

Inducing Clean Technology in the Electricity Sector: Tradable Permits or Carbon Tax Policies?

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Tradable permits and carbon taxes are two market-based instruments commonly considered by policymakers to regulate pollutions. While a tax is fixed, predetermined by authorities, the uncertain permits price is driven by market dynamics, fluctuating with the prices of natural gas and electricity. Both instruments offer firms different incentives for adopting clean technologies. This paper explores the optimal investment timing when a coal-fired plant owner considers introducing clean technologies in face of these two policies using a real options approach. We find that tradable permits could effectively trigger adopting clean technologies at a considerably lower level of carbon price relative to a tax policy. Higher levels of volatility in permit prices are likely to induce suppliers to take early actions to hedge against carbon risks. Thus, offset and other price control mechanisms, which are designed to reduce permit prices or to suppress prices volatility, are likely to delay clean technology investments.

1. INTRODUCTION

Climate Change is an unprecedented challenge faced by our society today. The Fourth Assessment Report (AR4), released by the IPCC (Intergovernmental Panel on Climate Change) in 2007, indicates that the link between the increase of greenhouse gases (GHG) in the atmosphere and global warming is evident by the trend of warming of the oceans, rising sea levels, widespread ice melting in the Arctic, etc (Intergovernmental Panel on Climate Change 2007). As the power sector constitutes one of the main sources of GHG, numerous resources and policies are expected to be devoted to controlling GHG emissions from the power and other energy-intensive sectors.

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Policy choice in combating climate change, like climate change itself, has been a longstanding debate. Two types of policies are generally implemented to control for pollution emissions: command-and-control and market-based instruments. Command-and-control policies consist of technology and performance standards, which mandate specific control technology to be installed and to stipulate emissions limits on emissions sources.¹ Within the command-and-control mechanism, performance standard grants owners the flexibility to decide their preferred technologies and tailor them to the design of their facilities. Industry would favor the performance over the technology standard because of the flexibility, whereas government might incline to set the technology standard if the transaction cost is substantially higher under performance standard.

While the market-based instrument is a generic label for various types of environmental standards that take advantage of competition in the polluting industries, it generally refers to price and quantity instruments. The price instrument, commonly known as “tax,” acts as a cost adder internalizing pollution damage (i.e., “externality”) created by the polluting industries that is not fully reflected in product prices. The second type regulates pollution quantity, or known as “cap-and-trade” (C&T), which first allocates a fixed amount of emissions quantity (i.e., permits/allowances) to affected facilities. These facilities need to demonstrate their compliance by “surrendering” sufficient allowances to cover their emissions at the end of each compliance cycle (e.g., the annual cap for SO₂ and summer months for NO_x). The allowances can be traded freely in the secondary market. Under this approach, the aggregate cost for pollution control of a regulated sector (e.g., electricity) for a given reduction target is expected to be the least if the market is competitive among other conditions (Stavins 1995). The economic efficiency gains of the programs are due to heterogeneity in abatement costs: companies with low control costs would control more, while their counterparts would purchase surplus allowances from them.

There is a rich body of literature comparing command-and-control and market-based instruments. Economists have long advocated for market-based approaches on the grounds of economic efficiencies. A number of frequently cited advantages of market-based instruments over command-and-control policies are summarized as follows. First, a market based instrument results in an equalization of marginal abatement costs across all polluters. This is a basic condition for a least-cost outcome (i.e., static efficiency). Moreover, regulators do not need to know the marginal abatement costs of the polluting industries, which normally is private information. Second, both C&T and tax instruments offer polluters incentives to undertake R&D (research and development) activities for exploring cost-saving abatement options (i.e., dynamic efficiency). Third, revenues raised by tax or permits auctions can be recycled, for instance by lowering other taxes and, hence, reducing distortions induced by pre-existing taxes (i.e., double dividend) (Parry et al. 1997).

1. Examples of technology standard include scrubbers and SNCRs (selective non-catalytic reduction systems) for SO₂ and NO_x emissions from power plants.

Although in theory these two market-based approaches, tax and permits, can result in the same outcomes if the tax is set to equal the marginal control/damage cost defined by the emission cap, fundamentally they offer firms distinct economic incentives for investing in emission reductions. More specifically, the level of an emissions tax is pre-set by an authority and exogenous to the product market. As for emissions permits, producers might realize that permit prices fluctuate constantly, reflecting market participants' expectations concerning demand and supply conditions. The permit prices could therefore be affected by changes of pivotal producers' net positions in permits markets. For example, retrofitting pollution control devices or fuel-switch could lower the demand for permits, effectively suppressing permit prices.

Following the seminal work by Weitzman (1974), there is a rich body of literature comparing the performance of these two market-based instruments. For example, work by Mansur (2007) examines strategic behavior in an oligopoly electricity market when producers are subject to either a tax or tradable permits regulation. The results show that, unlike a tax, the polluters' decisions under a tradable permits system would affect the permit price, which might actually increase a strategic firm's output, thereby leading to a lower deadweight loss relative to a tax system. A more recent paper by Green (2008) examines market risks faced by generators under the tax and permits systems. This paper concludes that, relative to a permits program, a carbon tax would reduce risk faced by nuclear generators, but it would raise the risk associated with fossil-fired units. This can be attributed to the fact that the permits price is closely correlated with fuel costs, and such a correlation further amplifies profit volatility faced by the fossil units.

However, to our knowledge, there is no formal treatment based on real options in the existing literature that compares the investment timing between these two instruments. As in most competitive markets, the electricity price is set by the generating cost of the marginal unit, ignoring network congestion and other complications. The extent to which carbon costs (in the form of permits and tax) would be passed on to the electricity price depends on the marginal technology, which differs by markets.² Although both the carbon tax and permit cost will be passed onto the electricity price, their underlying economic force is different, and their relation with respect to fuel costs, such as natural gas (NG), is distinct. In particular, the permit's price, the electricity price, and the NG price are idiosyncratic and are likely to be positively correlated. This is because an elevation of NG prices (e.g., due to shortage or other reasons) would increase coal consumption because coal and NG are substitutable goods. This in turn would

2. For instance, it is estimated that 40–80% of the permits price of the European Union Emissions Trading Scheme was passed on to electricity prices in 2005 (Sijm et al. 2006). Theoretically, the level of CO₂ pass-through costs depends on demand, supply elasticities, market competition, etc. If no changes in the merit order for determining the marginal unit is assumed, the pass-through cost is positively associated with supply elasticity, but is negatively associated with both demand elasticity and the number of firms in the market (Chen et al. 2008).

increase the demand of the permits and would induce a positive pressure on the permit price, as well as the electricity price. On the contrary, the tax is determined a priori (or fixed) by the government and is insensitive to any market dynamics.

This paper studies the timing that a firm invests in a less CO₂-intensive technology under some emission control policy. This is especially critical for a firm to mitigate the financial impacts resulting from climate policy. Because the impact of climate change is irreversible, firms that take precautionary actions to reduce GHG emissions could have profound effects, but they may need to bear substantial investment costs. From the perspective of technology diffusion³, a desirable climate change policy should provide polluting industries with strong incentives to take early preventive actions. Several studies examined technology diffusion under tax and C&T based on game-theoretical framework, e.g., see Milliman and Price (1989), Kennedy and Lapiente (1999), Requate and Unold (2003), Coria (2009), Montero (2002a), and Montero (2002b). Their focus was on the comparison of incentives provided by different policy instruments. Our paper explores the timing of investment as a function of data-generating processes underlying various prices using a real options approach.

We assume that a price-taking firm (who is small relative to the entire market) owns a coal plant (i.e., polluting energy resource) subject to load obligation and faces three exogenous price shocks: electricity, NG, and permits. Considering two different policies, tax and C&T, we examine the timing under each policy such that the firm adds an NG power plant (i.e., clean technology) in order to meet the load obligation while maximizing its expected long-run profit with emission-related costs considered. Whereas the prices for electricity, permits, and NG are closely correlated in the emission trading system⁴, the level of tax mandated by authorities is assumed completely independent from electricity and NG prices. We explore the relation of investment timing under each policy in terms of the price parameters. Although we focus on the choices of a new NG plant, the implication could be generalized to other decision contexts, such as retrofitting pollution control devices, carbon capture and storage (CCS), or other alternatives mitigating CO₂ emissions.

In order to evaluate the profitability of capacity expansion, our model focuses on “operational” perspective of the policies in terms of the investment timing for inducing new technologies. First, the decision leadtime (e.g., the re-

3. Economic theories define technological change by three consecutive stages: invention, innovation, and diffusion (Jaffe et al. 2002). Invention constitutes the initial conversion of scientific or technical knowledge into new products or processes. Innovation defines as the commercialization of new products or processes based on the invention and make them available to the public. Finally, diffusion refers to the adoption of products by firms or individuals. In this paper, the term “investment” refers to *diffusion* of a low-CO₂ generating technology.

4. In fact, the correlation among these three prices depends on the generating mix in a market. When a market is competitive, a diversified generating portfolio that allows for a greater fuel substitution when facing permit prices would result in a strong correlation between fuel costs and electricity prices.

quired time for applying for permits and/or constructing the power plant) will be modeled, and its impact on profitability and investment timing will be studied. In particular, we explore the effect of correlations among electricity, permits, and NG prices on the firm's investment decisions. Second, we deploy a more realistic model that includes the firm's ability to produce the power flexibly (by dispatching both coal and NG units) based on price spreads.

The rest of this paper is organized as follows: In Section 2, an economic model is presented. A case analysis based on real price data used to illustrate our results is presented in Section 3. We conclude the paper in Section 4.

2. MODEL SETUPS

This section provides detailed model setups, including the uncertainty model, the problem formulation, the model interpretation, and the solution procedure.

2.1 Uncertainty Model and Emission Policies

Three uncertainties are considered in this paper at day t in the planning horizon for $t \geq 0$: prices for electricity X_t (\$/MWh), natural gas G_t (\$/MMBtu), and emission permits Y_t (\$/MWh)⁵. As already mentioned, we will consider two emission control policies in this paper: tradable permit and tax. The price for emission permits Y_t will be used in evaluating the policy of tradable permits. These three uncertainties are assumed to evolve following the geometric Brownian motions, for any time $s \geq t$:

$$dX_s = \mu_x(X_s, s)ds + \sigma_x dB_s^x \quad (1a)$$

$$dY_s = \mu_y(Y_s, s)ds + \sigma_y dB_s^y \quad (1b)$$

$$dG_s = \mu_g(G_s, s)ds + \sigma_g dB_s^g, \quad (1c)$$

where B_s^x , B_s^y , and B_s^g are correlated Wiener processes such that

$$dB_s^x dB_s^y = \rho_{xy} ds \quad (2a)$$

$$dB_s^y dB_s^g = \rho_{yg} ds \quad (2b)$$

$$dB_s^g dB_s^x = \rho_{gx} ds \quad (2c)$$

In equations (1a)–(1c), the price evolutions are assumed to follow some stochastic processes, where μ_x , μ_y , and μ_g are the drift functions for the processes, respec-

5. The unit is \$/ton, since CO₂ emission of a typical coal plant is roughly a ton per MWh generation, however, it can also be approximated as \$/MWh.

tively, and $\sigma_x, \sigma_y, \sigma_g$ are constant (but may be time dependent) volatilities. Assume at time 0, the prices of $X_0, Y_0,$ and G_0 are $x, y,$ and $g,$ respectively. That is,

$$(X_0, Y_0, G_0) = (x, y, g). \quad (3)$$

When the taxation policy is considered, Y_t is reduced to a constant Y by setting $\mu_y = \sigma_y = 0$. In this case, Y represents the tax payment and is time-invariant. The correlation terms ρ_{xy} and ρ_{yg} in equations (2a)–(2c) are also set to zero. Since the constant Y may be viewed as a special (degenerate) case of Y_t , in the remainder of the paper, our analysis will focus on valuation under these three uncertainties.

2.2 Problem Formulation: A Per MW Analysis

This section considers a decision problem concerning the capacity investment faced by a risk-neutral price-taking producer who owns an existing coal plant. As the pressure for employing cleaner power-generating technologies is mounting, the producer considers to add a NG plant in the future. Of course, capacity additions could be driven by factors other than CO₂ policy, such as easy access to capital, friendly regulatory environment, etc. However, we limit our analysis to situations exclusively related to CO₂ policy. Currently with the existing coal plant, the costs for generating one MWh electricity at t include the cost of coal, assumed to be a constant C (\$/MWh)⁶, and the emission cost Y_t (\$/MWh), determined by the emission market. Therefore, for the existing coal plant the per MWh profit at time t is denoted by f_t^0 as follows.

$$f_t^0(X_t, Y_t) = X_t - C - Y_t, \quad (4)$$

where the superscript 0 implies no expansion yet.

If an NG plant is built, using the NG plant to generate one MWh results in a profit of $X_t - G_t H - 0.5Y_t$ at time t , where G_t is the NG price and H (MMBtu/MWh) is the heat rate of the plant. Since in general, an NG plant emits about half of the CO₂ emitted by a coal plant on a per MWh basis, the emission cost for the NG plant is set to be $0.5Y_t$. We ignore the possibility of further reduction of CO₂ emissions from the NG plant by means of other advanced technology when they become available. With the new NG plant, the decision maker can generate power by the portfolio of these two power plants. The dispatch of both power plants will be conducted in a cost-minimizing manner. Therefore, the per MWh profit of the portfolio at t takes the following form:

$$\text{Portfolio's per MWh profit} = \quad (5)$$

$$\max_{0 \leq \alpha_t \leq \alpha} [(1 - \alpha_t)(X_t - C - Y_t) + \alpha_t(X_t - G_t H - 0.5Y_t)],$$

6. Of course, one could add a stochastic coal price in the model. However, the curse of dimension might make computation much difficult. We believe our assumption is reasonable since the historical data also suggest that the costs of coal are considerably stable compared to NG prices (Sijm et al. 2006).

where α_t is a dispatch factor at time t and is between 0 and $\bar{\alpha}$, which is a constant representing the ratio of the capacity of the NG plant to that of the coal plant. Since in general the capacity of a coal plant is greater than that of an NG plant, $\bar{\alpha}$ is assumed to be less than 1.

Recognizing that the portfolio profit in (5) is a linear function of the prices, X_t , Y_t , and G_t , an optimal dispatch will only occur on the boundary points, $\alpha_t=0$ or $\alpha_t=\bar{\alpha}$. Therefore, the two possible dispatches correspond to either (i) the coal plant is fully on with the NG plant off ($\alpha_t=0$); or (ii) the NG plant is fully on with the coal plant picking up the residue ($\alpha_t=\bar{\alpha}$) at time t . Therefore, the (portfolio) profit function (5) at time t can be summarized by the following function:

$$f_t^1(X_t, Y_t, G_t) = \max_{\alpha_t \in \{0, \bar{\alpha}\}} [(1-\alpha_t)(X_t - C - Y_t) + \alpha_t(X_t - G_t H - 0.5Y_t)], \quad (6)$$

where the superscript 1 implies that expansion has occurred.

Assume that the decision maker would build an NG plant at a future time τ , which requires a capital investment of K (\$/MW), deposited at τ . The construction will need v months to complete. The optimization involved in this decision making includes the optimal timing (τ) for building the NG plant, and if so, the optimal dispatch (α_t) between the existing coal plant and the new NG plant.

To focus on how emission policies induce the expansion decision for building the NG plant, we assume the existing coal plant to be perpetual (but not the NG plant). In reality, the coal plant's life may be prolonged by regular, continuous maintenance and upgrade. The reason for this assumption is more academic than practical. We basically assume that the NG plant may come and go (built, operated, and retired); but the coal plant remains there. Since we are interested in finding the optimal timing to build the NG plant under different emission policies, this assumption enables us to focus solely on the NG plant without worrying about possible retirement of the coal plant during the life cycle of the NG plant. This assumption also helps to reduce the complexity of the problem, which will become clear in Section 2.3.

Consider a decision period $t \in [0, T]$, within which a new NG plant is expected to be added. The profit maximization for the decision maker of this investment problem can be formulated as follows:

$$J(x, y, g) = \max_{\tau \in [0, T]} E_0 \left[\int_0^{\tau+v} f_s^0(X_s, Y_s) e^{-rs} ds - K e^{-r\tau} + \int_{\tau+v}^{\tau+v+l} f_s^1(X_s, Y_s, G_s) e^{-rs} ds + \int_{\tau+v+l}^{\infty} f_s^0(X_s, Y_s) e^{-rs} ds \right]. \quad (7)$$

The optimization in (7) is subject to an additional constraint that the real option of expansion expires after T . In equation (7), it is clear that the NG plant is built

at τ with a construction leadtime v . After the completion of the construction, the NG plant has a life of l time periods and after that will be disposed without any salvage value. Note that the optimization problem depends on the prices (x, y, g) at $t=0$. The optimal (stopping) time τ to build is a random variable, which is uncommitted at $t=0$. Since we consider expansion as a real option, it is possible that the expansion is never exercised during $[0, T]$. Since the purpose of this paper is to see how quickly an emission policy induces adoption of clean technology, for the instance where the expansion option expires without being exercised, we will manually register its adoption time as T , which is a large number ($T=120$ months in our case study in Section 3). This enables us to provide an expected waiting time $E[\tau]$ for each scenario investigated. Therefore, when $E[\tau]$ is large in our case study, it should just be interpreted as that expansion is highly unlikely within the finite horizon of $[0, T]$.

2.3 Real Options Perspectives

In our problem setup, the decision to build an NG power plant is clearly a real option of the decision maker. There are other less obvious real options to be interpreted next.

First, equation (6) reveals a *dispatch* (or *switching*) real option for the decision maker after the new NG plant has been built. The decision maker can observe the prices and decide whether it is more profitable to generate the one-MW power using only the coal plant or both. To justify whether the NG plant should be built, the overall value resulted from exercising the dispatch option over the life time of the NG plant must be compared with the construction cost of the plant, which may be viewed as the premium of having the dispatch real options.

To see the next real options interpretation, we rewrite the formulation in equation (7). With some algebra, equation (7) is equivalent to the following:

$$J(x, y, g) = E_0 \left[\int_0^{\infty} (X_s - C - Y_s) e^{-rs} ds \right] + \max_{\tau \in [0, T]} E_0 [-K e^{-r\tau} + \bar{\alpha} \int_{\tau+v}^{\tau+v+l} \max(0.5Y_s + C - G_s H, 0) e^{-rs} ds]. \quad (8)$$

In equation (8), we separate the role that each plant plays. The first integral refers to the operation of the perpetual coal plant. The second integral reveals a *spread option* (e.g., see Carmona and Durrleman 2003) between Y_t and G_t with the payoff function $\max(0.5Y_s + C - G_s H, 0)$. Interestingly, the electricity price X_t drops out of the payoff function. This is because the power output from either plant is indistinguishable and must add up to one MW. What matters is the difference between the saving of the emission costs, $\bar{\alpha}(0.5Y_t)$, and the additional cost for having the NG plant, $\bar{\alpha}(G_t H - C)$.

Since the first integral in equation (8) has nothing to do with the expansion decision, in the remainder of the paper we shall ignore the first integral and focus on the remaining term within the maximization operator. That is, we shall consider \bar{J} that is equivalent to J as follows.

$$\bar{J}(y, g) = \max_{\tau \in [0, T]} E_0[-Ke^{-r\tau} + \bar{\alpha} \int_{\tau+\nu}^{\tau+\nu+t} \max(0.5Y_s + C - G_sH, 0)e^{-rs} ds]. \quad (9)$$

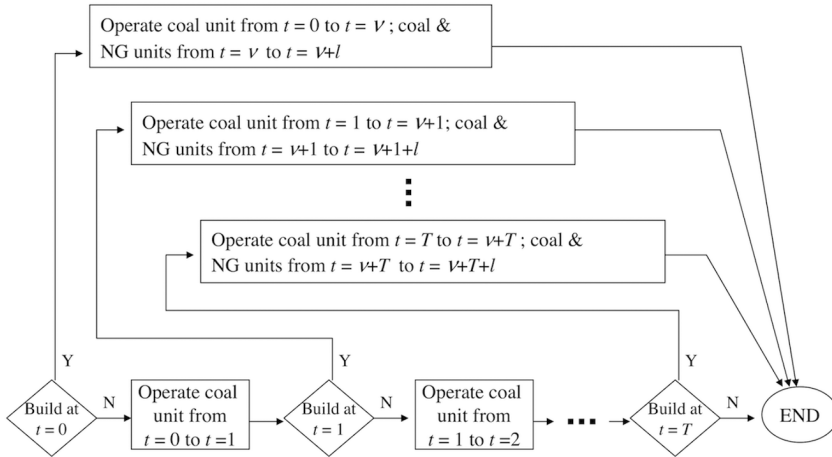
Equation (9) has reduced the number of uncertainties underlying the proposed stochastic problem from three to two. This variable reduction has significantly reduced the numerical complexity for solving the problem. The equation shows that the supplier who owns a coal and an NG plant is equivalent to own a series of emission-NG price-spread call options (if an uncertain coal price is considered, it is an emission-coal-NG price-spread option). Owning this type of spread option has some financial implications. For example, consider the case that the supplier has purchased and stocked coal and NG previously at a low price. When the emission price is low and the NG price is high on the spot markets such that $0.5Y_t + C - G_tH < 0$, the supplier can purchase a permit to generate power using the coal plant and sell NG to the spot market and gain profit. There are other positions that the electric suppliers may consider for hedging purposes. This, however, is beyond the scope of this paper.

The expression in (9) also sheds some light on different perspectives of the problem facing the decision maker under the two different emission policies. With C&T, the decision maker faces uncertain profit, which is determined by the spread of two uncertainties, $(0.5Y_t - G_tH)$, and the decision maker's objective is to maximize the expected profit by choosing the investment timing. On the other hand, under a fixed carbon tax rate Y_t , the decision maker receives a deterministic revenue stream $(0.5Y_t + C)$ and faces a cost uncertainty from G_t . It will be shown in our case study that the problem of the decision maker under tax policy focuses on the profitability of the investment (yes or no) rather than the timing (when).

2.4 The Solution Procedure

Problem \bar{J} in equation (9) can be solved using standard numerical methods. In reality, the capacity expansion decision does not need to be carried out in a continuous time domain. The expansion decision may be visited on monthly basis or even annual basis until the capacity has been added. In this paper, we assume that the expansion decision can only be considered at the beginning of each month. The dispatch decisions, however, are made at a higher frequency, on a daily (or even an hourly) basis.

In our modeling of the uncertainties processes in Section 2.1, the time unit t is in days. To reflect the nature of the timing of these decisions, we approximate problem (9) in the discrete time domain. We construct two-factor price lattices (trees) (of Y_t and G_t) such that the time step of the lattice is a fraction of

Figure 1: Interpretation of the Solution Procedure.

a day. For the lattice nodes at the times corresponding to the beginning of a single day, the dispatch decision is carried out to evaluate the payoff function of the spread. The expansion decision is then considered at the beginning of each month if the NG plant has not yet been added.

The solution approach is depicted in Figure 1. The time unit in Figure 1 is in months. The expansion decision is considered at the beginning of each month if the new NG unit has not been added by then. The rectangle blocks represent operations described in (7), depending on whether the new NG unit is in place. When both units are available, the operations involve the dispatch decisions, which are not shown in the figure. When the new NG unit is added, it takes a construction leadtime v and the life of the unit is l . Although the procedure in Figure 1 may suggest a forward moving approach to solve, it is actually more efficiently handled by backward stochastic dynamic programming (SDP) steps. Using SDP, each rectangle block is evaluated using the two-factor lattice models described. Therefore, at the decision nodes in Figure 1, the decision maker considers the two options: to wait or to act immediately.

At each decision node, in order to evaluate the expansion decision, all price nodes are evaluated. A boundary that separates the nodes that favor waiting and the nodes that favor expansion may be identified. Such a boundary describes the optimal exercise criterion at the time. Once all such boundaries are identified (through backward induction), we use the Monte Carlo simulation method to estimate (the distribution of) the optimal adoption time.

Each simulation run simulates the price evolution, (1a)–(1c), over the entire planning life cycle. In the beginning of each month if expansion has not yet been done, the investment decision is considered by comparing the prices (Y_t, G_t) at that time with the optimal exercise criterion of the same time. If ex-

pansion is more profitable than waiting, the NG plant would be built and this adoption time is recorded. The same simulation run then continues to simulate the construction period ν , followed by the operational period l of the new NG plant, and finally stops at the end of the life of the new NG plant. The profit associated with this investment over its life cycle can be evaluated. Such a process is repeated for N runs, with N adoption times recorded, along with N investment profits. The expected values of the optimal adoption time and the corresponding investment profit can be determined.

3. CASE STUDY

In 2005, an emission trading scheme was implemented in European Union (EU). The limited experience has shown some preliminary evidence of encouraging outcomes (Ellerman and Joskow 2008). Although the EUA (EU Allowance) market had tumbled over time in the first phase, the market prices have been relatively stable around 10–15 €/ton in the second phase (www.pointcarbon.com). We have obtained the daily EU EUA price data for years 2005 to 2007 (Point Carbon 2009). We keep the EUA prices for year 2007 in the sample, since the sharp falls of EU EUA prices since late 2006 due to unanticipated surplus EUA towards the end of first phase of EU ETS allows us to capture its relationship with NG and electricity prices. However, one should also cautiously note that the permit price during this period was also driven by other factors such as pilot phase of ETS, surprising permits surpluses as mentioned before, and no-banking permits between phrases. Altogether would make permit prices more volatile and less correlated with coal and electricity prices. We address the implications on the correlation and volatility in our sensitivity analysis. We collected the Dutch spot electricity and fuel costs for the same period from APX-ENDEX (www.apxgroup.com). Coal costs are based on the internationally traded commodity (ARA CIF API#2) and NG refers to the high caloric gas from the Title Transfer Facility (TTF).

Unlike the emission prices, NG is a popular commodity and its price behavior has been commonly modeled as a mean-reverting process, e.g., Barz (1999), Tseng and Barz (2002), and Tseng and Lin (2007). A mean-reverting process is one that reveals a *trend* or *seasonality*, characterized by mean levels. In this paper both uncertainties G_t and Y_t are assumed to evolve following the geometric mean-reverting processes:

$$d \ln G_t = \mu_t^g (m_t^g - \ln G_t) dt + \sigma_t^g dB_t^g \quad (10a)$$

$$d \ln Y_t = \mu_t^y (m_t^y - \ln Y_t) dt + \sigma_t^y dB_t^y \quad (10b)$$

where μ_t^g and μ_t^y are reverting coefficients; m_t^g and m_t^y are the mean levels of NG and emission prices at time t , respectively; and σ_t^g and σ_t^y are constant volatilities at time t . In our case, the time variable t in equations (10a) and (10b) are in days (for daily dispatch); however, we use a much smaller step size (fraction of a day)

Table 1: Summary of Price Parameters

t	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
m_t^g	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61
μ_t^g	0.58	0.37	0.35	0.39	0.41	0.36	0.61	0.34	0.36	0.22	0.43	0.26
σ^{t^g}	1.14	0.44	0.35	0.31	0.41	0.35	0.39	0.41	1.08	1.39	1.89	0.72
m_t^y	2.60	2.67	2.86	2.74	2.61	2.73	2.71	2.70	2.67	2.60	2.48	2.40
μ_t^y	0.10	0.10	0.10	0.10	0.20	0.20	0.15	0.15	0.15	0.20	0.10	0.15
σ_t^y	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38

for constructing the lattice. For price parameters, we estimate their values by months. That means, all parameter values remain the same within each month. The parameter values are summarized in Table 1. Based on our tests over historical price data, the correlation coefficient between the prices of NG and emission permits is about 0.2.

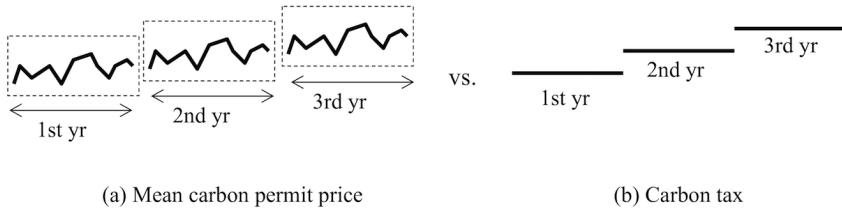
The price parameters are estimated following standard steps using the maximum likelihood method given in the appendix of Tseng and Barz (2002). To estimate the volatility of the emission prices Y_t , we eventually estimated a constant volatility, instead of monthly ones, to increase the number of sample data points for better estimation.

To see under which emission policy, permits or tax, the decision maker would have a higher incentive to expand the capacity earlier, it seems obvious that one key factor is the long-term prospects of the permit price and the carbon tax; both are denoted by Y_t in this paper. In this paper we do not focus on forecasting future emission prices and tax rates. In addition, given the short history of the EUA markets, there is no reason to judge the future purely based on limited price information about the past. To deal with this issue, we shall consider sensitivity analysis. We also need to set up a platform that can provide fair comparisons between the two emission policies.

The assumption that Y_t follows a mean-reverting process becomes useful because m_t^y can be viewed as the long-term mean levels of (the logarithm of) the permit price at future time t . On one hand, when Y_t is used to model the stochasticity for the permit price, we have a profile of its monthly mean levels $\{\exp(m_t^y)\}$ (see Figure 2a); on the other hand, when Y_t is considered deterministic and is used to model the carbon tax, its profile is constant each year (Figure 2b). So we argue that to make a fair comparison, the (annual) *average* Y_t profiles, both stochastic and deterministic, must be equivalent. That is, the carbon tax level should be equal to the average of the 12 values of $\exp(m_t^y)$ of the same year. Furthermore, we assume that the carbon tax rate will increase by 5% annually, so the evolution of deterministic Y_t looks like an increasing step function as shown in Figure 2b. The same 5% growth rate is also applied to the “blocks” of annual $\exp(m_t^y)$ profile, as shown in Figure 2a, to ensure that the comparison remains fair.

To facilitate the comparison, we create a new parameter \bar{y}_0 as the “average carbon price” of the first year. In the deterministic case, \bar{y}_0 equals the carbon

Figure 2: The Profile of the Future Carbon Prices.



tax rate of the first year, and the average of the twelve $\exp(m_t^y)$ values of the first year in the stochastic case. We shall show that to trigger capacity expansion, the carbon tax policy requires a much higher \bar{y}_0 than C&T.

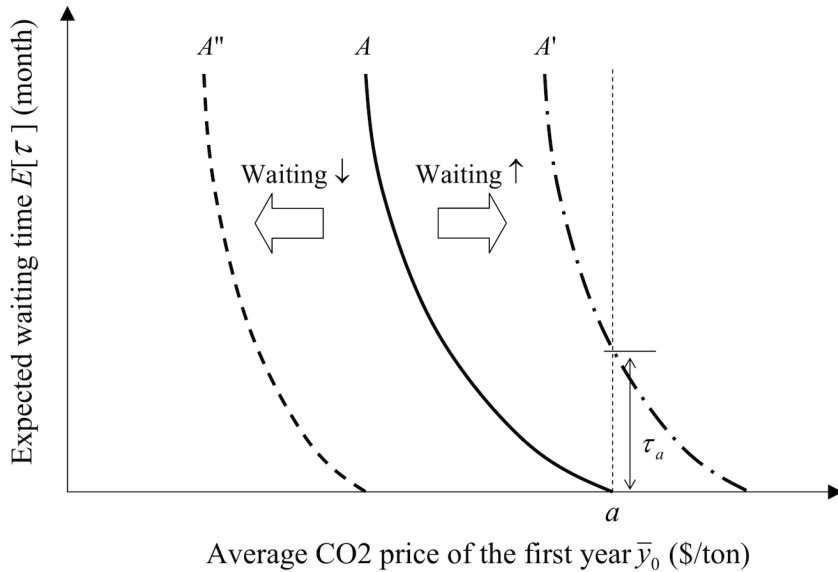
In this case study, we consider a decision period of 10 years ($T=120$ months), within which the NG plant is expected to be added. Assume it costs the existing coal plant \$22 to generate one MWh. Using the data suggested by the National Energy Modeling System (Energy Information Administration 2009), the new NG plant has a heat rate of 10,807 Btu/KWh. Its construction cost is \$420,000/MW. We assume the NG plant has a life of 20 years and the capacity ratio $\bar{\alpha}$ is 0.5, so the actual capacity of the NG plant is only half of the coal plant.

3.1 Time to Adoption

To discuss the time to adopt new technology, we first compare our model with the canonical real options model (e.g., in Dixit and Pindyck 1994) that addresses the value of waiting for investment. In the canonical model, the project value V is commonly assumed to follow a geometric Brownian motion (with a positive drift). One important result is that under some conditions waiting may yield a higher value even if the payoff of the investment has already been positive. In this paper, although we follow a similar approach to address the value of waiting, there are at least two fundamental differences worth noting between our model and the canonical one.

First, in our model the value of the “project” (referring to adopting new technology) at any single moment is not immediately obvious as that in the canonical model. This is because the project is described in terms of the operations during its life cycle in our model. Therefore, our project value is realized by operating the power plant(s). This difference in how the project value is realized may lead to seemingly opposite results. For example, in the canonical model, when the volatility of V gets higher, there is a higher threshold value await. However, in our case, facing a prospect of profit surge, the decision maker may want to start the operation sooner than later, in order not to miss the profit opportunity.

Second, most existing results in literature analyze waiting time with respect to the value of some underlying uncertainty (e.g., the project value V).

Figure 3: Expected Waiting Time Against the First Year Average Carbon Price.

But in this paper we will analyze the waiting time with respect to \bar{y}_0 , which is the average carbon price of the first year. This parameter \bar{y}_0 is not stochastic, but it certainly affects the evolution of the carbon price Y_t under C&T. This is because we focus on comparing the effectiveness of emission policies in terms of inducing new technology.

As the decision maker evaluates the expansion investment based on current available information, we characterize the optimal waiting time τ to add clean technology (i.e., a NG plant) as a function of the current level of carbon price \bar{y}_0 . Intuitively, regardless of the emission policies, when \bar{y}_0 is sufficiently low, the expansion would never happen $\tau = T$; on the other hand, if \bar{y}_0 is adequately high, it would trigger an immediate expansion $\tau = 0$. A typical expected waiting time function versus \bar{y}_0 is illustrated in curve A of Figure 3: a decreasing function of \bar{y}_0 with *threshold price* a (\$/ton), beyond which an immediate expansion becomes optimal. If under other conditions, the expected waiting time function and the threshold price are shifted towards the right to curve A' , for point $\bar{y}_0 = a$ immediate action is no longer optimal. The waiting time for adopting new technology is estimated to be τ_a time periods. On the other hand, if the function shifts towards the left to curve A'' , immediate action would remain optimal.

To wait or to act immediately in our model depends on the interplay between early profit and the value of waiting. The early profit is highly uncertain, depending on the realization of the underlying price uncertainties, which can be further complicated by the construction leadtime. On the other hand, the value of

Table 2: Comparison of Threshold Prices of Both Emission Policies

C&T			Tax		
\bar{y}_0 (\$/ton)	$E[\tau]$ (m)	Profit \bar{J} (\$)	\bar{y}_0 (\$/ton)	$E[\tau]$ (m)	Profit \bar{J} (\$)
30.3	120.0	0.0	79.3	120.0	0.0
30.4	112.2	17.6	79.4	120.0	0.0
30.5	99.7	49.1	79.5†	0.0	0.0
30.6	71.1	107.9	79.6	0.0	947.5
30.7	9.5	641.9			
30.8†	0.0	1636.0			

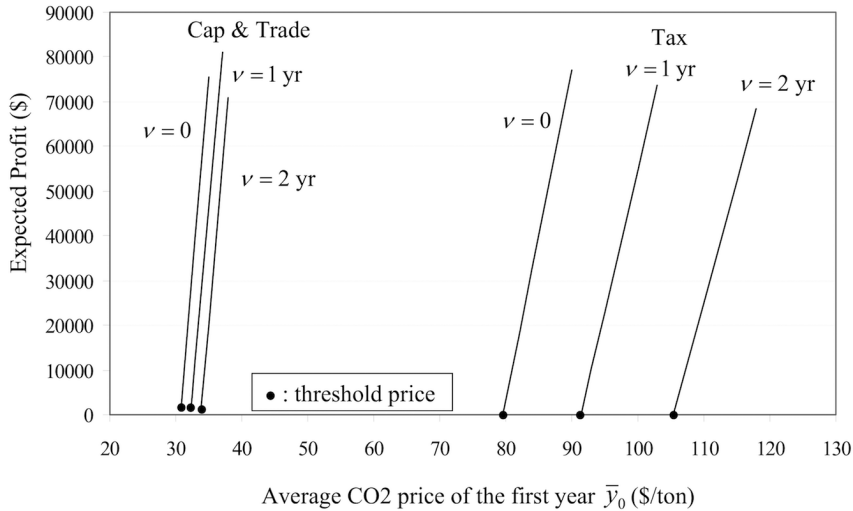
†: threshold price

waiting includes interest saving from deferring the payment and the typical option value of waiting. Both are uncertain. To simplify the matter, we first assume that the construction of the new NG plant can be done instantaneously (i.e., $\nu=0$). (The impact of a non-zero construction time will be analyzed later.) We then focus on analyzing the threshold prices under both emission policies. The results concerning the threshold prices are summarized in Table 2. The threshold prices for the C&T permit and tax are \$30.8 and \$79.5, respectively. This suggests that it requires a much higher level of tax ($\bar{y}_0 \approx \$80$) than permit prices ($\bar{y}_0 \approx \31) to induce capacity expansion.

Table 2 implies that for C&T when the first year carbon price \bar{y}_0 is above \$30.3 but less than \$30.8, the investment yields a positive but non-optimal expected profit. The average waiting times are estimated using the Monte Carlo simulation. When \bar{y}_0 is very close to \$30.8, almost all simulation instances recommend immediate action; on the other hand, when \bar{y}_0 is close to \$30.3, most simulation instances recommend doing nothing, i.e., setting $\tau = T = 120$ months. For tax policy, it turns out that the threshold price is the same as the break-even price, where zero net profit is achieved. This issue will be discussed in greater detail later.

Table 2 also indicates that when \bar{y}_0 increases, the expected waiting time $E[\tau]$ decreases very quickly to 0 (from 120 months down to 0 within 50 cents) for the permit case. When the tax policy is considered, the behavior of $E[\tau]$ versus \bar{y}_0 is similar to that of the permit case except that the curve decreases abruptly, resembling a step function. To explain the steepness of the function under C&T, note the definition of \bar{y}_0 , which is the mean carbon price of the first year. The mean carbon prices in subsequent years are compounded annually with a fixed rate. So a 50-cent difference in \bar{y}_0 has a significant profit impact in this operation that only generates 1MW of power.

To explain the sudden drop of the expected waiting time function under tax policy, we need to revisit the payoff function in equation (9). As mentioned previously in Section 2.3, under tax policy the decision maker faces a fixed revenue stream $(0.5Y_t + C)$ and a cost uncertainty G_t , with the growth rate of the revenue less than the discount rate. Without considering the cost uncertainty G_t ,

Figure 4: The Expected Profit Against the First Year Average Carbon Price.

it is easy to see that the value of the project (investment) V decreases over time. Facing such a project, if it is to be carried out, the best strategy would be to collect the revenue flow as soon as possible, and there is no value of waiting. Now we add the cost uncertainty G_t , which is modeled in this paper as a mean-reverting process with a constant mean and increases each year with inflation. Since the cost also increases over time, there is still no value to delay the project. Overall, we can conclude under tax policy the project value decreases over time. Therefore, there exists a threshold of \bar{y}_0 (revenue) to determine whether the project is worthy or not. When the value of \bar{y}_0 is below the threshold, no action should ever be taken. Since there is no value of waiting, the threshold price is the break-even price under tax policy.

Given that the carbon threshold price for C&T is much smaller than that for tax, we next compare the producer's expected profit under these two policies. To be more realistic, the construction delay ν is now taken into account, with ν ranging from zero to two years. The expected profit against \bar{y}_0 is depicted in Figure 4, with the data summarized in Table 3. The solid dot at the lower end of each curve is the corresponding threshold prices. Several observations emerge from Figure 4. First, it generally requires a higher \bar{y}_0 to trigger expansion for the tax policy. Second, the expected profit increases roughly linearly with \bar{y}_0 for both policies, and the increase rate gauged by the slope for C&T policy is greater than that for the tax policy. This suggests that at the prices that trigger immediate expansion in both policies, we expect that the producer is much better off under C&T.

Table 3: Threshold Price and Expected Profit vs. the Leadtime

Policy v (month)	C&T		Tax	
	\bar{y}_0 (\$/ton)	Profit \bar{J} (\$)	\bar{y}_0 (\$/ton)	Profit \bar{J} (\$)
0	30.8	1636	79.5	0
12	32.3	793	91.4	0
24	33.8	468	105.4	0

Furthermore, for each policy, when the delay v increases, the curves become less steep (though it is more visually recognizable in the tax case). Delay for exercising a real option normally decreases the option value. This is because without any delay, when the holder of a real option observes a positive payoff, the option holder can enjoy the benefit by immediately exercising the real option. With delay, however, it is no longer certain that the observed benefit can be sustained over the delay time. In our case, the construction of a NG power plant cannot be done overnight. In addition to the construction time, it also requires time for the producer to apply for permits and perform relevant environmental studies. As implied from Figure 4, for a fixed \bar{y}_0 , the construction time reduces the expected profit; and for the same level of profitability (expected profit value), a technology with a shorter construction time requires a smaller \bar{y}_0 to trigger its expansion. Figure 4 implies that the threshold price elevates with the construction leadtime v . According to Figure 3, this means longer waiting when the construction leadtime increases. This is reasonable because the construction leadtime lowers the investment value and makes the expansion less likely.

To interpret further the results in Table 2, consider the adoption decision of clean technology under a stochastic Y_t (for C&T) versus a deterministic Y_t (for tax). To the coal plant owner, carbon cost is nevertheless undesirable. Intuitively, the plant owner would be forced to change if the carbon cost is high enough. From Table 2, for a risk neutral owner, the threshold price under C&T is less than 40% of that under tax policy, yet C&T is expected to result in a profit while tax policy only breaks even. This can be explained in part by our interpretation that C&T offers the investors potential profit opportunities (e.g., through the proposed spread options in Section 2.3), while tax policy provides a steady revenue flow. Therefore, both policies provide a different incentive to the investors. In our view, C&T offers “carrot” while tax offers “stick.” With a smaller amount of “carrots,” C&T induces the owner to explore profit opportunities; whereas the tax simply imposes a big “stick,” to make clean technology become a less costly option.

The implication that a stochastic Y_t (for C&T) can create profits through the spread options discussed in Section 2.3 shows that the volatility has value. As is already well known in financial options, volatility increases option values by creating profitable opportunities. In contrast, tax policy gives absolutely no uncertainty on the carbon cost for power generation per MW over the entire year. It would be interesting to see how the volatility of Y_t affects the investment timing.

In the next section we shall show that higher volatility makes C&T more attractive and reduces the waiting time.

While tax could be preferred by risk-averse producers or plant owners, who generally dislike market uncertainties created by C&T, our study shows that for the tax policy to be as effective as C&T (in terms of inducing clean technology), the tax level must be very high, and as a result, producers and plant owners are actually better off under C&T (see Figure 4). Thus far we have considered the decision maker to be risk neutral. What if the decision maker is risk-averse? Would risk aversion make the tax policy more appealing? It turns out that with risk aversion the plant owners are even much better off under C&T. This will be demonstrated in a later section.

3.2 Sensitivity Analysis

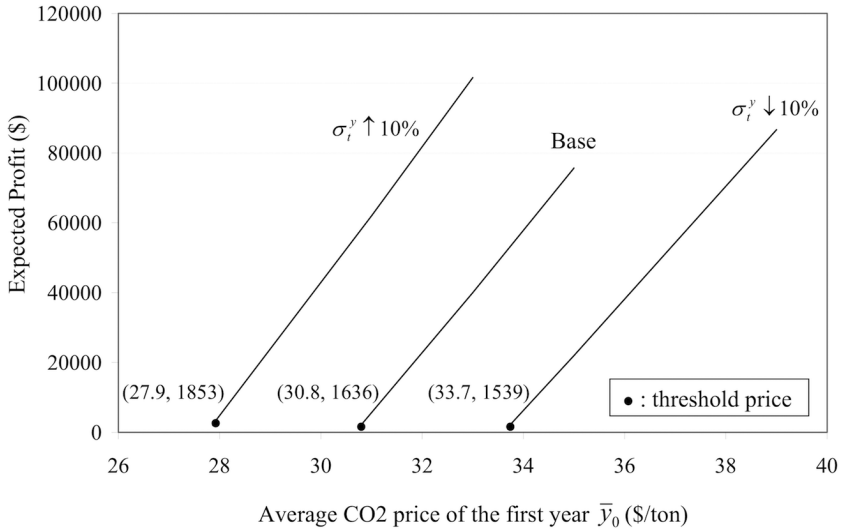
With the limited experience we have so far about the Regional Greenhouse Gas Initiative in the US, the future permit price and relationship with electricity prices remains unknown even if the offset provision is in place to contain permit prices. In this paper, we have estimated the parameters based on the historical data of the Dutch electricity, fuel, and EU permits markets. It may be more insightful to interpret our result from the comparative perspective by performing sensitivity analyses on key parameters. The two parameters for which we will change values are the volatility of permit price (σ_p^2) and the correlation between the prices of NG and the permit.

Changing volatility σ_p^2

As we have argued, the volatility is the main factor that C&T yields more expected profit than tax to the plant owner. In Figure 5, we show the extent that the expected profit would change if the value of the volatility for the permit price given in Table 1 is increased (or decreased) by 10%. Figure 5 suggests that when the volatility increases (decreases), the relationship of the expected profit shifts almost parallel to the left (right) from original curves, indicating a smaller permit price is required to trigger a capacity expansion under a greater volatility. As seen, roughly a 10% increase in volatility lowers the trigger price by three dollars. The result also shows that even if the volatility that we use in this case study is underestimated, the C&T policy is still likely to be more effective than the tax policy in terms of inducing capacity expansion.

This result has another implication. As a large fraction of coal producers facing the carbon regulation would adopt clean technologies simultaneously (e.g., NG plant), it would effectively increase the demand of NG and suppress the demand for coal and CO₂ permits. In the extreme, if NG plants always stay at marginal, and CO₂ costs are fully passed through, the electricity prices will be closely related to NG and permit prices. The volatilities would likely escalate as the demand of NG from these producers move in the same direction simulta-

Figure 5: Sensitivity Analysis by Changing the Volatility σ_t^y .



neously. As alluded to by Figure 5, this implies that it advances introducing clean technology considerably under C&T.

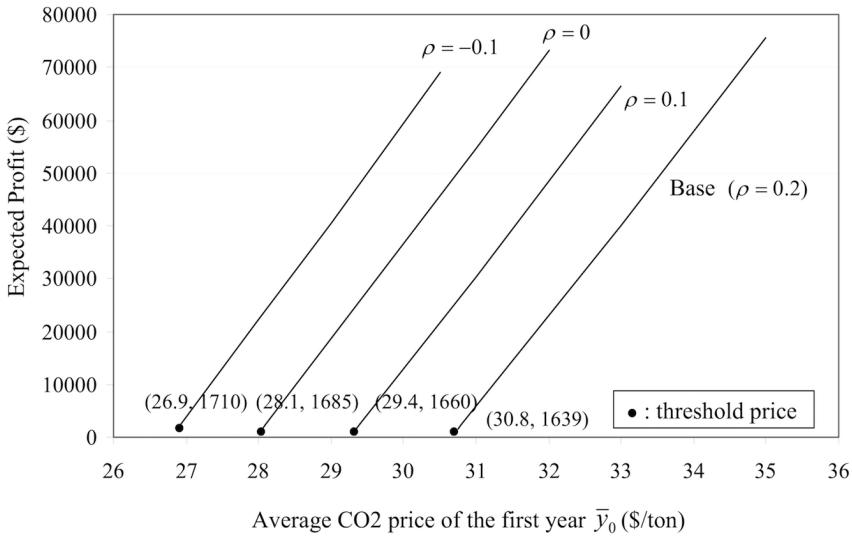
Changing correlation ρ

The correlation between permit and NG prices also separates a tax from a C&T policy. In our base case, by using historical data the correlation is set to be 0.2. Although a positive correlation is economically reasonable, we are interested in what might happen if the correlation becomes negative (e.g., an increasing permit price accompanied by a lower NG price.) It is possible that the permit and NG prices are negatively correlated, though this may only occur transiently. For example, a possible scenario is that a hot summer followed by a warm winter could drive the NG price low in winter (due to mild NG demand), but the permit price may still be high due to a cumulative permit demand from the summer. We argue that another advantage of C&T is that the change in the correlation of the permit and NG prices may also contribute to the early induction of new capacities relative to a tax. Figure 6 shows that as we gradually reduce the correlation from 0.2 to -0.1 , the average permit price that is needed to trigger adopting clean technology becomes smaller.

3.3 Risk Consideration

In comparing the two emission policies C&T and tax, we have investigated the investment timing and profit of clean technology under stochastic Y_t ,

Figure 6: Sensitivity Analysis by Changing the Correlation ρ .



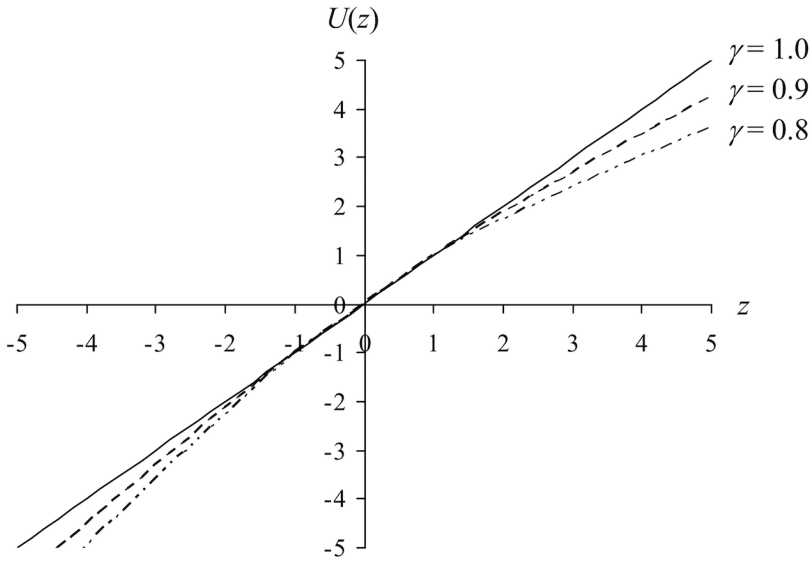
(permit price) and deterministic Y_t (emission tax). To make our comparison reasonable, both the permit price and the emission tax have the same annual mean level over the life cycle of the investment, as illustrated in Figure 2. This property is consistent with our risk neutral assumption. In this section, we relax risk neutrality assumption by introducing a utility function in order to examine the effect of risk aversion.

Finding an appropriate utility function for our application is not trivial. This is because our uncertainties are realized on the daily level. The daily electricity revenue and generating cost generally are no more than \$1,000; yet the one-time investment cost is \$420,000. With such a big range to apply, existing (risk-averse) utility functions, such as a negative exponential one, tend to amplify excessively or inappropriately the investment cost, and thus discourage expansion. The ideal utility function is one that is concave and can converge uniformly to the identity function when risk aversion vanishes to neutrality. This can help to connect with our previous results in the neutral case and we can observe how the threshold prices change with risk aversion. The following utility function has been devised, where $\gamma \leq 1$ is a constant:

$$U(z) = \begin{cases} z^\gamma, & \text{if } z > 1, \\ z, & \text{if } -1 < z \leq 1, \\ 2z + (-z)^\gamma, & \text{if } z \leq -1. \end{cases} \tag{11}$$

The utility function $U(z)$ is depicted in Figure 7. When $\gamma = 1$, $U(z) = z$ is risk neutral. The idea is to use concave z^γ with $\gamma < 1$ to construct the utility function

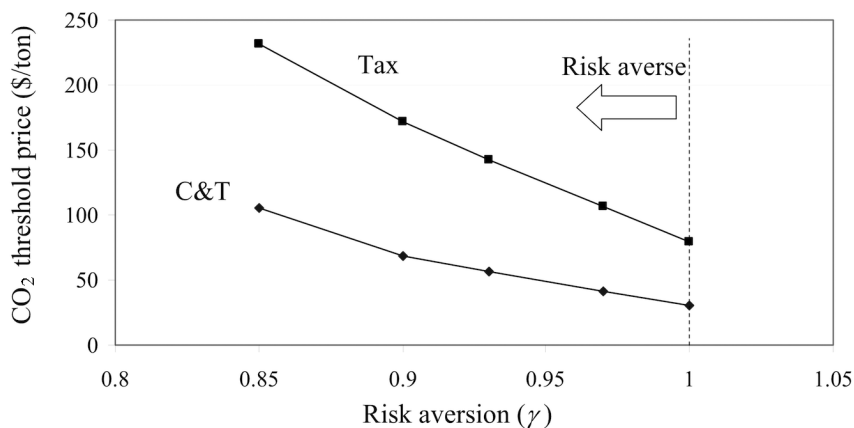
Figure 7: The Utility Function.



for $z \leq 0$. Using $U(z) = -z$ as the axis of symmetry, we reflect the part in R^+ for $z < 0$. However, z^γ , with $\gamma < 1$, does not always underestimate the identity function, for a small range of z between \pm one (dollar), we set $U(z) = z$ to be risk neutral. This should not have any adverse impact to our analysis. When $z \leq -1$, $U(z) = z - (-z - (-z)^\gamma) = 2z + (-z)^\gamma$ due to the symmetry. It is clear that as γ decreases, risk aversion increases.

The risk-averse utility function is simply applied at each node of our SDP lattice. Following the same procedure, we obtain the carbon threshold prices for expansion under both emission policies. The result is depicted in Figure 8 with the data summarized in Table 4. Since risk aversion increases as γ decreases, it is better to view the curves in Figure 8 from right to left. It can be seen that for either emission policy the threshold price increases with risk aversion. This is reasonable since a risk-averse investor would only invest clean technology when the carbon price is higher than the price that his risk neutral counterpart would invest. What is somewhat surprising is that the gap between the threshold prices of both emission policies also increases with risk aversion. That means a risk-averse plant owner would prefer C&T to tax much more than a risk neutral one.

To explain this, let us use the two threshold prices for expansion in the risk neutral case as an example: \$30.8 under stochastic Y_t and \$79.5 under deterministic Y_t , obtained previously. This risk neutral investor can see a profit when the carbon price is \$30.8 under C&T. Given the opportunity embedded in the uncertainty (real options) discussed earlier, the investor would not consider ex-

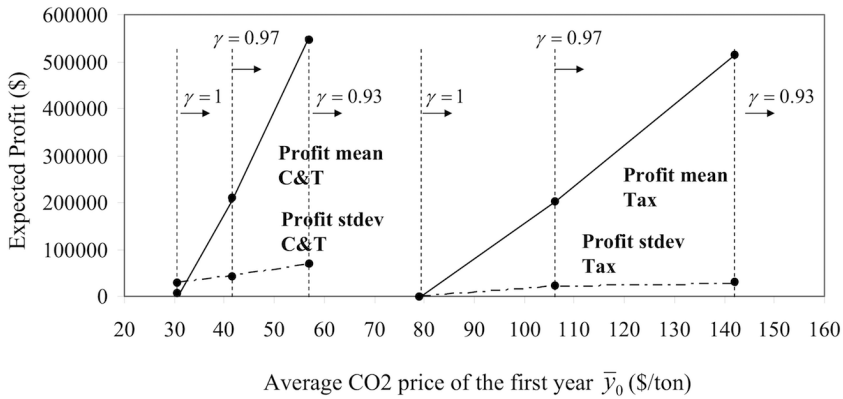
Figure 8: The Threshold Carbon Price vs. Risk Aversion.**Table 4: Threshold Price and Expected Profit vs. Risk Aversion**

Policy	C&T			Tax		
	\bar{y}_0 (\$/ton)	Profit mean (\$)	Profit Stdev (\$)	\bar{y}_0 (\$/ton)	Profit mean (\$)	Profit Stdev (\$)
1	30.8	1,636	28,757	79.5	0	0
0.97	41.4	202,363	43,651	106.3	203,476	20,719
0.93	56.7	548,039	66,828	142.2	515,748	25,902
0.90	68.8	861,740	85,837	171.3	768,663	29,662
0.85	110.0	1,883,623	152,225	231.6	1,404,557	37,283

panation without the price uncertainty and the opportunities as well, unless the deterministic carbon price can be increased to \$79.5. For this investor, we can say that \$79.5 is the “deterministic equivalent” of the uncertain carbon price at \$30.8. The idea of the deterministic equivalent is very much like that of *certainty equivalent* (CE), except that CE has a specific definition and is equal to the expected value under risk neutral behavior. The difference between these two threshold prices, $\$48.7 = (\$79.5 - \$30.8)$, is the *assurance of additional carbon price* required by the investor for removing the carbon price uncertainty (cf. risk premium in utility theory). Based on this interpretation, a more risk-averse decision maker would ask for a higher deterministic equivalent and a larger assurance of additional carbon price to build a NG plant, which seems quite intuitive.

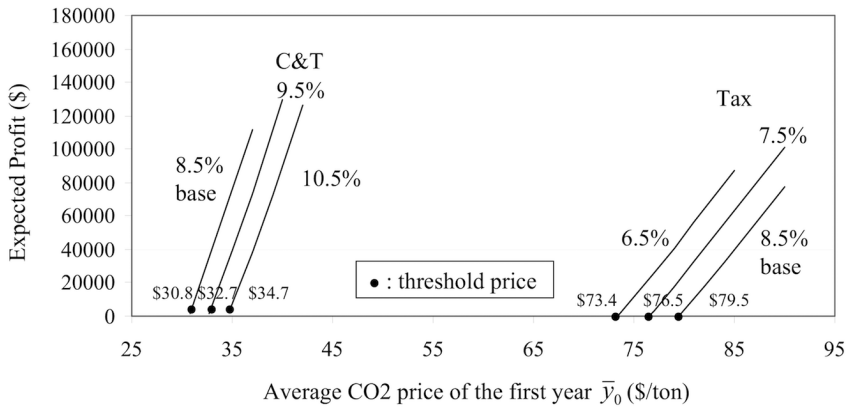
Figure 9 shows the mean and the standard deviation of the profits at various threshold prices for different levels of risk aversion, using a simulation based on the strategy developed by considering risk aversion. In Figure 9, for either emission policy, C&T or tax, risk aversion elevates the profit expected by the decision maker when considering expansion. Although the risk (measured by the standard deviation of the profit) increases with the mean of the profit, it

Figure 9: Profits at Various Threshold Prices vs. Risk Aversion.



increases in a much smaller rate. This is consistent with the fact that the threshold price increases with risk aversion. Under C&T, the standard deviation of the profit is higher than the mean of the profit in the risk neutral case ($\gamma = 1$), which, however, would not be accepted by a risk-averse decision maker. Finally, in terms of the expected profit at the threshold price, there is not much difference between both policies, except that they happen at very different carbon (threshold) prices. Compared with our earlier result under risk neutrality, we can conclude that with risk aversion: (i) the waiting time for adopting clean technology increases for both C&T and tax from Figure 3; (ii) C&T is much more effective than tax in terms of inducing clean technology; and (iii) the expansion under C&T is much more profitable than under tax given the same carbon price from Figure 9.

In addition to the risk attitude of the investor, another risk concern is associated with the “project” (for adopting new technology). Thus far we have assumed that the decision maker use a fixed, subjective discount rate to value the project under either policy. This discount rate is based on the decision maker’s expected rate of return. It is clear that under different emission policies, the project has a different level of riskiness. Figure 9 shows that the standard deviation of the profit under tax policy is much smaller than that under C&T. On the other hand, the expected profit under C&T is much greater due to the fact that the carbon price has volatility. Volatility increases the (spread) option value in equation (9). However, one must note that volatility also increases the riskiness of the investment. From the payoff function in equation (9), it can be seen that tax offers a guaranteed revenue stream, while emission trading cannot. If the decision maker would like to value the project with market risks accounted, he may use a higher discount rate to value the project under C&T than under tax to address the embedded riskiness. Such market-based discount rates may be estimated using models like CAPM (capital asset pricing model), which requires additional market data, and is beyond the scope of this paper. This will certainly reduce the gap

Figure 10: Profits vs. Discount Rate.

between the expected profits under these two policies. In Figure 10, we show the sensitivity analysis results with respect to the change of discount rate, with the discount rate for C&T increased and that for tax decreased by 1 percent each time. It can be seen that roughly every 1 percent increase (decrease) in the discount rate under C&T (tax) increases (decreases) the threshold price by about \$2 (\$3). Although the threshold prices of both policies are brought closer, they remain far apart. So it is likely that the decision maker is still much better off under C&T than tax even with the market risks considered.

4. CLOSING REMARKS

In the time of global climate change, policy choices are critical in steering polluting industries towards more timely adoption of clean technologies. This paper examines the optimal investment timing under two policy choices that are constantly subject to debates: tax and C&T (cap-and-trade). We study their ability to induce investment by formulating it as a supplier's decision problem when considering whether he should introduce a clean technology or not. We have two central findings. First, C&T policies could effectively trigger adoption of clean technologies at a considerably lower level of carbon prices relative to a tax policy. Second, higher levels of volatility in the permit prices are likely to induce suppliers to take early actions to hedge against carbon risks. Our results are qualitatively robust to the values of parameters as we illustrated by the sensitivity analysis and could also be generalized to other decision contexts. Our approach overcomes a number of modeling challenges as well. First, we model daily production decision by nesting it within monthly capacity expansion. Second, lead-time in constructing clean technology is explicitly incorporated in the price lattices, which is important in real options valuation. Based on our study, both the offset and other price control mechanisms, which are commonly stipulated in the

proposed and the existing climate policies with an attempt to reduce permit prices or suppress price volatility, may delay clean technology investments. This suggests that if leveling the playground of these highly affected industries is the main purpose, a lump-sum rebate from permits auctions' revenues might be a better choice without postponing clean technology adoptions.

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