Intertemporal Emission Permits Trading in Uncertain Electricity Markets[1]

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1. Introduction

Cap-and-trade emission permit systems that allow permits to be traded across compliance periods (hereafter *intertemporal emissions trading* or *bankable emission permit trading*) are witnessing growing regulatory interest as a cost-effective way to reduce total emissions. The U.S. sulfur dioxide (SO_2) emission trading program is one of the first, and by far the most extensive application of bankable emission permit trading. Under Title IV, firms are not only allowed to transfer allowances[2] for emissions of SO_2 between facilities, but also to bank them for use in future years. Emission permit trading is also a centerpiece of the Kyoto Protocol, which allows participating nations to trade and bank greenhouse gas permits under the Framework Convention on Climate Change (Intergovernmental Panel on Climate Change, 1996).

Despite the considerable interest in intertemporal emission trading, important theoretical and policy issues surrounding this trading mechanism remain unexplored. Although the theoretical literature on tradable emission permits began a discussion regarding the efficiency and properties of their use as early as 1970s[3], most of the literature considers trading between units, implicitly within a single time period. Theoretical analyses of intertemporal emission trading have only recently appeared.[4] These studies typically assume firms have perfect foresight[5]. Neither the

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[2] For the purpose of this paper, I use the terms 'permits' and 'allowances' interchangeably.

[3] Examples include Montgomery (1972), Hahn (1984), and see Titenberg (1985) and Cropper and Oates (1992) for thorough reviews.

[4] Studies that analyze intertemporal emission trading include Rubin (1996), Cronnshow and Kruse (1996), Kling and Rubin (1997), Schennach (2000), Yates and Cronshaw (2001), Leiby and Rubin (2001), Stevens and Rose (2002), Sedio and Marland (2003), Maeda (2004), Stranlund, et al. (2005), van Steenbergh (2005), Feng and Zhao (2006), Wirl, F. (2006).

[5] Studies that mention uncertainties include Schennach (2000), Feng and Zhao (2006).

theory nor the empirical assessment of the implications of uncertainty has been examined thoroughly. In this paper, I seek to fill this gap in the literature.

This paper makes two specific contributions. First, I introduce uncertainty into the intertemporal trading model, which is theoretically more interesting and empirically more relevant. In this model, a firm decision regarding permit trading is an *ex ante* choice in the sense that optimal emissions and permit banking decisions depend not only on current output and input prices, but also on expectations of future prices. Assuming risk neutrality and a competitive permit market, I show that a mean-preserving increase in electricity price volatility would decrease *ex ante* emissions. Second, I empirically test the theoretical prediction in a real trading program, the U.S. SO_2 allowance trading. To the best of my knowledge, this is the first study that quantitatively estimates the effects of uncertainty on emissions trading based on actual market data. Although the analysis is conducted in the context of the U.S. SO_2 allowance trading program, the model is flexible enough to be extended to other intertemporal trading initiatives, such as the global carbon trading program, for which uncertainty is a prevalent feature in many of the policy parameters.

This paper is related to three strands of literature, one discussing intertemporal emission permit trading, another on capital investment under uncertainty, while the third concerns the impact of electricity restructuring on the environment.

Among previous theoretical investigations of intertemporal permit trading, Schennach's (2000) paper is a first effort to study the implications of uncertainty on the time-series properties of emissions trading. Schennach suggests that the higher the expected electricity price, the lower the emissions in the *ex ante* period. Feng and Zhao (2006) also discuss effects of abatement costs uncertainty and conclude that more permits will be banked when the expected marginal value of permits rises. While constituting important steps toward an understanding of the potential consequences of uncertainty, these papers do not answer the question of how increased output price volatility would modify the path of emissions. After all, it is the significant variation, not the level of prices that defines a volatile market.

In spirit, this paper is closer to those of Hartman (1972) and Abel (1983, 1985), which discuss the relationship between increased uncertainty about future price and the expected marginal revenue product of capital. However, the analysis of the marginal value of a permit has no direct analogue in the capital investment literature. In addition, I derive the model in a more general framework, without assumptions of constant-returns-to-scale or perfect competition in the output market.

This paper also contributes to the policy discussion on the implications of electricity restructuring for the environment. Policy debates on the potential environmental impact of restructuring, in large measure, have focused on the effects of market liberalization on the mix of generation technologies (electricity produced from gas, coal, hydro, nuclear and non-hydro renewable sources of energy).[6] I address the question from a new perspective by analyzing the impact of electricity market restructuring on the environmental performance of the single most polluting type of generation technology, coal-burning power generation. I show that, in the short term, electricity restructuring contributed to coal power industry emission reductions by providing incentives for early abatement.

The remainder of the paper is organized as follows: Section 2 provides background on the U.S. SO_2 allowance trading program; Section 3 analyzes the impact of electricity restructuring on the allowance market; Section 4 develops a firm model of intertemporal emissions trading and derives the relationship between emissions banking and uncertainty; Section 5 and 6 present the empirical and numerical models and the estimation results. Section 7 concludes the paper.

2. The U.S. SO_2 Allowance Trading Program

The U.S. SO_2 allowance trading program, also known as the Acid Rain Program, was established under Title IV of the Clean Air Act Amendments of 1990 (CAAA90). Under the program, the Environmental Protection Agency (EPA) first sets a cap that limits the total SO_2 emissions of the power industry by less than half of their 1980 level (from 18.9 million tons in 1980 to 8.9 million tons by 2001). It then divides the quantity up to a number of tradable allowances and allocates them to individual firms based on their historical heat inputs. Each allowance grants the holder the right to emit one ton of SO_2 emissions. The SO_2 allowance

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[6] For example, Palmer and Burtraw (2006) argue that expanded interregional electricity trading will increase the use of older low-cost coal power plants which would in turn lead to an increase in emissions; Holland and Mansur (2004) show that real-time pricing, an anticipated feature of a competitive market, will shift load from peaking to baseload plants. Depending on which type of plants is dirtier, real-time pricing will have different environmental impacts in different regions. Mansur (2005) suggests that changes in air pollution emissions resulting from the exercise of market power will depend solely on the technologies that dominant firms use to withhold output in contrast with the technologies that the competitive fringe uses to meet demand. Other qualitative analyses raise the concern that a cost-conscious marketplace will invest less in renewable energy.

trading program institutionalized a couple of innovations in that it not only allows unlimited trading of permits among firms, but also allows permits to be traded over time. So power producers who reduce emissions below the number of allowances they hold may sell allowances to other firms, or bank them for future use.

Another important feature of this program is that it was phased-in. Phase I, which ran from 1995 through 1999, affected 263 units at 110 mostly coal-burning (and a few oil-fired units) electric utility plants located in 21 eastern and Midwestern states. Most Phase I units had emissions greater than 2.5 pounds of SO_2 per MMBtu and a generating capacity greater than 100 megawatts (MW). Phase II began in the year 2000. It established a permanent cap of 8.95 million per year and affects all existing utility units with an output capacity of 25 MW and larger, and all new utility units.

Figure 1 shows the annual emission cap, aggregated emissions and banked allowances from 1995 to 2004. The temporal dimension is clearly a key component of this trading program. From 1995 to 1999, 11.65 million allowances were banked, which was about 30% of the total allowances allocated during Phase I.[7] These extra allowances were produced through reducing emissions below the allowable standard.

Units banked permits primarily because the program was phased-in: an allowance is perceived to be worth more in later years under the stricter cap of the Phase II. As expected, in 2000 firms began drawing down the bank to ease the transition to Phase II. However, the size of the bank generated in Phase I was unexpectedly large. Some argue that banking in this program has been excessive and was economically inefficient (Ellerman, et al., 2000; Smith, et al., 1998). In addition, the draw-down rate at the beginning of Phase II was lower than previously expected (Ellerman and Montero, 2005). In the remainder of the paper, I explore the question of how to interpret this temporal banking trend.

3. Electricity Market Restructuring and Price Volatility

The implementation of Title IV happens to have coincided with electricity restructuring which dramatically changed the way the power industry was structured and regulated over the

[7]The number of banked allowances does not include allowances sold at public auction each year, nor does it include contributions from substitution units that entered or exited the market in different years.

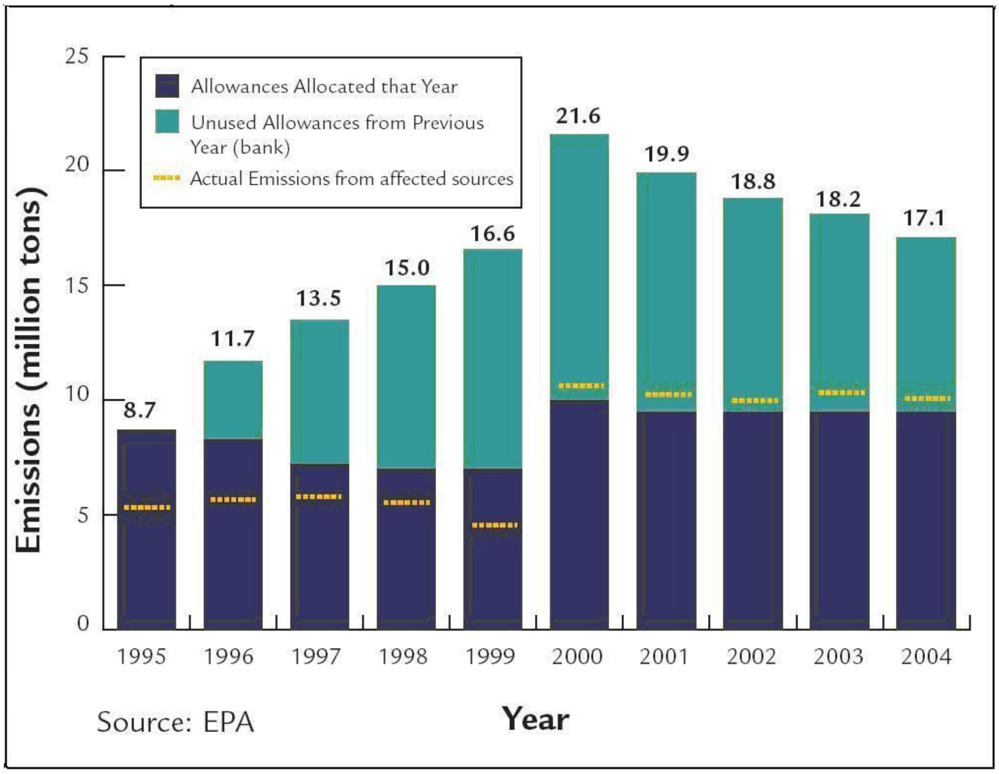

Figure 1 Annual Emission Cap, Aggregated Emissions and Banked Allowances: 1995-2004

past decade.[8] The goal of electricity restructuring is to increase competition in the electricity generation sector. This is implemented by significant changes in the pricing of electricity generation. Before restructuring, electricity price is set administratively on the basis of the average production cost. In contrast, competitive generation prices are determined by market forces. Given open access to the transmission system, a number of auction-based regional wholesale markets were established. In these markets, producers submit bids to supply power and the dispatch order is set by the bids. In most cases, the marginal production cost of the marginal producer determines the market-clearing price and is paid to all plants that are dispatched. In the restructured retail markets, the retail rate is linked to wholesale prices, as competitive retail sellers compete with utilities to sell electricity to consumers.[9]

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[8] For a comprehensive review of the drivers and the process of electricity restructuring in the United States, see Joskow (1997), U.S. Energy Information Agency (EIA) (2000) and EIA (2003)

[9] Retailers either buy electricity from wholesale markets or generate it themselves.

Competitive pricing induced a significant variation in the price of electricity, which can be translated into fluctuating demands for coal generation. The principal drivers behind this volatility in recent years are the fluctuations in natural gas prices. Since the operating cost of natural gas-fired power plants exceeds those of most other generation technologies, natural gas power plants usually set the market price. As has been observed, however the natural gas market behaves, the electricity market behaves similarly.

Natural gas price volatility in recent years was mainly driven by factors exogenous to electricity markets, such as persistently colder-than-normal temperatures that increased demand for heating fuel, frozen gas wells and pipelines that reduced regional gas production, and multiple hurricane seasons that disrupted supply. Natural gas is a substitute fuel for oil and petroleum, so political unrest in key oil producing nations also contributes to natural gas price volatility (Villar, 2006).

On the demand side, record high temperatures in recent years drove up the demand for electricity. As more and more power plants use natural gas to generate electricity, the growing electricity market tightened the demand and supply balance of natural gas and induced natural gas price spikes. Natural gas price fluctuations in turn exacerbated electricity prices.

As coal is one of the cheapest and most widely available fuels in the United States, coal prices remain quite stable compared to those of natural gas. When natural gas prices rise sharply, coal prices become more competitive. Power producers will shift toward coal either by increasing the capacity factor of incumbent coal units, or by importing cheaper coal-fired power from other areas. When the price increases to a level higher than the long-run average production cost of coal power plants, new entries by coal units will also be triggered. Refer to Zhang (2007) for a graph demonstration of the interrelationship between natural gas prices and coal-based power generation.

Higher demand for coal-based generation means higher demand for SO_2 emission allowances. Since the supply for allowances is generally fixed, increased demand will drive up the allowance price, imposing an industry-wide shock in the national allowance market. Such aggregate shock affects the expected path of permit price through new entries or expansion of current ones. Facing aggregate volatilities, the industry may reduce its dependence on the spot market through overcompliance and banking. In doing so, firms adjust *ex ante* emissions in anticipation of future demand and future price changes.

4. Modeling Framework

This section contains the basic theory of intertemporal permit trading under uncertainty. I begin by setting up a firm's dynamic optimization problem, then state and prove Proposition 1 and Lemma 1 on the relationship between uncertainty, and banking/emissions. I also discuss the effects of joint constraints from environmental and rate-of-return (ROR) regulations on banking incentives, and show how conclusions can be affected by imperfect competition in the electricity and allowance markets, and by returns to scale of production technology.

4.1 A Firm Model of Intertemporal Permit Trading under Uncertainty

Consider a risk neutral firm that uses adjustable levels of low- and high-sulfur coal to produce electricity. In each time period, the firm decides the electricity output (g_t), chooses the mix of low- and high-sulfur coal (l_t and h_t), and the amount of allowances (x_t) to buy ($x_t > 0$) or sell ($x_t < 0$) to maximize its discounted present profits for a constrained level of emissions. Uncertainty exists in the supply and demand for electricity. Suppose this uncertainty is characterized by electricity prices (P_e), which is a random variable that follows a Markov process. The probability law of P_e is known to all firms. At the start of period-t, the firm observes electricity price (P_{et}), allowance price (P_{at}), the price for low- and high-sulfur coal (P_{lt} and P_{ht}), and the initial endowment of allowances which is the sum of allowances issued by the government in current period (A_t) and the amount of banked allowances carried forward from the previous period (B_t).

Firms face a dynamic optimization problem because they must choose how many allowances to save for the future before uncertainties over future prices are resolved. Assuming that firms are price takers in all markets, I model individual firm behavior as an intra-firm game. Taking the strategies of other firms as given, each firm picks a strategy in each time period that is optimal from the firm's perspective in that period. The firm's strategy is thus a map from the

Markov state $\Lambda_t = \{P_t, A_t, B_t\}$ to choice variables l_t, h_t, x_t, where P_t is a price vector, i.e. $P_t = \{P_{et}, P_{at}, P_{lt}, P_{ht}\}$.

I assume that firms employ three compliance strategies: abating emissions through blending with or switching to low-sulfur coal, purchasing allowances in addition to initial allocation, and adjusting output levels. Other capital intensive strategies such as scrubbing, re-powering or permanently retiring a facility are not considered because regulatory, financial and other uncertainties, during a period of industry restructuring, provide firms incentives to avoid capital intensive investment as long as possible.[10]

Let $V_i(P_t, B_t, A_t)$ denote firm i's value at time t. The firm's maximization problem can be written as:

$$V_i(P_t, B_{it}, A_{it}) \equiv \max_{l_{it}, h_{it}, x_{it}} \{P_{et} g(l_{it}, h_{it}) - c(l_{it}, h_{it}) - P_{at} x_{it} + \beta E_t[V_i(P_{t+1}, B_{i(t+1)}, A_{i(t+1)}) \mid P_t]\} \quad (1)$$

$$s.t. \quad B_{i(t+1)} = A_{it} + B_{it} - e_{it}(l_{it}, h_{it}) + x_{it} \quad (2)$$

$$B_{i(t+1)} \geq 0 \quad (3)$$

where β is the discount ratio. In a discrete-time setting, $\beta = 1/(1+r)$, and r is the risk-free interest rate.[11] $\mathrm{E}[\cdot]$ is the expectations operator. Based on the realized current price (P_t), the firm formulates expectations on its future value. Eq.(2) is the state equation and defines the stock of banked allowances in period t. Eq.(3) corresponds to the non-negativity constraint. According to the acid rain program, borrowing against future emission reductions is not allowed. For simplicity, I suppress unit index i in section 4.1.

The production function with low- and high-sulfur coal as two distinct inputs is represented by $g(l,h)$, which is assumed to be quasi-concave, increasing in both arguments, homogenous of degree 1, and twice differentiable everywhere.[12]

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[10] Indeed, firms have preferred fuel switching/blending and allowances purchasing that require less capital investment: 52% of the 263 Phase I units chose fuel-switching/fuel-blending and 32% chose to purchase allowances.10 While only 17 units during 1995-2004 have installed new scrubbers (EIA, 1997).

[11] The assumption that interest rates are risk-free corresponds to the assumption that firms are risk-neutral.

[12] To include labor and capital inputs in the production function is straightforward and yields an almost identical analysis.

$c(l,h)$ is the cost function. When a firm undertakes production, it incurs costs that can be described in terms of three components: (1) fuel costs, (2) adjustment costs associated with fuel-blending or fuel-switching,[13] and (3) other fixed costs including capital costs for mixing fuel. Once the binary choice determining whether or not to switch/blend fuel has been made, this sunk cost will have no impact on the factor input ratio. Thus I do not explicitly take account of the initial capital cost in this analysis and assume that both low- and high-sulfur coal are used.

For the model to be tractable, I assume that the adjustment costs are continuous and linear in l.[14] Specifically, I combine the variable adjustment cost and the purchasing cost of low-sulfur coal as an augmented cost and represent the cost function as a standard linear one. That is, $c(l,h) = P_h h + P_l l$, where P_l is the sum of both purchasing cost and the variable adjustment cost of low-sulfur coal. Although low-sulfur coal may be cheaper than high-sulfur coal in certain areas, given the extra adjustment cost incurred, I assume that P_l is strictly less than P_h.

Finally, I denote the emission function as $e(l,h) = \gamma(\delta_l l + \delta_h h) = \mu_l l + \mu_h h$, where δ_l and δ_h are the sulfur contents of low- and high-sulfur coal ($\delta_l < \delta_h$), γ is the conversion rate from sulfur to sulfur dioxide and μ_l and μ_h are the SO_2 content of low- and high-sulfur coal.

To analyze the above constrained stochastic dynamic optimization problem, consider a firm that is in place for two periods $t = 1,2$. The Kuhn-Tucker necessary conditions for a maximum at (h^*, l^*, x^*, μ^*) yield the following first-order conditions:

$$P_{a1} = \beta E_1[V_{B_2^*}] + \omega^* \tag{4}$$

$$P_{e1} g'_{f_1^*} = c'_{f_1^*} + (\beta E_1[V_{B_2^*}] + \omega^*) e'_{f_1^*} \quad (f = l,h) \tag{5}$$

[13] Typically, the transition from high-sulfur to low-sulfur coal incurs the following extra operating and maintenance expenses: (i) more aggressive dust suppression and dust collection procedures, and more diligent housekeeping in coal handling areas, since low-sulfur coal, especially coal from the Powder River Basin (PRB) are very dusty;(ii) more extensive fire protection procedures, due to a higher tendency for spontaneous combustion which increases the risk of fire and explosion; (iii) increased drying requirements in the pulverization process, because some low-sulfur coals have a higher moisture content;(iv) increased pulverizer maintenance because low-sulfur coal are more difficult to pulverize, with their Hardgrove Grindability Indices in the range of 40 to 50; (v) costs incurred to reduce other pollutants as burning western lower sulfur coal results in more particular matter (PM) emissions; and,(vi) increased expenses for storage because lower sulfur coal is usually lower in heating value and requires a larger volume of coal to generate the same amount of power. For a detailed discussion on the impact of lower sulfur coal on an individual plant, see Energy Information Administration (EIA) (1994).

[14] As I will show, the abatement cost is strictly convex.

$$A_1 + B_1 + x_1^* - e_1^* \geq 0,\ \omega^* \geq 0,\ \omega^*(A_1 + B_1 + x_1^* - e_1^*) = 0 \tag{6}$$

where ω is the Lagrangian multiplier associated with the non-negativity constraint on B_{t+1} described by (3). $\omega > 0$ if and only if the constraint is binding, i.e. $A_1^* + B_1^* + x_1^* - e_1^* > 0$ implies $\omega^* = 0$.

Eq.(4) is the Euler-intertemporal condition. Eq.(5) discloses that producers choose the optimal levels of coal so that coal's marginal value product equals its marginal cost. The marginal cost includes both the direct production cost ($c'_{f_1^*}$) and the opportunity cost of surrendering the option to use allowances in the future ($\beta E_1[V_{B_2^*}] + \omega^*)e'_{f_1^*}$). Therefore, expectations on the marginal value of a unit of allowance for period-2 $(E_1[V_{B2}])$ affect current emission decisions.[15]

The second-period optimization problem is

$$V_2 = \max_{l_2, h_2, x_2} P_{e2} g(h_2, l_2) - c(h_2, l_2) - P_{a2} x_2 \tag{7}$$

$$s.t. \quad A_2 + B_2 - e(h_2, l_2) + x_2 = 0 \tag{8}$$

Eq.(8) shows that firms deplete the allowance bank in the terminal period. The solution (l_2^*, h_2^*, x_2^*, λ_2^*) is described by the following first-order conditions:

$$P_{a2} = \lambda_2^* \tag{9}$$

$$P_{e2} g'_{f_2^*} = c'_{f_2^*} + \lambda_2^* e'_{f_2^*} \qquad (f = l, h) \tag{10}$$

λ_2 can be interpreted as the shadow value of a unit of banked allowance in period-2. Eq.(9) says that firms will buy or sell allowances such that the shadow value of the marginal allowance equals its market price. The optimal input mix is given by Eq.(10).

[15] $g'_f = \partial g / \partial f, c'_f = \partial c / \partial f, e'_f = \partial e / \partial f \, (f = l, h)$ represent the marginal productivity, marginal production cost, and marginal emission rate of the two types of coal. Hereafter, ' represents the calculation of a derivative.

An important feature of the above optimal solution is that it is independent of the level of banked allowances B_2. The value function in period 2 is only linearly linked to (B_2) through the profit function. Specifically, the value function in Eq.(7) can be written as

$$V_2 = P_{e2}g(h_2^*(P_2),l_2^*(P_2)) - c(h_2^*(P_2),l_2^*(P_2)) - P_{a2}[A_2 + B_2 - e(h_2^*(P_2),l_2^*(P_2))] \quad (11)$$

where $P_2 = \{P_{e2}, P_{l2}, P_{h2}, P_{a2}\}$. Differentiating Eq.(11) with respect to B_2 gives us the marginal revenue product of allowances:

$$V_{B_2^*} = P_{a2} \quad (12)$$

Substituting this expression for V_{B2} into Eq.(4) leads to a non-arbitrage pricing formula:

$$P_{a1} = \beta E[P_{a2}] + \omega^* \quad (13)$$

The right side of Eq.(13) is the expected return of holding one unit of allowance.: expected present allowance price in period 2 plus a convenience yield ω^*. The left side of the equation represents the opportunity cost of carrying an additional unit of allowance, which is an instantaneous gain from selling it in the spot market. Given the substantial number of allowances banked by the industry during Phase I, and that the SO_2 allowance market has been fairly liquid, I assume that the convenience yield related to the scarcity of the allowance bank equal to zero, i.e. $\omega^* = 0$.

Combining Eqs.(5) and (12) yields the following policy function for intertemporal emission trading:

$$\beta E[P_{a2}] = \frac{\xi_1^* P_{l1} - P_{h1}}{\gamma(\delta_h - \xi_1^* \delta_l)} \quad (14)$$

where $\xi_1^* = g'_{h_1^*}/g'_{l_1^*}$ is the ratio of the marginal productivities of high- and low-sulfur coal.[16] The right side of Eq.(14) is the additional cost an operator has to pay in order to reduce one ton of SO_2 emissions. It reflects both price and productivity differences between low- and high-sulfur coal. Following Montgomery (1972), emission abatement costs are defined as the difference between unconstrained profits and profits in which the firm adopts an emission level lower than

[16] The expected permit prices are positive, implying $\delta_h/\delta_l > g'_h/g'_l$.

the unconstrained emission level. Therefore, the right side of Eq.(14) presents a notation for marginal abatement cost.

Eq.(14) together with Eq.(13) exhibit the spatial and temporal efficiency properties of a tradable emission permit regime: in each period, the marginal abatement costs are equalized across firms through the current allowance price (thereby the total pollution reduction cost is minimized)[17]; the present value of the marginal abatement costs are equalized across time periods in an expectation sense. Thus, expectations about higher future allowance prices raise the current abatement level.

Eqs.(13) and (14) show that firms have incentives to save allowances for future use (forward banking) every time they expect the discounted future allowance price to be greater than the current market price.

4.2 Uncertainty, Banking and Emission

Although a price is given for each individual unit in the allowance market, allowance price is endogenously determined by the aggregate behavior of the generating units. Previous theoretical analysis of emission permit trading reveals that when allowed to trade with one another in a competitive allowance market, units will collectively behave like a central planner who efficiently allocates emission permits to each unit in a manner that minimizes total costs (Rubin, 1996; Schennach, 2000; Feng and Zhao, 2006). This suggests a model of aggregate industrial behavior as that of a single representative unit, and to solve the equivalent problem without considering internal spatial trading. For simplicity of exposition, I assume the representative agent produces electricity according to the Cobb-Douglas production function[18] $g(l,h) = Gl^{\alpha}h^{1-\alpha}$, where G is a productivity parameter, and $0 < \alpha < 1$ is the share of low-sulfur coal. To avoid confusing increasing price volatility with increasing price trends, I consider electricity price P_e evolves following a mean-preserving stochastic process with the mean equal to $\overline{P}_e$. Formally, I define the probability distribution function of P_e as $f(\cdot,\theta)$ such that

[17]This conclusion is based on the assumption that firms have interior solutions, i.e. both low- and high-sulfur coal are used. If firms only use one type of coal, marginal abatement costs are not equalized between firms having interior solutions and firms having corner solutions; however, an emission trading program still yields a cost effective result.

[18]In Zhang (2007), I extend the model to a more general CES production function and prove that the conclusions do not change.

$$\int P_{e2} df(\cdot,\theta) = \overline{P}_e \quad \forall \theta \tag{15}$$

where θ is an index of the mean-preserving spread and if $\theta' > \theta, f(\cdot,\theta)$ second-order stochastically dominates $f(\cdot,\theta')$ (or $f(\cdot,\theta')$ is more risky than $f(\cdot,\theta)$). Therefore, the value of θ characterizes the level of market-wide risk. The representative firm's optimization problem in period 2 is simplified by leaving out the term x:

$$\max V = P_{e2} g(l_2,h_2) - c(l_2,h_2) \tag{16}$$

$$s.t. \quad A_2 + B_2 = e(l_2,h_2) = \mu_l l_2 + \mu_h h_2 \tag{17}$$

There is no closed-form solution for the above optimization problem. Nonetheless, I prove analytically in Appendix A that the marginal profitability of allowances $\partial V/\partial B$, or the allowance price P_a, is convex in the stochastic variable P_e. This leads to a negative relationship between *ex ante* emissions and the level of uncertainties about electricity prices.

Proposition 1 *Increasing uncertainty over electricity price generates lower ex ante emissions and higher banking in the following sense: For* $\theta' > \theta, B(\theta') > B(\theta)$, *and* $e_i(\theta') < e_i(\theta)$, *where* θ *is an index of the mean-preserving spread of electricity price,* B *is the industry's total banked emissions permits, and* e_i *is the individual unit's ex ante emissions.*

Proof. Because the marginal profitability of allowances is convex with respect to P_e, it follows directly from Jensen's inequality that an increase in the mean preserving spread of P_e increases the expected marginal value of allowances. According to Eq.(14), in anticipation of higher future marginal value of allowances, firms will reduce *ex ante* emissions by increasing current marginal abatement costs, leading to an increased aggregate stock of allowances at the industry level.

It is essential that the marginal value of allowances be convex with respect to electricity prices to derive the above conclusion. This convexity reveals an asymmetric distribution of future marginal values of allowances due to output prices changes. To understand the intuition, note that because the total number of allowances is fixed, and is less than the emissions expected to be produced by all of the affected units, the rise of electricity prices increases the counterfactual emissions (through the mechanism explained in section 3), as well as the total required pollution reduction. Since abatement costs are convex (further discussion of this property appears in the next section), marginal abatement cost rises with the quantity of abatement. Therefore, when electricity price increases, the marginal abatement cost increases faster than it decreases when electricity price falls. So the potential gain from saving an additional unit of allowance when electricity price increases is higher than the potential loss when electricity price decreases. When uncertainty is more pronounced, very high and very low electricity prices are more likely, and this asymmetric relationship becomes more salient. In the presence of extreme prices, firms would have a higher incentive to save allowances as the potential gain is much higher than the potential loss.

In addition, across multiple time periods, the convexity effect also works through a firm's ability to vary the input of allowances in response to the resolution of uncertainty. When a `bad' shock occurs, such that the stock of allowances exceeds the desired stock of allowances, firms can choose not to use extra allowances. Thus, the expected profit from saving a unit of allowance today equals $E[max(\beta P_{a2} - P_{a1}, 0)]$. The gain from a 'good' shock is unchecked, while the loss from a 'bad' shock is bounded below. A unit of allowance is like a set of American call options on future production, which is worth more when good and bad outcomes are more extreme (with the same expected mean value).

Based on a similar analysis, I show that the marginal value of allowances is also a convex function of input costs (the prices of low- and high-sulfur coal) and industry average productivity (*G*). For proof, refer to Zhang (2007).

Lemma 1 *The greater the uncertainty in input costs P_l and P_h, and industry average productivity G, the lower the ex ante emissions.*

To be mentioned, although Proposition 1 and Lemma 1 are proved under the assumptions that individual firms are price-takers and that production technology is linearly homogeneous. I also show that imperfect competition in an electricity market and decreasing returns to scale do not affect the negative relationship between uncertainty and emissions. However, this negative relationship may not be robust given increasing returns to scale or imperfect competition in the allowance market. Finally, I show that electricity price uncertainties affect banking decisions according to the same mechanism for regulated and unregulated firms. However, firms generally would have less incentive to accumulate permits by overcompliance during a transitional period of restructuring, since moving towards restructuring implies the eventual loss of cost recovery, thus reducing the expected marginal value of allowances. For a detailed discussion and anytical proofs, refer to Zhang (2007).

5. Empirical Analysis

Building on previous discussions on the dynamics of intertemporal emissions trading under uncertainty, I empirically explore the electricity utilities' responses regarding emissions reduction to price fluctuations in the U.S. electricity markets. The analysis is based on a panel dataset consisting of 207 Phase I coal-fired generating units from 1996 to 2004. In what follows, the model specification, data sources and estimation results are discussed.

5.1 Econometric Specification

I assume a generating unit i has a production function of the following form: $g_i = G_i l^a h^b$ $(a_i > 0, b_i > 0)$; electricity price is given by $P_e = W g_i^{\varepsilon - 1}$. Recall that W is an exogenous process that influences the value of P_e and ε indicates the elasticity of demand. When the unit is a price-taker in the electricity market, $\varepsilon = 1$ and $W = P_e$.

By deriving the input demand functions for low- and high-sulfur coal, I show that a electricity generating unit's emission rates can be identified by the following reduced form model[19]

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 \Delta P_{eit} + \beta_2 lnP_{eit} + \beta_3 \ln P_{lit} + \beta_4 \ln P_{hit} + \beta_5 \ln P_{at} + \beta_6 R_{it} + \beta_7 Z_{it}(\varepsilon_i, \alpha_i, \varpi_{it}) \\ &+ \beta_8 R_{it} \Delta P_{et} + \beta_9 Z_{it}(\varepsilon_i, \alpha_i, \varpi_{it}) \Delta P_{et} + \sum_{j=1}^{20} \nu S_j + \sum_{t=1997}^{2004} \kappa T_t + \alpha_{it} + u_{it} \end{aligned} \tag{19}$$

where the dependent variable $Y_{it} = ln(\frac{e}{g})_{it}$ is the observed annual average SO_2 emission rate (in log form) of unit i in calendar year t. Emission rate is calculated by dividing the total annual emissions (tons) by the annual electricity output in megawatt hours (MWh).

ΔP_{eit} is electricity price volatility. I measure ΔP_{eit} as the standard deviation of the percentage change (between two adjacent months) of monthly average electricity price in the state where unit i is located. The coefficient of ΔP_{et} provides a measure of the elasticity of

[19] Refer to Zhang (2007) for the derivation of the reduced form model.

annual average emission rate to electricity price volatility. A negative coefficient will provide supporting evidence for the theoretical prediction in previous sections.[20]

P_e is an electricity price, P_t is a price vector including the price of allowances (P_{at}), low-sulfur coal price (P_{lt}), high-sulfur coal price (P_{ht}), and retail electricity price to industrial customers (P_{et}).

To estimate the impact of ROR regulations on emissions behavior, I construct two dummy variables $RETAILACESS_{it}$ and $TRANSIT_{it}$. $RETAILACESS_{it}$ takes the value 1 if the state where unit i is located has begun retail access to industrial customers during year t, 0 otherwise; $TRANSIT_{it}$ takes the value 1 when unit i is located in a state that is in a transitional period of electricity restructuring but has not yet started retail access, 0 otherwise. I define a state as undergoing a transition to retail competition when either of the following two events occurs: (1) PUC issues a final order that contains a date by which all PUC-regulated utilities in the state must open their markets to retail competition; (2) PUC has required retail restructuring filings from its regulated utilities in preparation for competition by a particular date, even if it has not yet issued a final comprehensive order. Based on the previous analysis, if regulated units have lower incentives to reduce emissions, and transitional units are less motivated to bank permits, the coefficients of $RETAILACESS_{it}$ and $TRANSIT_{it}$ would be negative and positive, respectively.

Z_{it} is a vector of unit specific characteristics that may also determine emission performances, which include: $SCRUBBER_{it}$, a dummy constructed to be 1 if a scrubber is installed to reduce SO_2 emissions. AGE_{it}, the age of the boiler installed. $HEATRATE_{it}$ is a measure of unit efficiency in transferring energy into electricity. It is calculated by dividing the net kilowatt hours (KWh) of power output by the Btu content of the fuel input. CAP_i is the design capacity of the boiler expressed in MW. $WORKLOAD_{it}$ is the ratio between the actual operating hours during year t and the maximum working hours of a year (8640 hours)(%). $INITIAL_{it}$ is the

[20]The above analysis implicitly assumes current price fluctuation as a proxy for expected price uncertainty in the future. One concern with this specification is whether current price uncertainty reflects plant operators' expectations of future price uncertainty at the time of making operation decisions. To evaluate the possibility that historical price uncertainty does not provide insights into expectation of future price changes, I also assume mangers perfectly predict price volatility in the future ($\Delta P_{e(t+1)}$), and test for the response of current emission rate to future price fluctuation. This alternative specification does not change the result qualitatively.

initial allocation of allowances (tons) issued by the EPA. $MUNI_i$ is a dummy equal to 1 when the generating unit is municipally or cooperatively owned, and 0 otherwise. I also include year and state dummies T_t and S_j.

An unobservable time-invariant unit-specific characteristic is represented by α_i and would likely to affect emission performance as well. The disturbance term u_{it} is assumed to be an idiosyncratic shock to units' operating performance and is drawn from an identical and independent distribution: $u_{it} \sim N(0, \sigma_\varepsilon^2)$. $\beta_0, \beta_1, \ldots, \beta_4$, ν and κ and are the coefficients.

Based on Eq.(19), I also test whether the percentage change in the amount of allowances banked between two time periods has any bearing on output price uncertainty (the dependent variable is $[B_{i(t+1)} - B_{it}]/B_{it}$).The coefficients of the above explanatory variables would have similar interpretations but are expected to have opposite signs.

5.2 Disturbance Term and Alternative Specifications

The above reduced form analysis assumes that the disturbance term μ_{it} is not correlated with the other explanatory variables. I have done a series of robust checks to test the assumption. I use the annual average natural gas wellhead price[21] as an instrument for the allowance price P_{at}, I also dropped potential noisy observations for the early years (1996 and 1997)[22] and compare the results of this reduced sample estimation with those of the full sample. Given the potential endogeneity of coal prices, I use the distance of a unit from the Powder River Basin (PRB) in Wyoming and Montana as a proxy for the prices of the low-sulfur coal available to the units. In addition, I estimate Eq. (19) based on observations after year 2000 and compare the results with a full sample estimation to test if state restructuring activities were endogenously determined by large coal power plants' emissions levels. Finally, the results could be affected by sample attrition issues due to plants being divestitured and removed from the reporting database. To assess if there is sample attrition bias, I obtain the estimation results from a balanced sub-panel

[21] Wellhead price is the value at the mouth of the well. In general, the wellhead price is considered to be the sales price obtainable from a third party in an arm's length transaction.

[22] Emission price endogeneity may be particularly relevant during the first couple of years of the trading program when the market was not liquid enough and the price determination process might have involved significant interplay of supply and demand between only a few companies.

composed of units that remain in the database through 2004. The sample selection problem would be most severe in this specification if observations were not missing at random. For details of the robustness checks, refer to Zhang (2007).

The stochastic disturbance (u_{it}) in the estimation equations are assumed to be correlated across observations.[23] To obtain robust standard errors, I adjusted standard errors for clustering by unit in the following estimations.

5.3 Data and Descriptive Analysis

I began construction of the dataset with all privately and publicly owned Phase I coal-fired generating units. For these units, I built a panel dataset beginning in 1996, the first year for which coal prices are available, and ending in 2004, the last year for which the allowances transaction data were updated. The data are collected and merged from several data sources to obtain information concerning annual aggregate productions, quality and quantity of coal used, SO_2 emitted during the production process, allowances allocated and banked, electricity prices, input fuel prices, regulatory statuses, as well as a variety of unit-level characteristics. This merging process reduced the sample size, both because of differences in units covered by various datasets, and because divestitures removed plants from the reporting database after 1998. The final dataset is unbalanced and composed of 207 Phase I coal-fired generating units. All prices are adjusted to real terms using a 5% discount rate and presented in 1995 dollars. Details of the dataset collection and construction procedures are provided in Zhang (2007).

Table 2 presents summary statistics. Table 3 offers the unit per year observations concerning the number of units affected by electricity restructuring, those which installed scrubbers, switched to low-sulfur coal, or used only high-sulfur coal for production.

Table 2 Summary Statistics

Variables	Obs.	Mean	Std.Dev.	Min	Max
Emissionrate(tons/MWh)	1595	0.011	0.007	0.00008	0.041
ΔP_e (%)	1595	0.05	0.037	0.014	0.17
P_a (dollars/ton)	1595	133	55	80	285

[23] Estimated average first-order autocorrelation coefficients indicate u_{it} is likely to be serially correlated. In the emission rate equation, the coefficient is 0.26 in the fixed effects model; in the fixed effects estimation of percentage change in annually banked allowances, the coefficient is -0.38.

P_e (cents/KWh)	1595	4.21	0.95	2.68	9.54
P_l (cents/MMBtu)	1595	127.8	28	71.3	279
P_h (cents/MMBtu)	1595	126.7	43.2	76.7	418.6
P_{ng} (dollars/thousand cubic feet)	1595	2.97	1.34	1.77	5.45
VINTAGE (years)	1595	1964	7.8	1949	1978
AGE (years)	1595	36	8.1	18	55
HEATRATE(MMBtu/MWh)	1595	10.23	1.05	2.5	17.9
WORKLOAD (hours)	1595	7253.5	1077.8	792	8760
INITIAL (tons)	1595	17467	17877	144	192637
CARRY (tons)	1595	11187	18472	0	155236
MUNI	1595	0.021	0.144	0	1
CAP (MW)	1595	356	254	75	1300
δ_l (lbs/MMBtu))	1452	1.64	0.68	0.41	2.98
δ_h (lbs/MMBtu))	1452	4.41	1.28	3	8.95
DPRB (miles)	1461	1063	327	87	1773
RTE93(lbs/MMBtu)	864	2.32	1.79	0.01	8.06

Table 3 Yearly Observations on Regulatory Statuses, Scrubber Installation and Fuel Switching/Blending

Year	Retail Access	Transit	Scrubber	Switch	No-blend
1996	28	165	23	34	21
1997	44	141	23	38	15
1998	58	127	23	35	23
1999	105	83	21	54	8
2000	87	85	21	56	15
2001	55	85	17	40	3
2002	55	84	19	65	11
2003	49	85	16	50	13
2004	49	86	17	36	7

5.4 Estimation Results

Table 4 reports results from estimating equation (19). Based on the fixed effects specification, a one percent increase in price volatility is associated with a decrease in units' annual average emission rate by 0.88%. This means a one-standard deviation increase in electricity price volatility would induce an `average' unit to reduce annual aggregate emissions by 423 tons. With a 95 percent confidence interval, the emission reduction would be anywhere from 383 to 827 tons.

Table 4 Estimates for Emission Rates (in Log Form)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ΔP_e	-0.878**	-0.858**	-0.865**	-0.901**	-0.896**	-0.937**
	(0.401)	(0.335)	(0.307)	(0.407)	(0.409)	(0.365)
$\ln P_a$	-0.031	-0.051	-1.807***	–	-0.196**	-0.024
	(0.065)	(0.060)	(0.478)		(0.079)	(0.038)
$\ln P_e$	-0.269	-0.249	-0.221	-0.305	-0.153	-0.234**
	(0.224)	(0.177)	(0.163)	(0.222)	(0.252)	(0.118)
$\ln P_l$	0.047	0.139*	0.008	-0.003	0.016	0.046
	(0.086)	(0.076)	(0.075)	(0.106)	(0.094)	(0.100)
$\ln P_h$	0.103	0.041	0.118**	0.037	0.133	0.103*
	(0.089)	(0.058)	(0.056)	(0.085)	(0.091)	(0.051)
RETAILACCESS	-0.047	-0.059	-0.048	-0.030	0.009	0.092
	(0.051)	(0.039)	(0.035)	(0.050)	(0.064)	(0.046)
TRANSIT	0.069	0.073	0.073	-0.005	0.083	-0.054
	(0.042)	(0.085)	(0.079)	(0.061)	(0.096)	(0.050)
SCRUBBER	-2.447***	-2.158***	-2.313***	-2.138***	-2.442***	-0.396**
	(0.036)	(0.081)	(0.138)	(0.031)	(0.038)	(0.068)
AGE	-0.023	-0.006	-0.023	0.012	-0.003	0.008
	(0.026)	(0.017)	(0.019)	(0.035)	(0.026)	(0.019)
AGE2	-0.00009	-0.0002	-0.0001	-0.0004	-0.00009	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0005)	(0.0003)	(0.0002)
lnHEATRATE	0.163*	0.271**	0.133	0.231**	0.234**	-0.247
	(0.098)	(0.114)	(0.110)	(0.089)	(0.094)	(0.205)
WORKLOAD	-0.053	-0.085	-0.059	-0.139	-0.013	-0.092
	(0.088)	(0.075)	(0.070)	(0.095)	(0.092)	(0.068)
INITIAL	1.20e-06	1.31e-06	1.18e-06	1.20e-06	8.85e-07	-3.62e-07
	(9.33e-07)	(9.55e-07)	(8.83e-07)	(1.90e-06)	(9.74e-07)	(4.04e-07)
MUNI ΔP_e	0.245**	0.113	0.245**	0.104	0.236**	0.135**
	(0.095)	(.107)	(0.112)	(0.077)	(0.099)	(0.042)
RETAILACESSΔP_e	0.301	0.459	0.368	-0.176	-0.367	0.091
	(0.520)	(0.531)	(0.487)	(0.523)	(0.545)	(0.046)
CAP	–	-1.691	–	–	–	–
		(1.846)				
CAP2	–	0.061	–	–	–	–
		(0.173)				
Constant	-7.258***	264.390***	–	-4.959***	-11.209***	-17.074
	(0.660)	(97.189)		(1.013)	(0.858)	(4.224)
R^2	0.930	0.717	0.929	0.944	0.859	0.961
Observations	1586	1586	1552	871	1291	1032

Note: The dependent Variable is the units' annual average emissions rate (in log form) Ln(Emissionrate). Columns (1) and (2) report results from estimating Eq.(30) via fixed effects and random effects models. A Hausman test rejects the null hypothesis that there is no systematic difference between fixed and random effects estimations. The test statistics are χ^2 (19) = 61.84, *P*-value=0.0000. Column (3) reports IV/2SLS estimation using natural gas wellhead price as an instrument for SO2 allowance price. The first-stage F-statistics is 22.08. Column (4) reports estimation results based on data from 1998 to 2003. Column (5) reports estimation based on a balanced panel dataset, which restricts the sample to 145 units that were active from 1996 to 2004. Column (6) reports fixed e_ects estimation for Eq.(32). The sample is composed of 118 units that were operating in 1993. Standard errors clustered by unit are reported in parentheses. *** indicates significant at the 1% level; **indicates significant at the 5% level; * indicates significant at the 10% level. Reported R^2 is the adjusted R^2 for fixed effects and random effects models and the centered R^2 for the IV/2SLS model.

Overall, results from alternative specifications closely resemble the basic, fixed effects estimation in column (1). In all cases, the relationship between electricity price volatility and emission rate, shown in the first row of Table 4, is statistically negative, with an estimated elasticity around 0.8% - 0.9%.

The columns in Table V are structured in a manner similar to those in Table 4. Based on column (2) in Table V, a one percent increase in electricity price volatility is on average associated with an increase of 2.46% in the size of the allowance bank.

Table V Estimates for Annual Percentage Change in Banked Allowances

Variables	(1)	(2)	(3)	(4)	(5)
ΔPe	2.410**	2.457**	2.358**	2.759**	1.615**
	(1.059)	(1.108)	(1.088)	(1.408)	(0.509)
lnPa	-0.171	-0.216*	-0.294**	–	-0.327***
	(0.113)	(0.118)	(0.133)		(0.093)
lnPe	0.135	0.369	0.249	0.389	-0.169
	(0.416)	(0.586)	(0.385)	(0.671)	(0.287)
lnPl	-0.235	-0.110	-0.327	-0.073	-0.013
	(0.361)	(0.206)	(0.343)	(0.279)	(0.093)
lnPh	-0.021	-0.021	-0.020	0.007	-0.117
	(0.114)	(0.151)	(0.109)	(0.199)	(0.097)
RETAILACESS	0.085	0.101	0.140	0.119	-0.012
	(0.120)	(0.126)	(0.122)	(0.358)	(0.229)
TRANSIT	-0.078	-0.077	-0.143	-0.051	-0.117
	(0.108)	(0.286)	(0.154)	(0.104)	(0.231)
SCRUBBER	-0.520***	0.043	-0.338**	-0.666***	-0.491**
	(0.052)	(0.126)	(0.126)	(0.045)	(0.050)
AGE	0.028	0.035	0.041	0.111*	0.023
	(0.035)	(0.041)	(0.034)	(0.051)	(0.033)
AGE2	-0.0006	-0.0006	-0.0005	-0.002**	0.00002
	(0.0005)	(0.0005)	(0.0004)	(0.0008)	(0.0004)
lnHEATRATE	-0.463	-0.064	-0.498	-0.548**	-0.241
	(0.300)	(0.301)	(0.266)	(0.216)	(0.229)
WORKLOAD	0.541**	0.240	0.518	0.105	0.579***
	(0.183)	-0.227	-0.467	-0.91	-0.137
INITIAL	2.60E-06	2.20E-06	2.31E-06	3.16E-06	-1.41E-07
	(2.30E-	(2.94E-06)	(2.41E-06)	(4.09E-06)	(1.32E-06)
MUNIΔPe	-0.043	0.054	-0.041	-0.102	-0.057
	(0.049)	(0.220)	(0.173)	(0.071)	(0.045)
RETAILACESSΔPe	0.616	1.308	0.925	-1.089	–
	(1.518)	(1.751)	(1.684)	(1.528)	
CAP	–	-1.767	–	–	–
		-2.304			
CAP2	–	0.175	–	–	–
		-0.215			
Constant	1.100	10.890	–	-5.280	4.089**
	(1.413)	(122.6)		(4.782)	(1.219)
R^2	0.226	0.046	0.228	0.301	0.201
Observations	1586	1586	1552	871	1291

Note: The dependent variable of Table 6 is $(B_{i[t+1]} - B_{it})/B_{it}$ (%). Columns (1) and (2) report estimation results from the fixed effects and random effects models. A Hausman test does not reject the null hypothesis that the error term α_i is not correlated with the other explanatory variables. The test statistics are $\chi^2(19) = 17.72$, *P*-value=0.5412. Column (3) reports IV/2SLS estimation using natural gas wellhead price as an instrument for SO_2 allowance price. The first-stage *F*-statistics is 22.08. Column (4) reports reduced sample estimation based on sample observations from 1998 to 2003. Column (5) reports estimation results based on a balanced panel dataset, which restricts the sample to 145 units that were active from 1996 to 2004. Standard errors clustered by unit are reported in parentheses. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level. Reported R^2 is the adjusted R^2 for the fixed effects and random effects models and the centered R^2 for the IV/2SLS model.

This suggests that when electricity price volatility increases by a one-standard deviation from the sample mean, an `average' unit will carry forward an additional 1027 tons of allowances to the next period.

6 Welfare Analysis and Policy Implications

6.1 Numerical Simulation of Intertemporal Emission Permits Trading

To gain further insights into the effects of uncertainty on the time-series behavior of banking and emissions, I numerically simulate the temporal banking pattern resulting from varied price volatilities. In specific, I assume the electricity price P_{et} evolves following a mean-preserving stochastic process:

$$P_{et} = \begin{cases} \overline{P}_e + \theta & \text{with probability } q \\ \overline{P}_e & \text{with probability } 1-2q \\ \overline{P}_e - \theta & \text{with probability } q \end{cases} \tag{20}$$

where $\overline{P}_e$ is the expected mean of the electricity price; q denotes the probability that a price moves up or down by θ. Both q and θ measure the magnitude of uncertainty. To be consistent with previous analyses, I vary the value of θ from 0 to 1, while keeping q constant at 0.3. To focus attention on the impact of uncertainty, I maintain a constant realized electricity price in each period at $\overline{P}_e = 4.8$ cents/KWh. Annual initial allocation is 7 million tons in the first five years and is permanently capped at 3.5 million tons from the year 2000. Production parameters are chosen with the following values: $G = 55, a = 0.6, \varepsilon = 0.9$.[24] Discount ratio β is assumed to

[24]Ideally, I would estimate the production function based on actual data. However, besides observations on purchasing choices of low- and high-sulfur coal, there are no data on actual inputs of low- and high-sulfur coal. Production factor G is chosen to be large enough so that the emission standard imposes a binding constraint on the

be 0.95. Values of the following parameters are chosen around the sample means: $\overline{P}_e = 4.8$ cents/KWh, u_l =1.64lb/MMBtu, u_h = 4.41 lb/MMBtu, P_l = 120 cents/MMBtu, P_h = 100 cents/MMBtu.[25] Permit price is endogenously determined by the aggregate operational behavior of firms.

Figure 2 depicts the total amount of banked emission permits as a function of time. It is obvious that the largest θ , corresponding to the highest price uncertainty, generates the largest banking and longest banking period. Figure 2 also indicates that the electric industry has been successful in planning emissions banking. The actual banking path follows the optimal routes closely.

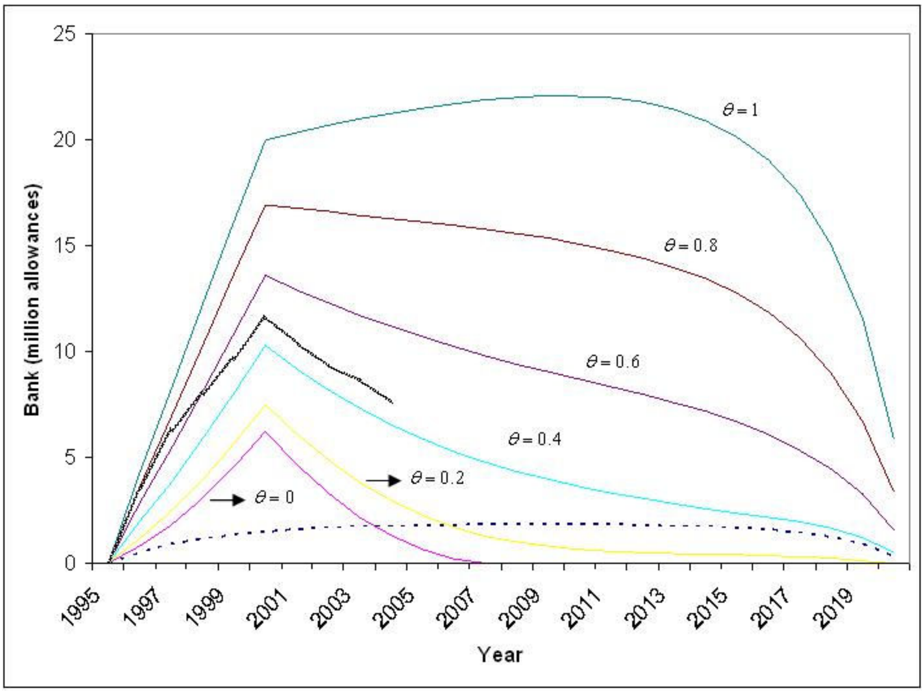

Figure 2 Total Amount of Allowances Banked under Different Price Volatilities

Note: The vertical axis describes the total amount of banked permits of the polluting industry during each year (million tons). θ is the mean-preserving spread of stochastic electricity prices. The dashed line corresponds to a scenario in which θ =0.2 and the emission cap remains constant at 7 million tons across all years. The shaded, fuzzy line tracks actual allowance stock in the SO_2 allowance market. The other lines correspond to a two-stage schedule of declining emission standards, with total emissions capped at 7 million tons from 1995 to 1999 and at 3.5 million tons during and after 2000.

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production decision. As a sensitivity analysis, I analyze the change in *G* on the results and find it does not change their qualitative pattern.

[25]The price premium of low-sulfur coal, considering the coal blending adjustment cost, is chosen at 20 cents/MMBtu. I examine the importance of the value on the results in the sensitivity analysis.

6.2 Welfare Analysis

From the standpoint of economic efficiency, uncertainty shifts emissions abatement to earlier periods, raising abatement costs due to the discounting effect. Assume $\beta = 0.95$, when θ increases from 0 to 1, the sum of the discounted net payoff is reduced by 9%; when $\beta = 0.85$, the net payoff declines by 20%. Furthermore, high initial compliance costs generated by high uncertainty would deter new entrants and have a negative impact on the development of the competitive output market and the emerging environmental market. Although it is generally believed that intertemporal trading creates compliance flexibility that reduces abatement costs and increases efficiency, uncertainty may dampen the cost saving properties of emissions banking.

In addition to cost considerations, depending on the nature of the pollutants, early abatement also has different and important environmental implications. If the pollutants, such as greenhouse gases, create stock damage, voluntary early reduction would yield significant environmental benefits. However, in a finite planning horizon, early abatement increases the degree to which firms will concentrate emissions in later time periods, raising the potential for emission spikes. If the pollutants create flow damages, and if the damage function is convex, emission spikes may even trigger the threshold effect that dramatically impact human health. [26]

6.3 Policy Implications

It is generally concluded that uncertainty about the cost of controlling carbon dioxide emissions makes price instruments preferable to quantity instruments, because the cost of limiting one ton of emissions is expected to rise as the abatement increases; meanwhile the expected benefit of each ton of carbon reduced is roughly constant because climate change is driven by stock effects rather than flow effects (Hoel and Karp, 2001; Pizer, 2002).[27] However, for multi-period emissions control, when marginal abatement costs are also uncertain for regulated sources, a tradable quota system that allows banking creates incentive for early abatement and generates substantially greater environmental benefits than a tax schedule. In

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[26] For a numerical proof of conclusions in this section, refer to Zhang (2007).

[27] The conclusion follows from Weitzman (1974) that when the slope of the marginal cost function is greater than the slope of the marginal benefit function, price instruments are preferable to quantity instruments (and vice versa), because they are much more likely to minimize the adverse consequences of choosing the wrong level of control.

addition, since the initial caps on carbon emissions are likely to be relatively undemanding, the expectation of later, more stringent caps will produce even higher reduction in initial years when the cap is non-binding.[28]

On the other hand, if the marginal benefits of abatement are steep when compared to the marginal costs, a quantity instrument without restrictions on the temporal transfer of emissions, may not always be preferable to a price regulation. This is because a quota system exposes firms to volatile market prices, which induces reallocation of emissions in response to observed uncertainty. When marginal damaging effects increase rapidly along with the increase of emission flows, a price instrument would be advisable to directly control the marginal social cost. Another potential solution is to employ a hybrid approach that combines a tradable quota system with safety measures such as restricting the intertemporal trading ratio and/or applying discount to banked permits. The government may also consider incorporating multiple polluting industries into a national trading program so that uncertainties facing one industry can be diversified, and the importance of building up a bank to buffer unexpected price strikes may be reduced.

7. Summary and Conclusion

This paper has extended the existing literature by incorporating uncertainty over the demand for outputs, the supply of inputs, and over technological progress, into the analysis of multi-period emissions trading. Uncertainty affects optimal abatement decisions through its impact on the distribution of future permit prices. Under the assumptions of a competitive permit market and quasi-concave production function, I have shown that there is a convex relationship between the permit price and the different sources of uncertainty. Applying Jensen's inequality discloses that higher uncertainty over stochastic prices and productivity raises the expected value of permits. Since a risk neutral firm that maximizes the sum of discounted profits will always reduce emissions until marginal abatement costs equal the expected permit price (conditional on the existence of an interior solution), firms will emit less in volatile markets than they would if future market conditions were known; consequently, the industry as a whole will accumulate permits at a higher level in an *ex ante* period.

[28] Currently, the transfer of unused allowances from 2005 - 2007 to the first commitment period under the Kyoto Protocol, i.e. 2008-2012, is not allowed under an EU-wide ban on banking, which, from an environmental point of view, seems a troubling decision.

Building on the foregoing analysis, this paper has suggested an explanation for the puzzle of persistent overcompliance with the Acid Rain Program in Phase I. A panel data analysis has revealed that increased price volatility induced by electricity market restructuring could have contributed to 8-11% of the extra emission reductions during Phase I of the SO_2 trading program. From this perspective, electricity restructuring has contributed to emissions reduction in the short-term by providing incentives for early abatement. However, in the long term whether electricity restructuring benefits the environment still depends on whether the incentive is sustainable and whether regulated sources would concentrate emissions during short periods in later years. [29]

Results of these analyses have important policy implications. By showing that the timing of emissions is sensitive to the volatility of the economic environment, I demonstrate that the environmental impact of uncertainty depends on the degree to which social damages can be assumed to be linear or convex. Therefore, with regard to multi-period emissions control, regulatory policies should take into account both the dynamic effects of uncertainty and the characteristics of the pollutant.

Appendix A Proof of Proposition 1

The optimization problem for the central planner of the industry:

$$max \quad P_e g(l,h) - c(l,h) \tag{21}$$

$$s.t. \quad A + B = e(l,h) = \gamma(\delta_l l + \delta_h h) = \mu_l l + \mu_h h \tag{22}$$

where $g(l,h) = Gl^{\alpha}h^{1-\alpha}$, $c(l,h) = P_l l + P_h h$, B is the total emissions left at the beginning of the terminal period. Define the Lagrangian expression:

$$L = P_e g(l,h) - c(l,h) + \lambda(A + B - \mu_l l - \mu_h h) \tag{23}$$

The necessary first-order conditions determining a maximum at ($\tilde{l}$, $\tilde{h}$, $\tilde{\lambda}$) are

$$\partial L/\partial B = \tilde{\lambda} \tag{24}$$

[29] Also any benefits from early abatement should be compared with the potential cost of price uncertainty. For example, economic and regulatory uncertainties induced by electricity restructuring may have caused the delay of scrubber installation

$$P_e G\alpha \tilde{l}^{\alpha-1}\tilde{h}^{1-\alpha} - P_l - \tilde{\lambda}\mu_l = 0 \tag{25}$$

$$P_e G(1-\alpha)\tilde{l}^{\alpha}\tilde{h}^{-\alpha} - P_h - \tilde{\lambda}\mu_h = 0 \tag{26}$$

Cross-dividing (25) and (26) results in:

$$\frac{P_l + \tilde{\lambda}\mu_l}{P_h + \tilde{\lambda}\mu_h} = \frac{\alpha}{1-\alpha}\frac{\tilde{h}}{\tilde{l}} \tag{27}$$

The expression on the right side of (27) is the marginal rate of technical substitution (MRTS) between the two types of coal. Eq.(27) says that at the optimum the MRTS between l and h must be equal to their price ratio (including the opportunity cost of surrendering the option to use allowances in a future period [$\tilde{\lambda}\mu_l$ and $\tilde{\lambda}\mu_h$]).

Define the following: $d_l \equiv (1-\alpha)(P_l + \tilde{\lambda}\mu_l)$ and $d_h \equiv \alpha(P_h + \tilde{\lambda}\mu_h)$ and substitute them into (27)

$$\frac{\tilde{h}}{\tilde{l}} = \frac{(1-\alpha)(P_l + \tilde{\lambda}\mu_l)}{\alpha(P_h + \tilde{\lambda}\mu_h)} = \frac{d_l}{d_h} \tag{28}$$

Solving (28) and (22), we obtain the conditional factor demand functions:

$$\tilde{l} = \frac{d_h}{d_h\mu_l + d_l\mu_h}B, \quad \tilde{h} = \frac{d_l}{d_h\mu_l + d_l\mu_h}B \tag{29}$$

Substituting $\tilde{l}$ and $\tilde{h}$ from Eq.(29) back into (26) yields:

$$P_e = \frac{1}{G\alpha(1-\alpha)} d_h^{1-\alpha} d_l^{\alpha} \tag{30}$$

Differentiating (30) with respect to $\tilde{\lambda}$:

$$\frac{\partial \tilde{\lambda}}{\partial P_e} = G\frac{d_h^{\alpha} d_l^{1-\alpha}}{\mu_h d_l + \mu_l d_h} > 0 \tag{31}$$

(31) clearly holds for all values of P_e, d_h and d_l.

Differentiating (31) with respect to λ defines the key derivative of the theorem as

$$\frac{\partial^2 \tilde{\lambda}}{\partial P_e^2} = G(\frac{\partial \tilde{\lambda}}{\partial P_e}) \frac{d_h^{\alpha} d_l^{1-\alpha}}{(\mu_h d_l + \mu_l d_h)^2} [\alpha^2 \mu_h \mu_l + (1-\alpha)^2 \mu_h \mu_l + \alpha^2 \mu_h^2 (\frac{d_l}{d_h}) + (1-\alpha)^2 \mu_l^2 (\frac{d_h}{d_l}) - \mu_h \mu_l] \tag{32}$$

Let $d = d_l/d_h$. Note that the minimum value of $\alpha^2 \mu_h^2 d + (1-\alpha)^2 \mu_l^2 (1/d)$ in the last bracketed term of (32) equals $2\alpha(1-\alpha)\mu_h \mu_l$ evaluated at $d = [(1-\alpha)\mu_l]/(\alpha\mu_h)$.

Since by construction, there is

$d = [(1-\alpha)(P_l + \tilde{\lambda}\mu_l)]/[\alpha(P_h + \tilde{\lambda}\mu_h)] > [(1-\alpha)\mu_l]/(\alpha\mu_h)$, then

$\alpha^2 \mu_h^2 d + (1-\alpha)^2 \mu_l^2 (1/d) > 2\alpha(1-\alpha)\mu_h \mu_l$. Thus $\frac{\partial^2 \tilde{\lambda}}{\partial P_e^2} > 0$, which proves the convexity of the marginal value of allowances with respect to electricity price (recalling that λ is the Lagrangian multiplier and represents the marginal value of a unit of allowances).

References

[1] Abel,A.B. "Optimal Investment Under Uncertainty." American Economic Review, March 1983, 73(1), pp.228-33.

[2] Abel,A.B. "A Stochastic Model of Investment, Marginal q and the Market Value of the Firm." International Economic Review, June 1985, 26(2), pp.305-22.

[3] Arimura, T.H. "An Empirical Study of the SO2 Allowance Market: Effects of PUC Regulations." Journal of Environmental Economics and Management, 2002, 44, pp.271-89.

[4] Ellerman, A. D. and Montero,J-P. "The Declining Trend in Sulfur Dioxide Emissions: Implications for Allowance Prices." Journal of Environmental Economics and Management, 1998, 36(1), pp.26-45.

[5] Ellerman, A.D., Joskow, P.L. et al. Markets for Clean Air: The U.S. Acid Rain Program, Cambridge University Press. 2000.

[6] Ellerman A.D. and Montero,J-P. "The Efficiency and Robustness of Allowances Banking in the U.S. Acid Rain Program." Working Paper 05-005, MIT Center for Energy and Environmental Policy Research, 2005.

[7] EMF Report 17, Prices and Emissions in a restructured electricity market Vol I., Standford University, 2001.

[8] Hoel, M. and Karp, L. "Taxes and Quotas for a Stock Pollutant with Multiplicative Uncertainty." Journal of Public Economics, 2001, 82, pp.91-114.

[9] U.S. Energy Information Administration. “Electric Utility Phase I Acid Rain Compliance Strategies for the Clean Air Act Amendments of 1990.” DOE/EIA-0582, 1994, Washington, DC.

[10] U.S. Energy Information Administration. “The Effects of Title IV of the Clean Air Act Amendments of 1990 on Electric Utilities: An Update.” Energy Information Administration Report DOE/EIA-0582(97), Washington, DC, 1997.

[11] U.S. Energy Information Administration.“The Changing Structure of the Electric Power Industry 2000: An Update.” DOE/EIA-052(00), Washington, DC, 2000.

[12] Feng, H. and Zhao, J. “Alternative intertemporal permit trading regimes with stochastic abatement costs.” Resources and Energy Economics, 2006, 28, pp.24-40.

[13] Holland, S.P. and Mansur, E.T.. “Is Real-time Pricing Green? The Environmental Impacts of Electricity Demand Variance.” Working Paper, CSEM WP 136, 2004, University of California Energy Institute.

[14] Intergovernmental Panel on Climate Change(IPCC). Climate Change 1995. Economic and Social Dimensions of Climate Change: Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel Change. In J.Bruce, H.P. Lee, and E.F. Haites, eds. Cambridge University Press, Cambridge, 1996.

[15] Joskow, P.L.“Restructuring, Competition and Regulatory Reform in the U.S. Electricity Sector.” The Journal of Economic Perspectives, 1997, 11(3), pp.119-38.

[16] Kling, C. and Rubin, J. “Bankable Permits for the control of environmental pollution.” Journal of Public Economics, 1997, 64, pp.101-115.

[17] Leiby, P. and Rubin, J. “Intertemporal Permit Trading for the Control of Greenhouse Gas Emissions.” Environmental & Resource Economics, 2001, 19(3), pp. 229-256.

[18] Maeda, A. “Impact of Banking and Forward Contracts on Tradable Permit Markets.” Environmental Economics and Policy Studies, 2004, 6(2), pp.81-102.

[19] Mansur, E.T. “Environmental Regulation in Oligopoly Markets: A study of electricity restructuring”, Working Paper, 2005, Yale University.

[20] Montgomery,W.D. “Markets in licenses and efficient pollution control programs.” Journal of Economics Theory, 1972, 5, pp.395-418.

[21] Palmer, K. and Burtraw, D. “The Environmental Impacts of Electricity Restructuring: Looking Back and Looking Forward.” Environment & Energy Law & Policy Journal, 2006, forthcoming.

[22] Pindyck, R.S. “A Note on Competitive Investment Under Uncertainty.” American Economic Review, March 1993, 83(1), pp.273-77

[23] Pizer, W.A. “Combining Price and Quantity Controls to Mitigate Global Climate Change.” Journal of Public Economics, 2002, 85, pp.409-434

[24] Rubin, J.D. “A model of intertemporal emission trading, banking and borrowing.” Journal of Environmental Economics and Management, November 1996, 31(3), pp.269-86

[25] Smith, A.E., Platt, J. and Ellerman, A.D. “The Costs of Reducing Electric Utility SO2 Emissions may not be as low as You Might Think.” Working Paper 98- 010, MIT Center for Energy and Environment Policy Research, 1998.

[26] Schennach,S.M., “The Economics of Pollution Permit Banking in the Context of Title IV of the 1990 Clean Air Act Amendments.” Journal of Environmental Economics and Management, 2000, 40,pp.189-210.

[27] Sedjo, R.A. and Marland G. “Inter-trading permanent emissions credits and rented temporary carbon emissions offsets: some issues and alternatives.” Climate Policy, 2003, 3(4),pp.435-44.

[28] Stevens, B. and Rose, A. “A Dynamic Analysis of the Marketable Permits Approach to GlobalWarming Policy: A Comparison of Spatial and Temporal Flexibility.” Journal of Environmental Economics and Management, 2002, 44(1), pp.45-69.

[29] Stranlund, J.K. Costello, C., et al. “Enforcing Emissions Trading when Emissions Permits are Bankable.” Journal of Regulatory Economics, 2005, 28(2), pp.181-204.

[30] Tietenberg, T.H., Emissions trading: an exercise in reforming pollution policy, Resources for the future, Washington D.C. 1985.

[31] Van Steenberghe, V. “Carbon Dioxide Abatement Costs and Permit Price: Exploring the Impact of Banking and the Role of Future Commitments.” Environmental Economics and Policy Studies, 2005, 7(2), pp.75-107

[32] Villar, J A. and Joutz, F.L. “The Relationship Between Crude Oil and Natural Gas Prices.” Energy Information Administration, O_ce of Oil and Gas, October 2006.

[33] Weitzman, M. “Prices vs. Quantities.” Review of Economic Studies, 1974, 41, pp.447-491

[34] Wirl, F. “Consequences of irreversibilties on optimal intertemporal CO2 emission policies under uncertainty.” Resource and Energy Economics, 2006, 28(2), pp.105-123.

[35] Yates, A. J. and Cronshaw, M. B. “Pollution Permit Markets with Intertemporal Trading and Asymmetric Information.” Journal of Environmental Economics and Management, 2001, 42(1),pp.104-118

[36] Zhang, F. “Essays on Environmental, Energy and Natural Resource Economics”, Ph.D. Dissertation, Harvard University, 2007.