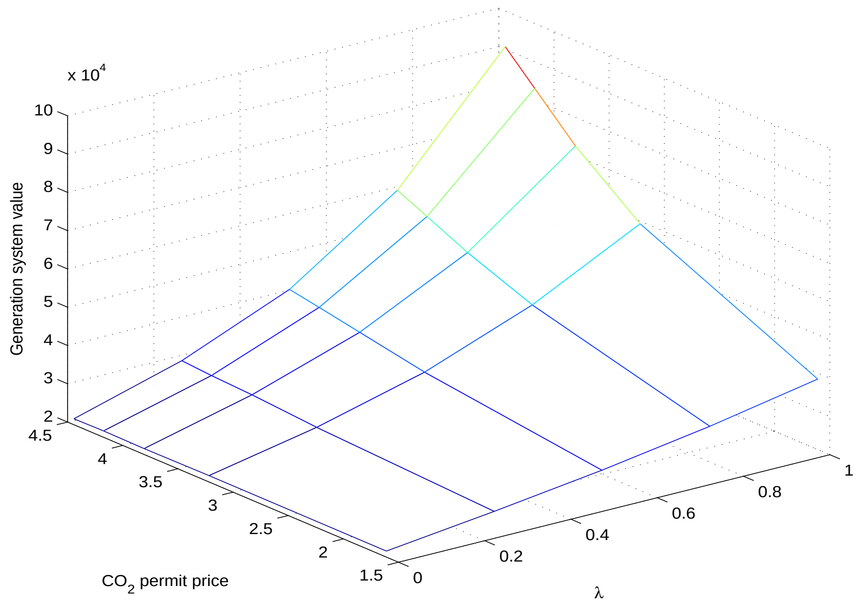

Figure 5: Value of a generation system under varying λ and CO_2 emission permits price.

fixed CO_2 emission price, the frequency of activation of the gas plant decreases. Similarly, for $CO_2 > CO_2^*(\lambda)$, where $CO_2^*(\lambda)$ is a threshold level for a fixed λ, the frequency of activation of the gas plant also decreases. The coal generation is now more profitable and, therefore, the operator of the system activates the coal plant more frequently.

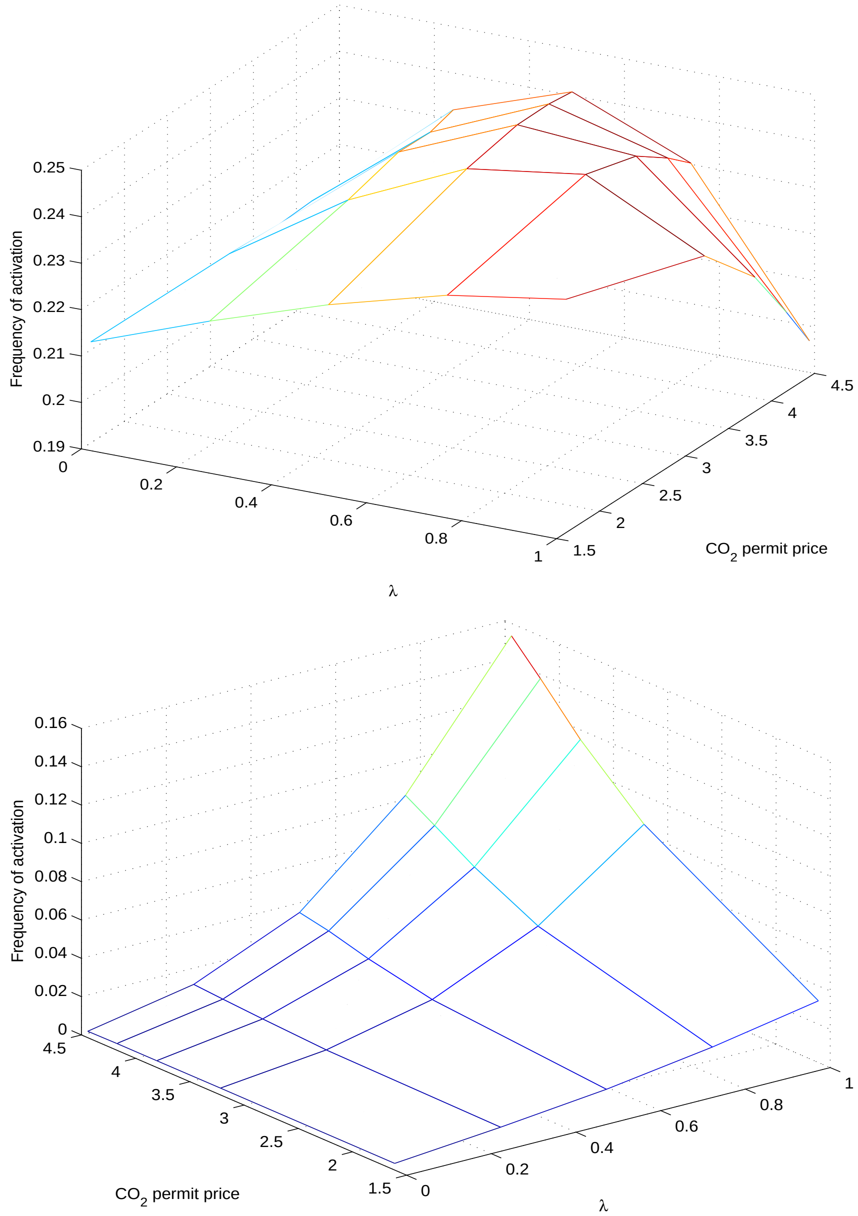

Figure 6: Frequency of activation of gas plant (top) and of coal plant (bottom) under varying λ and CO_2 emission permits price.

λ	CO_2 permit price	FA plant	FA Gas	FA Coal
0	5	0.215	0.212	0.003
0	25	0.215	0.212	0.003
0	65	0.215	0.212	0.003
0	85	0.215	0.211	0.003
0.25	5	0.229	0.221	0.008
0.25	25	0.237	0.228	0.009
0.25	65	0.244	0.231	0.013
0.25	85	0.247	0.233	0.014
0.75	5	0.272	0.236	0.022
0.75	25	0.289	0.243	0.046
0.75	65	0.311	0.235	0.075
0.75	85	0.315	0.231	0.084
1	5	0.215	0.240	0.032
1	25	0.316	0.230	0.085
1	65	0.345	0.207	0.138
1	85	0.351	0.198	0.154

Table 6: Frequency of activation (FA) of a generation system (plant), a gas plant, and a coal plant under varying λ and CO_2 emission permits price.

5 Conclusions

The EU ETS is a cap-and-trade scheme that allows utilities to achieve compliance by modifying the production process or trading emission permits. This is a market-based scheme and electricity generators can either use their permits to cover their CO_2 emissions resulting from the production of electricity or sell these permits on the market. So, the use of emission permits represents an opportunity cost that, in line with economic theory, should be added to the electricity price. Such an *expected* amount corresponds to the windfall profits identified by several recent papers. The presence of *expected* windfall profits raises the question of how they affect the profitability of a generation plant and its activation. As different generation technologies produce different levels of CO_2 emissions and, therefore, different opportunity costs, we address such a question modeling a generation system that consists of a coal-fired and a gas-fired plants. First, we show that the higher the plant efficiency, the higher the value of the generation asset, regardless of the pass-through of the opportunity cost of CO_2 emission permits. Second, if we do not account for such an opportunity cost, then the higher the heat rates, the lower the activation frequency of the generation system. In passing, it may be noted that the rate of reduction of the activation frequency of the coal plant is higher than that of the gas plant. Finally, we show that internalizing the opportunity cost and modeling the log-price of CO_2 emission permits, decreases (increases) the rate of activation of the gas (coal) plant for large λ and large log-price of CO_2 emission permits. Therefore, this paper deals with a topic that is relevant not only for the energy industry, but might also provide important results for changes in the design of the EU ETS or policy decision takers.

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