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Emission Discharge Permits, Ambient Concentrations, and a Margin of Safety: Trading Solutions with a Computer-Assisted Smart Market for Air Quality

Keith Willett · Anetta Caplanova · Rudolf Sivak

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Abstract The process of calculating market-clearing prices for cap and trade policies for air quality remains problematic. The permit trading processes are designed to mimic the cost-minimizing outcome. An additional shortcoming is the lack of attention to elements of uncertainty in the permit price calculations. In this paper, we design a market process for allocating permits to achieve the same type of behavior we observe for each decision-maker in the overall cost minimization model. We aim to design a modeling system that would be easy and efficient to operate. We use a method known as a computer-assisted "smart market" which has been used in a number of electricity-pricing situations proposed and applied to some types of environmental and resource management problems. The theoretical structure of the smart market model with a safety margin is provided and then the elements of the margin of safety are explored in depth. Finally, a set of pricing rules for the permits that reflect a margin of safety are examined, and issues related to their implementation are explored.

Keywords Environmental pollution policies · Air pollution · Permit trading · Smart markets · Margin of safety

K. Willett (✉)
Department of Economics and Legal Studies in Business, Spears School of Business, Oklahoma State University, Stillwater, OK 74078, USA
e-mail: keith.willett@okstate.edu

A. Caplanova
Department of Economics, Faculty of National Economy, University of Economics in Bratislava, Dolnozemska cesta 1, 85235 Bratislava, Slovakia
e-mail: anetta.caplanova@euba.sk

R. Sivak
Department of Finance, Faculty of National Economy, University of Economics in Bratislava, Dolnozemska cesta 1, 85235 Bratislava, Slovakia
e-mail: rudolf.sivak@euba.sk

1 Introduction

In 1960, Ronald Coase [1] argued that making property rights for environmental assets explicit and transferable would let the market value these property rights. If this proposition was applied, it would allow the market transactions to play a more central role in the pollution control policy. The practical applications of Coase's argument were developed by Dales [2] for water and Crocker [3] for air quality. Dales argued that the legal regimes imposed by governmental agencies for the pollution control were essentially property rights to emit, but they were not efficient because the property right was not transferable. Crocker made a similar observation using Coase's argument. The defined property right to emit, which would be transferable, had the potential to fundamentally change the information requirements imposed on the policy makers. That is, if the property right to emit and the corresponding market were established, the environmental regulatory authorities would no longer need to estimate the individual emitter and receptor preference functions.

The basic definition of the property right to be traded depends on the type of a pollutant. Tietenberg [4, 5] provides a general classification of pollutants that is widely used by economists. The first type of the pollutant is called the uniformly mixed assimilative pollutant. In this case, the spatial distribution of emissions sources is not important, and environmental policy instruments are directly focused on emissions. The second type of the pollutant is the non-uniformly mixed assimilative pollutant. In this case, the spatial distribution of emission sources relative to the impact at specific receptor locations is important. Moreover, environmental policy instruments are generally concerned with the permissible ambient concentration levels measured at specific receptor locations.

The objective of cap and trade policies is the cost minimization, while the policy target depends on the type of the pollutant under evaluation [5]. In case of a uniformly mixed assimilative pollutant, the policy target is the level of aggregate emissions or the total weight of emissions released into an environmental medium such as air. The property right that is traded for the cost-effective solution for this pollutant is an emission discharge permit (EDP). Tietenberg [5] classifies this as an undifferentiated permit (UDP). A legal limit is established for the allowable weight of emissions, and the emissions target is based on the cost-effective criterion [5]. The cost-effective allocation of the pollution control requires that the marginal cost of control related to each emission source was equalized. The same entitlement to emit is given to every emitter, and trades among emitters are carried out on one-for-one basis. EDPs have been defined and used in pollution trading for sulfurs dioxide (SO_2) and NO_x. Burtraw et al. [6] provide comprehensive discussion on the economics of these trading activities.

The non-uniformly mixed assimilative pollutants are described as local pollutants because the damage they cause is related to their ground level concentrations in the air [4]. These concentrations are based upon the relative location of emitters from each other, the process of their accumulation in the environment, and the amount of emissions emitted. The policy target level is set as an ambient concentration limit and measured at a specific location for a specific time. The impact of any individual emitter at a particular location depends on their location along with the flow characteristics of the environmental medium between the emitter's site and the monitoring or receptor site. Tietenberg [5] argues that the ambient cost-effective (ACE) criterion requires that the responsibility for the pollution abatement was allocated among emitters so as to minimize the cost of meeting the ambient standard measured at specific monitoring points. The key result for this environmental problem is that each emission source equates the marginal cost of emission reduction with a weighted average of the marginal cost of concentration reductions at each receptor point impacted by the emission source. The property right traded for the cost-effective solution is an ambient permit, and an ambient permit market is defined with respect to the location of each receptor. Each emission source is required to hold a portfolio of permits that legitimize their emissions.

Ideally, the prescription for the cap and trade policy is that the EDPs were traded in a competitive market that yields a cost-effective outcome corresponding to the cap or policy target. Montgomery [7] has shown in a rigorous manner that instantaneous multilateral trading of permits will yield a competitive equilibrium that coincides with the cost-effective outcome. Moreover, if transaction costs are low, this equilibrium is independent of the initial allocation of EDPs and the permit redistribution.

One important conclusion emerging from the previous discussion is that the ambient permit system is the best alternative to deal with the problem of a non-uniformly assimilative mixed pollutant. Nevertheless, this system is inherently complex and administratively difficult to implement. Tietenberg [4] classified the permit trading alternatives into following groups: (1) emissions permits, (2) different types of zonal permit systems, (3) single-market ambient permit systems, and (4) trading rules. These alternatives are not likely to sustain the least-cost allocation, but they might be less costly. A number of research studies examined a variety of these permit systems, considering both their respective theoretical and empirical properties, which can be found in Tietenberg [4]. Hanley, Shogren, and White [8] also provided a good discussion of the pollution permit trading process and pointed to their potential problems.

However, the literature seems to have little to say about two important problems of existing air quality policies. The first problem is related to the health risk and uncertainty. Lichtenberg and Zilberman [9] and Harper and Zilberman [10] used a safety rule model structure as a way to introduce health risk and uncertainty into the environmental regulation framework. Ellis et al. [11] and Batterman and Amman [12] provided examples of a safety rule model structure to address the acid rain strategies. The second problem is related to the ways of computing the market equilibrium prices and the efficient allocation of permits. Alternatives, which have been considered, include an introduction of a market coordinator acting like a Walrasian auctioneer.

In the paper, we use a "computer-assisted" smart market model to determine pollutant trades. A computer-assisted smart market is defined as a periodic auction where the market equilibrium is solved with a mathematical technique such as linear programming. The contributions of our paper are the following. We clearly define the property right to be traded as an EDP. First, the typical approach to permit trading is based on bilateral trades, which can lead to high transaction costs and negate the efficiency property of the permit trading, as suggested in Stavins [13]. Our first contribution to the literature is to show that a better option for permit trading is if it takes place within a common market pool. This does not require that the traders were matched up. The prices used in our system are based on key shadow prices reflecting each trader's impact on the environmental capacity. Our second contribution is related to the inclusion of regional pollutant constraints at key receptor points. This provides a cost-effective way to minimize the "hot spot" problem, while it continues to bring the benefit of the permit trading. The third contribution is related to the specification of the stochastic aspect of transporting the pollutants and the specification of a "health-risk" in a "safety-rule" model.

The remaining parts of the paper are organized as follows. First, we present a brief discussion of the permit trading market model typically found in the literature. Next, we present the theoretical structure of the "smart market" model with a safety margin, and consequently, the elements of the margin of safety are explored in depth. The model is extended with respect to the permit trading and market settlement activities. A set of empirical simulations is presented to illustrate the empirical implications of the smart market model with the safety rule specification for trading EDPs. In the last section, we provide the summary and conclusions along with suggesting further extensions of the smart market model.

2 Literature Review of the Smart Market Model Applications

Atkinson [14] presents a typical EDP market model structure often found in the literature. Unfortunately, this market equilibrium does not account for the possibility of hot spots. In such a case, we could use the actual air quality measurements taken at various receptor locations and adjust the number of permits accordingly. A second option is to put the emissions into an air dispersion model to determine the related air quality at the receptor locations. EDPs are not directly related to ambient degradation, so ambient standards will not initially be satisfied except if it happened by chance. This concern can be addressed by imposing trading rules on EDP trades. However, these additional regulatory actions can add to the complexity and increase the administrative and transaction costs and reduce the cost effectiveness of an EDP market.

In theory, the market-clearing price in an EDP market corresponds with the cost-effective solution shadow price associated with the cap imposed on emissions. But the process of actually solving an EDP market model for market-clearing prices remains problematic. Ermoliev et al. [15] argue that a Walrasian auction can be used to determine a set of ambient and discharge prices in a centrally controlled permit market. However, a major shortcoming of this process is that the price adjustments do not lead to the equilibrium quickly or monotonically. A central market coordinator can easily replace the Walrasian auction if emitters can provide the coordinator with the information on quantities of EDPs to be traded at each possible price. It is then possible to determine optimal prices and allocation of EDPs using a computer-assisted smart market model.

The central processing in this market uses submitted bids and offer messages in an optimization algorithm to find prices and EDP allocations that maximize net gains from trade. The market can be a periodic auction that is cleared using mathematical programming techniques such as linear programming. Pricing information is based on a range of generated shadow prices. The smart market is operated by a market manager, and all trades are within a pool, rather than bilateral trades. These markets are particularly useful in situations, where trades are likely to be associated with significant transaction costs.

Smart markets have been used in a wide range of applications such as the electricity and energy sectors in New Zealand and Australia as well as water markets in the USA. For example, the New Zealand electricity market has been designed as an online smart market trading system. Electricity generators offer electricity to the wholesale market for dispatch through a countrywide system called the national grid. Electricity retailers bid online to purchase electricity to supply their customers. The online system processes the bids and offerings and updates prices every 5 min. The New Zealand electricity transmission system is a detailed nodal model. In contrast, the Australian electricity system is a simple flow model connecting a set of regional hubs. In both cases, linear programming technique is used to find the equilibrium. The model objective function maximizes net gains from trade with regard to bids and offers submitted and subject to the constraints describing the physical interactions of the system. Electricity prices are derived from shadow prices specified within the model constraint set.

The computer-assisted smart markets have also been used in natural gas markets [16] as well as to deal with the water quality management problems [17, 18]. In their work related to the smart markets on the example of the Israeli water sector, Becker [19] used shadow prices based on a similar type of model structure to consider the value of moving from the central planning to a market system.

A smart market model designed for water allocation was developed in Murphy et al. [20]. An important element of the smart market model structure is the delivery of water through a simple pipeline-like network. The model was simulated by students, who made bids in a laboratory setting. Their model used the California water transfer system. The market transactions were represented by water allocations and water transportation capacity rights. They used the sealed-bid price double auction mechanism. In this type of auction, all of the bids submitted are sealed and the winning bidder pays a price equal to the second highest bid. The efficiency and other features of the market were evaluated using laboratory experiments. The efficiency of the bidding mechanism was based on ratios comparing the total calculated surplus from trades to the calculated surplus based on the competitive equilibrium outcomes for each trader. The calculated efficiency ratios ranged between 84 and 97 %. However, they did not report any information on the transaction costs related to the trading activities studied.

Zheng et al. [21] have put together a state of the art volume of research papers on how CO_2 issues are factored in power systems. One area examined is CO_2 policies and markets. Policy discussions concerned with managing CO_2 emissions include a carbon tax, a cap and trade system, and renewable portfolio standards. Rassia and Pardalos [22] have assembled a volume of papers that consider the design of cities that may offer alternatives between energy strategies and theories of optimization and mega-spaces in a territory or a landscape. An important issue with respect to energy futures is carbon releases from activities that evolve from the spatial and architectural design of cities.

3 Smart Market Model with Health and Uncertainty Formulation

3.1 Emission Permit Trading Decision for an Individual Firm

In this section, we develop the rationale an individual firm or emitter entering an emission discharge permit system (EDPS) would use to buy and sell permits, i.e., we elaborate the way the firm determines its value for an EDP. In this situation, the firm makes a trade-off between undertaking more emissions abatement and releasing more untreated emissions. In the latter case, the firm must have the appropriate number of EDPs. The existence of the trade-off between more abatement of emissions and holding more EDPs leads us to conclude that the firm's demand schedule is its marginal abatement cost function. Below, we derive an individual firm's decision model for EDP trades. We use a model formulation similar to those found in [14]. The decision problem for an emission source in the presence of an EDPS is equivalent to minimizing the cost of emission control.

Let us define the following variables. The discharge source or firm is denoted as $i(i=1,\ldots, I)$, e_i untreated emissions releases by firm i, l_i the volume of EDPs purchased or sold by the firm i, and P^e the market price of an EDP. In addition, let $\bar{e}_i$ represent the level of emissions for firm i without the pollution control. Also let $C_i(\ldots)$ denote the abatement or pollution control cost function for firm i. Following Kolstad [26], the control cost function for firm i is defined as follows:

$$C_i(e_i) = g_i\left(\bar{e}_i - e_i\right) + f_i\left(\bar{e}_i - e_i\right)^2 \tag{1}$$

where g_i and f_i are constant parameters determined for each firm. We assume that $g_i>0$ and $f_i>0$.

The individual firm's decision problem with respect to the abatement and purchasing of EDPs is defined as follows:

$$\text{Min } g_i\left(\bar{e}_i - e_i\right) + f_i\left(\bar{e}_i - e_i\right)^2 + P^e \tag{2}$$

Subject to

$$e_i \le l_i \quad (\pi_i) \tag{3}$$

The variable in parenthesis for Eq. (2) is a Lagrangian multiplier. Equation (2) states that untreated emissions for firm i must not exceed the firm's purchases of EDPs. We assume that the individual firm's manager does not have information on the abatement cost functions of other firms. The variable π_i represents the marginal value of an additional EDP to the firm i.

The marginal decision rule firm i should use in its decision on abating emissions and purchasing EDPs derived from the first-order conditions for the firm's constrained optimization problem. The conditions for the e_i and l_i are defined as follows:

$$-g_i - 2f_i\left(\bar{e}_i - e_i\right) + \pi_i \ge 0 \tag{4a}$$

$$\left[-g_i - 2f_i\left(\bar{e}_i - e_i\right) + \pi_i\right] e_i = 0 \tag{4b}$$

$$P^e - \pi_i \ge 0 \tag{5a}$$

$$(P^e - \pi_i) l_i = 0 \tag{5b}$$

$$e_i \le l_i \tag{6a}$$

$$(e_i - l_i)\pi_i = 0 \tag{6b}$$

Equations (6a) and (6b) represent marginal conditions for the constraint Eq. (3) defining the decision problem for the firm i.

If the constraint (3) is binding, then $e_i=l_i$ and $P^e=\pi_i$ in Eqs. (5a), (5b), and (6). If $e_i>0$, Eq. (4a) holds as a strict equality. If we substitute l_i and P^e into Eq. (4a), we can derive the following for l_i:

$$l_i = \bar{e}_i + \frac{g_i - p^e}{2f_i} \tag{7}$$

Equation (7) provides the solution for the number of EDPs the firm i will buy or sell. If $g_i>P^e$, $l_i>0$, which means that firm i will purchase EDPs. If $g_i>P^e$, $l_i>0$, the firm i will sell permits. Equation (7) is used by the market manager to identify the number of permits to be bought or sold by the firm i at each price presented.

3.2 Specification of a Smart Market Model

The basic structure of the computer-assisted smart market model we use closely follows the framework developed by Willett et al. [23]. The basic institutional structure for the smart market is set up as follows. A central market manager is assigned to coordinate the permit trading activity. Trades are based on buying and selling on the centrally controlled market. Bilateral trades are not allowed, and all trades are within the common market pool. Each firm determines its optimal response to a relevant range of prices as shown by Eq. (7). These responses are submitted to the market manager as a set of price and quantity pairs.

We note a number of important issues that must be clarified for the market-clearing process to be completed. First, the property right traded is an EDP, but all trades must lead to outcomes that satisfy all relevant regional air quality standards. Emitters bid on EDPs that have direct impact on air quality standards at different receptor locations, and since all trades are within the common pool, the bids are non-comparable between traders. Each firm is likely to face a different price. The market clearing is simulated with a linear programming model.

Below, we present the smart market mathematical programming model. First, we assume that the bid functions for each emitter are represented as discrete functions, where each step is called a tranche. The index for each bidding firm's tranche is denoted by the index n (n=1,…, N). Trading activities are assumed to account for the possibility of hot spots occurring spatially, so we include ambient air quality standards at various receptor points in the model. Let Q_j^0 represent the ambient concentration level at receptor location j, B_{in} the size (quantity) of the bid tranche n submitted by the bidding firm i, P_{in}^b the price specified in bid tranche n submitted by the bidding firm i, and l_{in}^b the quantity of EDPs accepted from the bid tranche n by the bidding firm i. The basic smart market model formulation is then as follows:

$$Max \sum_{i=1}^{I} \sum_{n=1}^{N} P_{in}^b l_{in}^b \tag{8}$$

Subject to

$$\sum_{n=1}^{N} l_{in}^b = l_i \qquad (\pi_i) \quad (9)$$

$$(i = 1, \ldots, I)$$
$$l_{in}^b \leq B_{in} \qquad (\theta_{in}) \ (10)$$

$$(n = 1, \ldots, N)$$
$$(i = 1, \ldots, I)$$
$$-l_{in}^n \leq 0 \qquad (\phi_{in}) \ (11)$$

$$(n = 1, \ldots, N)$$
$$(i = 1, \ldots I)$$
$$p_r\left\{\sum_{i=1}^{I} d_{ij} l_i \leq Q_j^0\right\} \geq (1-\alpha_j) \qquad (\rho_j) \ (12)$$

$$(j = 1, \ldots, J)$$
$$\sum_{i=1}^{I} l_i \leq \bar{l} \qquad (\psi) \ (13)$$

The variables in parentheses to the right of Eqs. (9)–(13) are Lagrangian multipliers.

The objective function Eq. (8) represents the joint net economic benefits of undertaking permit trading assuming the constraints on ambient concentration standards at a range of receptor locations are satisfied. The mathematical programming model is solved, and the optimal quantities of EDPs and the respective permit prices are determined for each bidder.[1]

The coefficients P_{in}^b in the objective function Eq. (8) show the worth of each block of EDPs for the bidder. The constraint (11) indicates that the quantity of bids accepted in each bid tranche must be positive. The constraint (10) sets an upper limit on each tranche, ensuring that the number of permits cleared does not exceed the limit set by the bidder. Equation (9) represents an allocation constraint, which specifies the quantities of EDPs accepted and the final permit positions. Constraints (12) are spatial constraints, which are designed to control for hot spots that might occur at respective receptor points. Constraint (13) states that the total number of EDPs purchased cannot exceed the total number of permits issued by the environmental authority.

The presence of emissions releases and their spatial transport to various receptor or monitoring points is modeled in a stochastic manner as shown by Eq. (12). These equations are called "chance constraints." The expression ($1-a_j$) is defined as an exceedance probability for the air pollutant at the receptor location j ($0<a_j<1$). These probabilities are assumed to be determined exogenously by environmental policy decision-makers given their aversion to uncertainty. The stochastic specifications in Eq. (12) include the transfer coefficients d_{ij}. These coefficients show the impact of emission releases from the source/firm i on the chosen measure of pollution at monitoring point j. Distributed parameter simulation models can be used to estimate the expected values and probability distributions of the transfer coefficients [9, 24]. The ambient concentration standard Q_j^0 is also assumed to be stochastic. We elaborate more on these assumptions later in the paper.

A range of perspectives can be used to rationalize the formulation used in Eq. (12), but the regulation of the environmental health risk under uncertainty is extremely relevant for our case [9, 10]. We follow Lichtenberg and Zilberman [9] and define the health risk as the probability that a person picked randomly from a group will experience some type of adverse health effect (the likelihood of morbidity or mortality). The existing relationship between the health risk and the corresponding variables generating it are not known with certainty. Moreover, health risks used for policy analysis are

[1] Maximizing the joint economic benefits as used in this model allows a straightforward calculation of the quantity of permits traded. We could also define the objective function to minimize the value of permits traded, for example, but this would not provide the convenient identification of the quantity of permits traded as it is the case for the objective function [18].

subject to error. The uncertainty is the measurement of the size of this error. Equation (12) combines the probabilistic risk assessment with a margin of safety. The margin of safety means that the risk must be constrained to remain below a given minimum level (or risk standard) with a given probability.

The nature of this specification can be examined in more detail by focusing more closely on Eq. (12). The terms on the left-hand side of the inequality sign show the emissions from all sources that can be transported to receptor location j. The term Q_j^0 on the right-hand side of the inequality sign is the health risk-based ambient concentration standard at receptor location j. It is assumed that Q_j^0 is determined using health risk-based procedures as described in Lichtenberg and Zilberman [9]. This constraint requires that the concentration of the air pollutant at receptor point j cannot exceed the health risk-based standard 100 $(1-a_j)$ percent of the time. Alternatively, the constraint can be violated $100a_j$ percent of the time.

The formulation of Eq. (10) is based on the idea of a safety rule approach as proposed by Lichtenberg and Zilberman [9]. The safety rule approach for this type of problem is justified for the following reasons. First, this is a way to derive a "conservative" estimate of the risk that has statistical meaning [24]. Second, the safety rule perspective conforms closely to the structure found in much of the environmental legislation that sets a goal to provide adequate protection for public health and/or the environment with a sufficient margin of safety [9]. Third, it can be thought of as an extension of the Baumol and Oates [25] standards and charges to the cases involving uncertainty [9].

Equation (12) must be converted to a more convenient form so as to solve the model as a mathematical programming problem.[2] The most widely used mathematical programming technique is chance-constrained programming. If the underlying probability distribution for the probability-based constraint (12) in our model is known, we can convert this probability statement into its deterministic equivalent and directly solve as a mathematical programming model. The deterministic equivalent includes the mean and variance for each of the stochastic parameters embedded in constraint (12). Harper and Zilberman [10] as well as Lichtenberg and Zilberman [9] note that the Q_j^0 is derived from health-risk studies and is stochastic. Ellis et al. [11] argue that the physics and chemistry of air pollutant transport along with the stochastic nature of the meteorological inputs used in air pollution transport models contribute to the various levels of stochasticity with respect to the d_{ij}. We use the following assumptions in this process. First, the d_{ij} and Q_j^0 are assumed to be normally distributed with means $d_{ij}^{'}$ and $Q_j^{'}$. The assumption of normality for the stochastic formulation of air pollution is widely used. More detailed discussion on this point is provided in Batterman and Amann [12] and Ellis et al. [11]. In addition, both sets of parameters are assumed to be statistically independent. These assumptions allow us to rewrite Eq. (12) as

$$\sum_{i=1}^{I} d_{ij}^{'} l_i + \varphi_{\alpha j}\left[\sum_{i=1}^{I} \sigma_{ij}^2 l_{ij}^2 + \varepsilon_j^2\right]^{0.5} \leq Q_j^{'} \, (j = 1, \ldots, J) \tag{14}$$

where the σ_{ij} is the standard deviations for the transfer coefficients, the ε_j is the standard deviations for the $Q_j^{'}$, and the φ_j is the critical values of the standard normal distribution exceeded only with probabilities $(1-\underline{a}_j)$. The smart market model with a safety margin now consists of the maximizing Eq. (8) subject to Eqs. (9), (10), (11), (13), and (14).

Equation (14) yields some interesting interpretations with respect to risk and uncertainty. We first move the $Q_j^{'}$ to the right-hand side of Eq. (14) and define the following:

$$\Phi_j = \sum_{i=1}^{I} d_{ij} l_j - Q_j^{'} \tag{15}$$

It is assumed that Φ_j is a normally distributed variable with the mean

$$\mu(\Phi_j) = \sum_{i=1}^{I} d_{ij}^{'} l_i - Q_j^{'} \tag{16a}$$

and variance

$$\Gamma_j^2 = \left[\sum_{i=1}^{I} \sigma_{ij}^2 l_i^2 + \varepsilon_j^2\right] \tag{16b}$$

We can make two important observations. First, regulatory decisions depend on two parameters: maximum allowable risk implied by $Q_j^{'}$ and the maximum margin of safety $(1-\underline{a}_j)$. Second, the constraint represents the health-risk standard as a combination of mean risk and a weighted value of uncertainty. Mean risk is defined by Eq. (16a), while weighted uncertainty is specified as

$$\varphi_{\alpha j}\left(\Gamma_j^2\right) = \varphi_{\alpha j}\left[\sum_{i=1}^{I} \sigma_{ij}^2 l_i^2 + \varepsilon_j^2\right]^{0.5} \tag{17}$$

The expression in brackets on the right-hand side of Eq. (17) shows the uncertainty inherent in estimating the value of the transfer coefficients as well as the uncertainty in determining the health risk-based ambient concentration standard

[2] Recall that the d_{ij} in Eq. 10 are assumed to be stochastic and the main focus of this discussion.

for an air pollutant at the receptor location j. The probability of exceeding a given level of risk is lower the larger the value of φ_{aj} is, which implies a higher weight on uncertainty. We can conclude that the parameter φ_{aj} reflects the environmental policy maker's aversion to uncertainty. We will subsequently show how this aversion is captured in the price of an EDP.

3.3 EDP Prices Reflecting Health Risk and Uncertainty

The information on the market-clearing EDP prices can be found from the first-order conditions for the smart market model; the derivations of which are shown in the Appendix A. Equations (A.2a), (A.2b), (A.3a), and (A.3b) can be rearranged to get the following:

$$\begin{aligned}&\theta_{in} = P_{in}^{b} - \pi_i\\&(n = 1, \ldots, N)\\&(i = 1, \ldots, I)\end{aligned} \tag{18}$$

$$\pi_i = \psi + \sum_{j=1}^{j} \rho_j \left\{ d'_{ij} + \varphi_{\alpha j} \left[\sum_{i=1}^{I} \sigma_{ij}^2 l_{ij}^2 + \varepsilon_j^2 \right]^{-0.5} \sigma_{ij}^2 l_i \right\} (i = 1, \ldots, I) \tag{19}$$

A number of important economic interpretations can be considered with regard to the shadow prices of the smart market constraints. Suppose initially that none of the health risk-based ambient concentrations are binding. Also, let us assume that the constraint (11) is binding. Then, we can conclude that

$$\pi_i = \psi \tag{20}$$

for all i (i=1,..., I). The shadow price ψ for the EDP constraint indicates the reduction in emission control costs if the environmental authority was to add one additional EDP to the total number of permits in the market. This shadow price is the market-clearing price in the EDP market, and in this case, all firms pay the same permit price. For the remaining part of the discussion we assume that the constraint (13) is binding.

The next case we consider assumes that the health risk-based ambient concentration standards are binding at all receptor points. In addition, we focus on the mean values for the transfer coefficients and do not consider the variance terms.[3] Then, we can reformulate Eq. (19) as follows:

$$\pi_i = \psi + \sum\nolimits_{j=1}^{J} \rho_j d'_{ij} \tag{21}$$

Equation (19) shows that each firm i pays a multipart price in our version of an EDPS. The first part of the multipart price is equal to ψ, which represents the price for an EDP. The remaining components are related to the economic value of the impact each firm i has on different receptor points. The shadow price ρ_j for the ambient concentration standard at the receptor location j indicates the reduction in emission control costs if firms are allowed to violate the ambient concentration standard by one unit. Firms can be restricted from violating the ambient concentration standard at receptor location j if they are charged ρ_j per unit of increase in the ambient concentration level. If the EDP bid functions are based on true marginal emission control cost functions, we can conclude that ρ_j is a marginal cost price that yields a cost-effective allocation of resources. Prabodanie et al. [18] call this type of shadow price a "resource price." Thus, ρ_j is the portion of the market price, which matches the demand and supply for the ambient concentration level or resource [9]. The EDP is equivalent to a bundle of resource permits (i.e., it represents the impact on concentration standards at a set of receptor locations), so the part of the price of an EDP for the firm i that includes the value of this firm's impact on the various receptor locations is defined as $\sum_{j=1}^{J} d'_{ij}\rho_j$.

The shadow price associated with the allocation constraint (9) tells us how much the objective function Eq. (8) would increase if the firm i were given one additional EDP. Note that π_i are indexed to particular firms and can be called "participant prices" [18]. In the model we use, π_i can be interpreted as "marginal-cost prices." Thus, each firm should pay the value of π_i for each EDP purchased, and it is likely that each firm will be charged or paid a different price. This follows from the fact that all trades by firms are within the common pool and traders are not matched up.

Let us now turn to the case with a safety margin. Equation (19) shows the shadow price including uncertainty. The variable ρ_j is then the shadow price for the health risk-based ambient concentration standard at the receptor location j as well as the uncertainty of this standard. If the ambient concentration standard at receptor location is reduced by one unit, given a particular level of uncertainty ε_j^2 for Q_j^0, the level of the trading surplus given by Eq. (8) is reduced by $\sum_{j=1}^{J}\sum_{i=1}^{I}\rho_j d'_{ij}$ across firms. On the other hand, if there is an increase in all ε_j, the marginal opportunity cost of the error in the health risk-based ambient concentration standards is measured by $\sum_{j=1}^{J}\sum_{i=1}^{I}\rho_j d'_{ij}$.

The marginal cost of uncertainty included in the estimates of the transfer coefficients is represented by the second part of the expression on the right-hand side of Eq. (19). The uncertainty, i.e., the transfer coefficient for each firm i at each receptor location j, is represented by σ_{ij}^2. As the size of this uncertainty for one firm i with respect to one receptor location j increases, the marginal opportunity cost also increases. Moreover, if there are increases in the uncertainty for all firms at all receptor locations, the corresponding increase in the marginal opportunity cost can be found by summing them up over all firms and receptor locations. The marginal

[3] This corresponds to the case without a safety margin.

opportunity cost of uncertainty about the estimates of the transfer coefficients also includes a weighting factor φ_{aj}, which reflects the prespecified margin of safety, which also represents the environmental policy makers' aversion to uncertainty. If the environmental regulatory decision-makers increase the margin of safety, then each φ_{aj} is adequately increased, and there is a corresponding increase in the marginal opportunity cost of the ambient concentration standard at each receptor point. Thus, the expression $\sum_{j=1}^{J} \rho_j \left\{ \varphi_{aj} \left[\sum_{i=1}^{I} \sigma_{ij}^2 l_{ij}^2 + \varepsilon_j^2 \right]^{-0.5} \sigma_{ij}^2 l_i \right\}$ represents the entire increase of the marginal opportunity cost, if the environmental decision-makers increase the margin of safety or the aversion to uncertainty. Eq. (19) makes it clear how health risk-based decisions regarding the ambient concentration standards at all receptor locations along with uncertainty are factored into the market-clearing prices for an EDP purchased by each firm and how these prices change with changes in uncertainty.

We now turn the attention to Eq. (18). The shadow price θ_{in} on the bid upper limit constraint (10) indicates the increase in the benefit measured by the marginal reduction of the emission control cost, if the firm i were able to release one more unit of emissions. The bid at tranche n for the firm i will be fully accepted if Eq. (16) applies. Prabodanie et al. [18] argue that the shadow price ϕ_{in} of the lower bound constraint (11) represents the loss of the economic benefit if one EDP was accepted from that bid. Thus, the bids are not accepted if

$$\begin{aligned} &\phi_{in} = \pi_i - P_{in}^b > 0. \\ &(n = 1, \ldots, N) \\ &(i = 1, \ldots, I) \end{aligned} \tag{22}$$

Notice that in Eq. (22), π_i is the marginal cost EDP price and P_{in}^b is the marginal benefit to firm i of accepting the bid. Equation (22) suggests that marginal emission control cost in this case for firm i is lower than the cost of an additional EDP. Bids will be partially accepted on the marginal tranche n for firm i if P_{in}^b and π_i are equal. In this case, it follows that

$$\begin{aligned} &\theta_{in} = \quad \phi_{in} \\ &(n = 1, \ldots, N) \\ &(i = 1, \ldots, I) \end{aligned} \tag{23}$$

3.4 Initial EDP Distributions, Market Settlements

The smart market model formulation discussed and analyzed in the previous section is represented as a "gross pool market." Raffensperger [27] argues that a gross pool market is easy to manage and is almost always feasible mathematically. This type of market begins by temporarily ignoring initial holdings of EDPs, and all revenues from the auction initially accrue to the market manager since the trades take place through the common pool. All market participants bid their entire demand schedules for EDPs. This demand schedule reflects the EDPs the firm wants to hold at each price under current conditions. Once the optimal solution for the market is found by solving the linear programming model, net trades are calculated on the basis of each market participant's initial allocation of permits. The market participants face marginal cost prices (instead of "priced-as-bid") which are shadow prices from the constraint set [28].

Two important conclusions with respect to the model formulation as a gross pool and the prices paid or received should be made. First, recall that the market equilibrium is independent of the initial allocation of EDPs. And if the transaction costs are low, the market equilibrium is also independent of EDP reallocations. Second, once the model solution is found, net EDP trades become decision-makers' initial EDP allocations. Moreover, permit holders face marginal cost prices based on shadow prices taken from the model solution. In our model, the prices include the marginal opportunity cost of the health risk, uncertainty, and the policy makers' aversion to uncertainty.

Let π_i^* denote the optimal marginal opportunity cost price adjusted for the health risk and uncertainty. Also, let l_i^* denote the optimal number of EDPs purchased by firm i, when the smart market model is solved and let $\widehat{l}_i$ be the initial allocation of EDPs for firm i. If $l_i^* > \widehat{l}_i$, firm i is a net purchaser of EDPs. The payment due from firm i for this purchase of EDPs is

$$\Omega_i = \pi_i^* \left(l_i^* - \widehat{l}_i \right). \tag{24}$$

If $l_i^* < \widehat{l}_i$, firm i is a net seller of EDPs. The payment due to firm i is

$$\Omega_i = \pi_i^* \left(\widehat{l}_i - l_i^* \right). \tag{25}$$

If $l_i^* > \widehat{l}_i$, firm i is neither buyer nor seller of EDPs.

4 Numerical Simulations of the Smart Market

A set of empirical simulations are presented in this section, which are designed to illustrate the empirical implications of the smart market model with a margin of safety for trading EDPs. We assume there is one pollutant which impacts two monitoring or receptor locations. The constraints include the margin of safety specification and are called regional pollutant constraints throughout the analysis in this section. We also assume that our application is based on a hypothetical case where the pollutant is SO_2. Following Ellis et al. [11], we express the $Q_j^{'}$ in tons of SO_2 deposited in the soils near receptor locations 1 and 2. The EDP prices shown for the numerical simulations in this section are computed by using Eq. (19). The payment for EDPs purchased is based on Eq. (24) for each firm buying EDPs, while revenue received by each firm selling EDPs is based on Eq. (25).

The numerical experiments shown in this section include three different safety levels, which are the basis for the particular experiments. We assume there are six firms with emission discharges, which seek to trade EDPs. The firms in the permit trading exercises are assumed to begin with an initial allocation of EDPs. We then assume the initial allocation is given and does not discuss its determination. This type of discussion is beyond the scope of our paper. Finally, the constraint (B.2) is used to replace the constraint (12) in the model.

The basic data inputs used to construct the smart market model are shown in Tables 1, 2, and 3. The data used to construct the individual firm inverse EDP demand functions shown in Table 1 is taken from Ando and Ramirez-Harrington [29]. We have chosen to use these formulations since they have the suitable mathematical form and properties for our exercise. The equations shown in Table 1 are the same numerical simulation counter parts to Eq. (7). The mean and standard deviations for the pollution transfer coefficients are shown in Table 2.[4] Information for the safety level parameters is shown in Table 3, while the initial allocation of EDP holdings and related data are shown in Fig. 1. We assume that the EDP market manager has previously issued 9000 EDPs. As will be shown below, the EDP limits provide relatively robust results.

We first provide a description of how the trading process works with the gross market formulation we have used in this research. First, we recall the use of a gross pool model, which ignores any initial allocation of EDPs. If there is an exogenous change in the conditions, firms are currently facing such as an increase in the safety level, this may cause firms to reevaluate their respective holdings of EDPs. This demand schedule is a reflection of the EDPs the firm wants to hold at each price. Each firm enters the market by bidding their entire EDP demand schedule. Once the optimal solution for the common pool market is found, net market trades are calculated based on each market participant's initial allocation of EDPs as shown in Fig. 1. The corresponding shadow prices[5] and allocation of EDPs from the model solution are used in Eqs. (22) and (23) to determine the number of EDPs bought and sold along with the respective permit expenditures and revenues associated with the transactions for each firm. It is not necessary to match the buyers and sellers up (such as in a bilateral trading scheme) since the trades take place within the common market pool.

Table 1 Individual firm inverse EDP demand functions

Firm 1	P^e=4000−2l_1
Firm 2	P^e=8000−4l_2
Firm 3	P^e=10,000−5l_3
Firm 4	P^e=4000−l_4
Firm 5	P^e=8000−2l_5
Firm 6	P^e=10,000−2.5l_5

l_i represents one EDP measured as 1 ton of emission releases

The trading experiment results are shown in Figs. 2, 3, and 4. We focus our attention on the trading activities shown in Fig. 2 first. First, note that the net number of permits bought and sold recorded for safety levels 90 and 95 % is zero, which means that the full 9000 EDPs issued by the market manager are fully allocated. If the safety level is 90 %, we see that firms 1, 4, and 5 have an increase in the optimal number of permits they want to hold, so they make purchases in this case as shown in Fig. 2. If we increase the safety level to 95 %, we see a similar set of decisions in Fig. 2, but the number of permits each of these firms' purchases is smaller. In contrast, we see from Fig. 2 that firms 2 and 3 are net sellers of permits for both safety levels. Finally, firm 6 is not an active participant in the permit trading market at either of these safety levels. These outcomes are driven in part by each firm's marginal abatement cost function.

We now turn our attention to the case when the safety level is 99 %. We see in Fig. 2 that firms 2, 3, 4, and 5 sell permits to the common market manager. In contrast, firms 1 and 6 do not participate in trades in the situation. We can also see that 826 EDPs in total are sold to the common pool manager, and there are no purchases. This outcome means that increasing the safety level to 99 % puts enough restrictions on the individual firm's emissions abatement and EDP purchase decisions that there is now an excess number of EDPs. These excess EDPs are bought by the common market manager, and each firm is compensated at the appropriate marginal cost price.

5 Numerical Simulation Results Compared to Models Used in Actual Practice

In this section, we compare our model numerical simulation results with models currently used in practice using the example of the EPA trading scheme. The most prominent and active permit trading system is the market for sulfur dioxide (SO_2) emissions in the USA. A good discussion of this allowance

[4] The reader should keep in mind that our numerical experiments are based on a hypothetical exercise. We have carefully selected the values shown in Table 2 to allow us to illustrate the functioning of the smart market trading model with different levels of a safety margin in a realistic manner.

[5] These are marginal cost prices and not the "priced-as-bid" alternative. See [28] for a detailed discussion.

Table 2 Pollution transfer coefficients and standard deviations

	Mean transfer coefficient receptor 1	Transfer coefficient standard deviation receptor 1	Mean transfer coefficient receptor 2	Transfer coefficient standard deviation receptor 2
Firm 1	$d'_{11}=0.035$	$\sigma_{11}=0.0002$	$d'_{12}=0.018$	$\sigma_{12}=0.025$
Firm 2	$d'_{21}=0.017$	$\sigma_{21}=0.002$	$d'_{22}=0.0318$	$\sigma_{22}=0.025$
Firm 3	$d'_{31}=0.046$	$\sigma_{31}=0.025$	$d'_{32}=0.227$	$\sigma_{32}=0.004$
Firm 4	$d'_{41}=0.046$	$\sigma_{41}=0.001$	$d'_{42}=0.067$	$\sigma_{42}=0.015$
Firm 5	$d'_{51}=0.038$	$\sigma_{51}=0.002$	$d'_{52}=0.031$	$\sigma_{52}=0.025$
Firm 6	$d'_{61}=0.027$	$\sigma_{61}=0.027$	$d'_{62}=0.062$	$\sigma_{62}=0.080$

trading program has been provided by Joskow et al. [30]. This paper is less recent, but the information in it remains very relevant and appears to be one of the best descriptions of the SO_2 allowance trading program. The legal status for this market was created in Title IV of the Clean Air Act Amendments of 1990 (CAAA) [30]. Title IV focused on the control of SO_2 emissions produced when coal and oil are burned in electric utility boilers. SO_2 is the primary precursor of acid rain and other acid depositions. This legislation created a property right called "allowances" that can be freely traded.

Title IV provided a venue for two different types of trading. The majority of trading has involved bilateral trades between utilities that own electric generators or between these utilities and third parties. The third parties include allowance brokers acting for their own account or they represent electricity generators. Third parties can also be fuel suppliers who bundle the sale of allowances with the sale of fuel to electric utilities. The bilateral trades continue to be confidential, and it is very difficult to get any information on these transactions. Allowances are also traded through a set of annual auctions the CAAA requires the US Environmental Protection Agency (EPA) to conduct. The EPA auctions take place in March of every year.

Title IV of the CAAA established the basic institutional structure of the allowance trading program. First, aggregate annual caps on national SO_2 emissions from certain electric generating units or "units" are specified in the law. The caps define the number of emission allowances to be issued in each year. The property right or emission allowance is defined as the right to emit 1 ton of SO_2 into the atmosphere. The restrictions on emissions in Title IV were applied to two phases. Phase I applied to the 263 dirtiest large generating units in the country. Initially, required aggregate emissions were to be reduced to 5.7 million tons per year. The reductions in this phase were to be accomplished during the period 1995–1999.

Table 3 Safety level parameters

Safety level (%)	Standard normal critical value
90	$\varphi_{90j}=1.282$
95	$\varphi_{95j}=1.645$
99	$\varphi_{99j}=2.326$

Phase II of the program began in 2000. Once again, the cap on emissions was to be lowered, and the program was extended to all of the electricity generating units in the USA. The plan was to issue about 9 million allowances annually during phase II.

Title IV of the CAAA also included a provision for making an initial allocation of SO_2 allowances. These allowances were given to existing electric generating units and units under construction. The allocation rules for the allowances are relatively complex [30], but the important consideration for our discussion is that the SO_2 allowances are available to existing sources at no charge. All allowances are fully tradable as noted earlier.

In each year, roughly 2.8 % of the allowances allocated to the utilities are held back and auctioned in the annual and 7-year advance auctions. The auction revenues collected in the

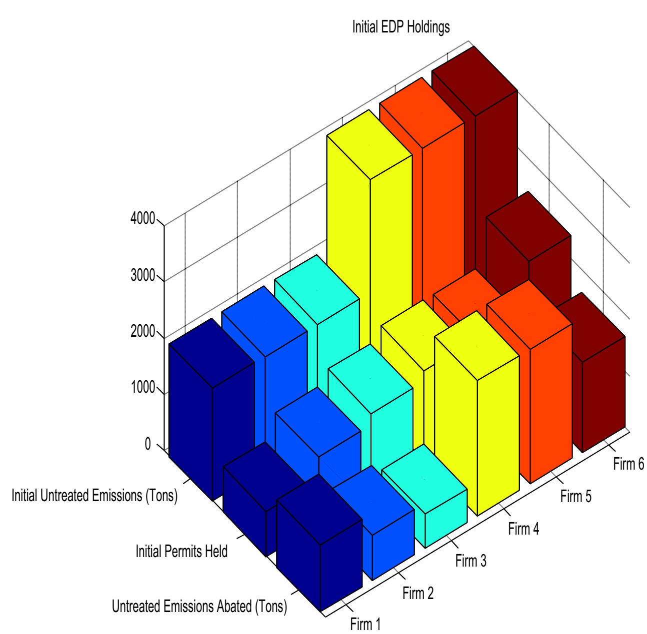

Fig. 1 The initial allocation of EDP holdings and related data

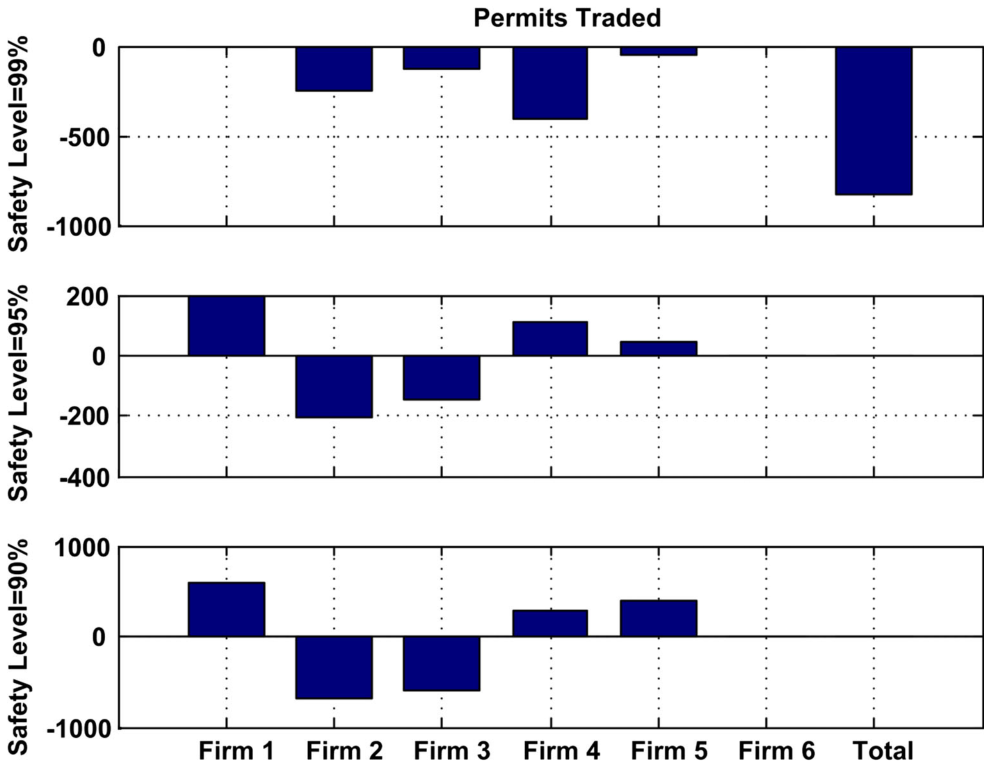

Fig. 2 Trading experiment results of permits traded

sale of allowances are returned to the utilities in proportion to their shares held back.

The primary source of allowances for the annual auctions are provided by EPA, but private parties can also offer allowances in this auction although it is not mandatory for them do so. The private voluntary offers to sell allowances in the EPA auction involving both a quantity and minimum acceptable price. This price is also called the seller's reservation price.

The prices for the allocations of allowances provided by EPA in the annual auction are sold on the basis of prices bid.

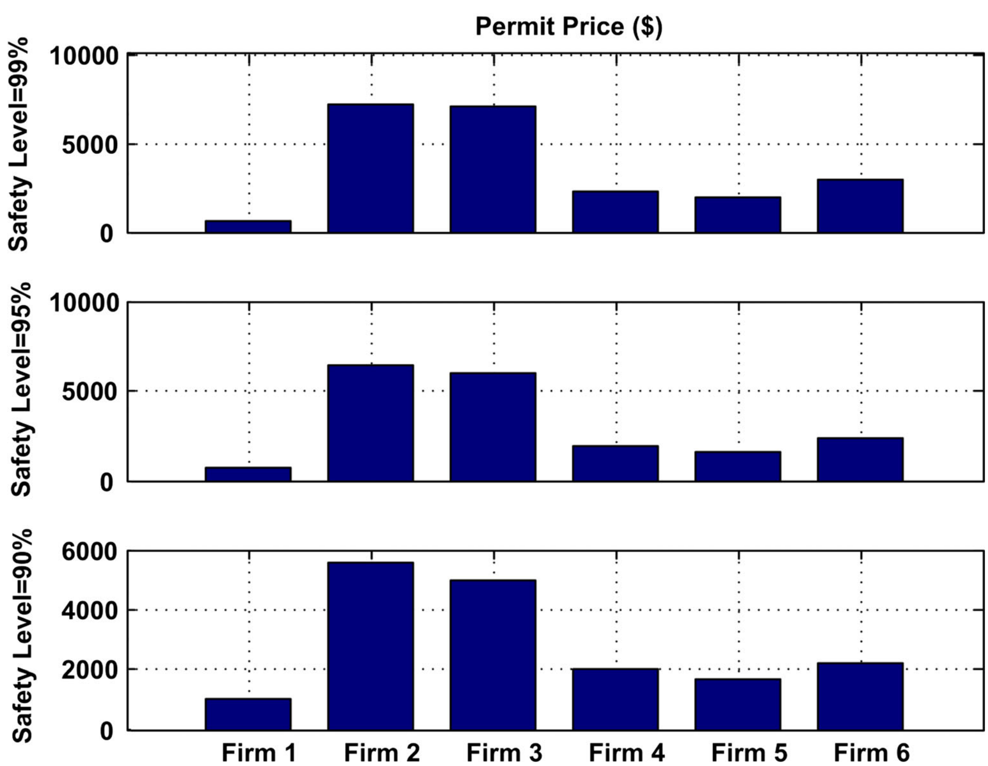

Fig. 3 Trading experiment results of permit price

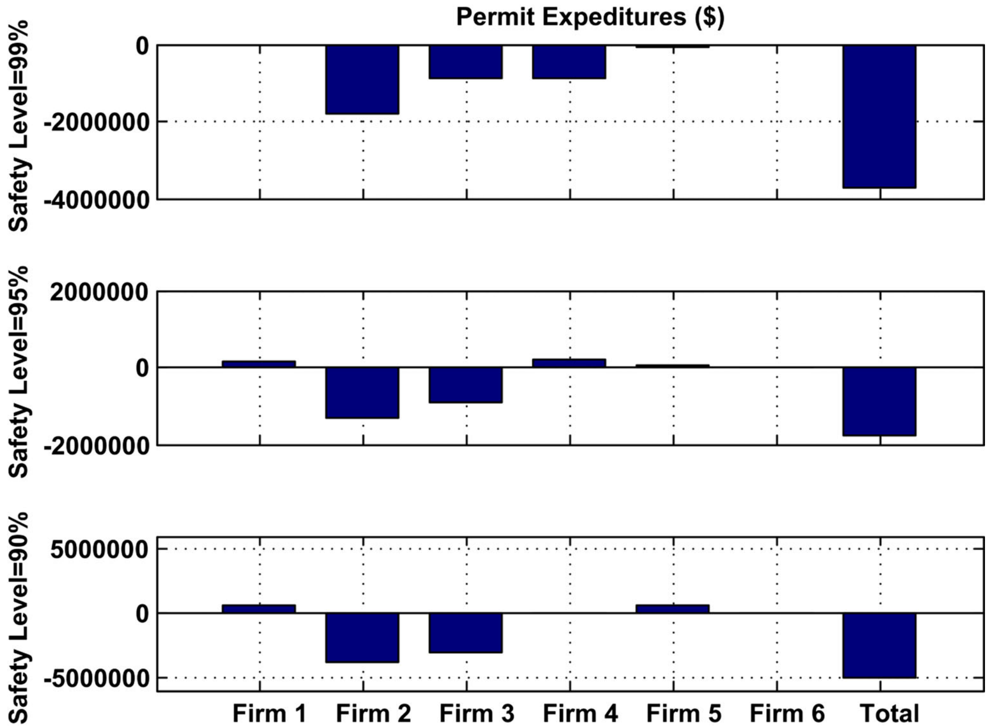

Fig. 4 Trading experiment results of permit expenditure

The process begins with the highest price bid and continues until all allowances for sale in the auction have been allocated. This is a "discriminatory" auction in which those allowances withheld by EPA are allocated to the highest bidder, and the winning bidders are required to pay their price bid instead of a uniform market-clearing price.

The private party allowances voluntarily submitted for the EPA are allocated only when the supply of EPA withheld allowances is fully allocated. The seller with the lowest reservation price is matched with the remaining buyer with the highest bid. Next, the seller with the second lowest reservation price is matched with the buyer with the second highest bid. This process for the private party allowances continues until there are no more bids to buy that exceed the reservation prices submitted by sellers. The sellers in this market receive the buyer's bid price.

The SO_2 permit expenditure and permit market-clearing price for the annual EPA spot market 5 for the period 1998–2014 are shown in Fig. 5. The market-clearing price is the lowest price at which a successful bid for allowances was made. The permit expenditures for this period are interesting and to a large extent reflect the movement of the market-clearing price.

We will focus our discussions on the market-clearing price. In 1998, the market-clearing price was approximately $115 for an allowance, increasing to $200 in 1999 and then varying between $126 in 2000 and $171 in 2003. We begin to see the market-clearing price increase to $200 in 2004 followed by a large spike in 2006 to $860. The market-clearing price began to decline to $380 in 2008. A significant drop in the market-clearing price is shown in 2009 and 2010. The market-clearing price dropped to $2.00 in 2011 and then went below $1 per allowance.

We have two tasks to address in this section. First, we need to consider the observed behavior of the market-clearing price [31]. The first factor is related to the Clean Air Interstate Rule (CAIR). CAIR was promulgated in 2005 to require "upwind" states in the eastern USA to control emissions that were predicted to contribute significantly to exceeding air quality standards "downwind." This rule was applied to SO_2. The EPA used CAIR to establish SO_2 budgets for 28 states and the District of Columbia. A two-phase compliance scheme to require that SO_2 emission budgets be met by 2010 and 2015. EPA developed annual SO_2 allowances for each of the states, and each state was to allocate the allowances within the state. The actual implementation was to be based on the cap and trade programs as following Title IV of the CAAA of 1990. CAIR was struck down by the DC Court of Appeals in July of 2008. The complex ruling of the court led to significant reduction in the value of SO_2 in the market at the end of 2008.

The second factor is the addition of environmental controls to electricity generator units. The new flue gas desulfurization (FGD) and selective catalytic reduction (SCR) pollution controls for SO_2 were installed by coal-fired generating units in anticipation of CAIR and state control requirements. FGD equipment and SCR equipment were added to about 69 and 23 GW, respectively, of coal-fired generating capacity between 2008 and 2011.

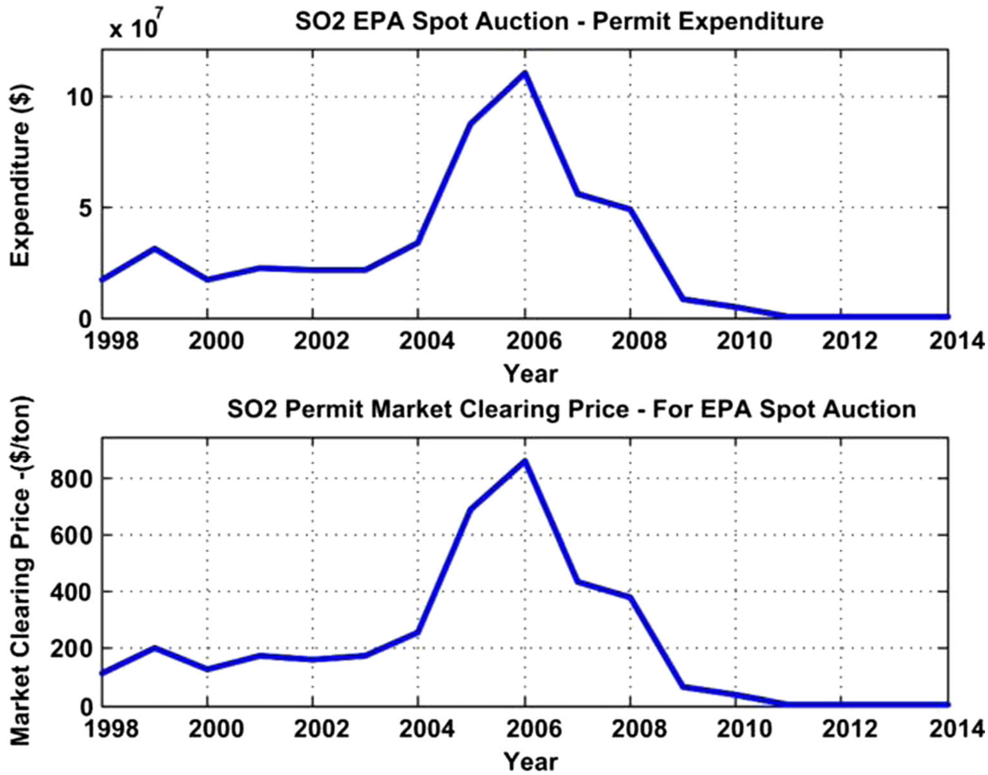

Fig. 5 The SO_2 permit expenditure and permit market-clearing price for the annual EPA spot market 5 for the period 1998–2014

The last factor which has impacted the market-clearing price of SO_2 in recent years is lower coal generation which contributed to a surplus of SO_2 allowances.

If we try to compare our model components directly with the model components that underlie the current SO_2 allowance markets, we can conclude the following. First, the firm level decision-making process for valuing allowances and the bid curves are very similar to those we have developed in Section 3.1 of the paper. However, there are some important differences at the allowance market level. Our market for EDPs is a smart market, a common pool market formulated as a gross pool. The nature of this modeling structure has been described in great detail in Section 3.2 of this paper. The trading prices for EDPs in our model are marginal cost prices constructed from key shadow prices taken from the smart market model constraint set. In contrast, the SO_2 allowance trading model used by EPA is a net pool formulation, where firms with allowances to sell on the market develop an offer curve, and firms seeking to buy allowances develop bid curves. The pricing strategy in the EPA market is based on priced-as-bid.

The above discussion of the EPA SO_2 allowance trading system has shown that the model developed in this paper can be useful also for the development of real-world trading schemes. First, EDP trades in our model take place in a common pool market. This means that all trades are with the market manager and trades do not need to be matched up. Second, the prices charged for the permits in our system are based on key shadow prices taken from the market model constraint set and reflect each trader's impact on the environmental capacity. Third, our model includes regional pollutant constraints at key receptor points as a cost-effective way to minimize the hot spot problem, while maintaining the benefit of permit trading. Our model also includes the stochastic aspects of pollutant transport along with health risk considerations. These features are not explicitly represented in the current version of the SO_2 trading market.

6 Summary, Discussion, and Conclusions

The idea that the property rights play an important role in the development of a market based on pollution control policy has been addressed in the literature for a long time. Practical applications of this idea initially focused on ensuring that such right was transferable, and it would provide significant reductions of the information needed by environmental authorities. In the latter case, environmental regulators would no longer need to estimate individual emitter and receptor preference functions.

The modern discussion on a market-based policy with well-defined property rights as its key ingredient has evolved into "cap and trade" policies. The policy goal here is to minimize the cost of emission control subject to an environmental quality target. In case of air quality problems, the environmental quality objective and the definition of the property right to be traded depend on the type of the pollutant under consideration. The environmental quality target for the uniformly mixed assimilative pollutant can be stated in terms of emissions given that corresponding damages from this type of pollutant are not related to the location of the emission sources. In contrast, the non-uniformly mixed assimilative pollutant characteristics are such that the policy target is stated in terms of ambient concentrations measured at a range of receptor points.

The property right for the uniformly mixed assimilative pollutant is an emission permit, while the property right for the non-uniformly mixed assimilative pollutant is an ambient permit. Given the spatial characteristics of this type of pollutant, emitters or firms entering this type of permit market must hold a portfolio of permits as described above. Many pollutants are appropriately placed in this category, and the use of the ambient permit system is most appropriate here. However, this system is inherently complex and difficult to implement and manage. A number of alternatives have been proposed to replace the ambient permit system, but they are equally administratively complex and may entail significant transaction cost [13].

In this paper, we developed a modeling system that would reduce complexities, administrative difficulties, and transaction costs of introducing a cap and trade policy for air quality. In our opinion, optimal prices and allocation of EDPs can be determined by using a computer-assisted smart market model, which allows for the pricing and allocation of resources in technologically interdependent environments. This system combines information and advantages created by economic incentives derived from a decentralized property rights system with the coordinating advantages of central processing based on an optimization process. The optimization data requirements include demand, supply, budget, capacity, and other problem-specific constraints. The data are provided by decentralized decision-makers whenever price and allocation decisions are needed. The central processing in such a market is based on the application of optimization algorithms to the submitted bid-offer messages to determine prices and allocations that maximize net gains from the exchange. In general, the market is a periodic auction that is cleared using mathematical programming techniques such as linear programming.

Our research resulted in the following findings. First, we derived a set of marginal cost pricing relationships that included a margin of safety. We next developed a set of numerical experiments which included a range of safety levels. The safety levels examined included 90, 95, and 99 %. Our examples were based on six firms which were emitting emissions and were likely participants in the EDP market. We also assumed that the 9000 EDPs were allocated to the market by the central market manager, and each firm began the trading exercises with an initial allocation of EDPs. At safety levels of 90 and 95 %, we found that the total number of permits bought and sold netted out to zero. If the safety level was set at 90 %, the total number of EDPs traded was equal to 1290. If the safety level was increased to 95 %, the total number of EDPs was reduced to 355. The decline in the number of EDPs is not surprising since the permit trading simply reflects the adjustments that these firms are making at the margin when the safety level has been increased. In addition, we found the same two firms selling EDPs and three firms purchasing permits at both of these safety levels. We also found that one firm did not participate in the EDP market at these two safety levels. Increasing the safety level to 99 % imposed severe restrictions on the firm managers' abatement and EDP purchases in that excess permits were sold back to the central market manager.

Our research can be extended in several ways. First, the model constraint set can easily be extended to include multiple pollutants with multiple receptor points. Second, varied procedures can be devised to test the capabilities of the smart market model in a policy setting. Our current numerical experiments described above are based on assumed EDP bid functions, but experimental economic procedures could be used to design the bid functions, which would be used in the smart market framework.

The last extension can be related to considering different ways the EDP auctions, which can be conducted. In our smart market exercise, we assume that the market manager asks the market participants to submit their set of EDP quantity bids for a range of EDP bids for each set of prices. The market manager makes an announcement that the market is closed and no further bids are accepted. The EDP bid schedules are placed in the smart market and solved. The relevant information, including the relevant shadow price values, is gathered by the market manager. The market manager will inform each market participant of the market outcome with respect to the number of EDPs bought or sold and the respective prices. This market is unlikely to be subject to the strategic behavior. According to Ando and Ramirez-Harrington [29], the bidding process eliminates the problem of strategic behavior, if the auction process is designed so that no trades will occur until the market clears. Moreover, the trades take place at the prices determined in the smart market solution. Firms have no incentive to withhold EDPs because actual trades occur only after the smart market model is solved. However, in our opinion, this conclusion requires further investigation, including the consideration of alternative auction mechanisms and could lead to additional extensions of our model formulation.

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Appendix A

The Lagrangian function and first-order conditions used to derive the pricing rules in the body of the paper are provided below:

$$\mathscr{L} = \sum_{i=1}^{I}\sum_{n=1}^{N} P_{in}^{b} l_{in}^{b} - \sum_{i=1}^{I}\pi_i\left(\sum_{n=1}^{N} l_{in}^{b} - l_i\right) - \sum_{i=1}^{I}\sum_{n=1}^{N}\theta_{in}\left(l_{in}^{b} - B_{in}\right) - \sum_{i=1}^{I}\sum_{n=1}^{N}\phi_{in}\left(-l_{in}^{b}\right) - \sum_{i=1}^{j} \rho_j\left\{\sum_{i=1}^{I} d_{ij}^{'} l_i + \varphi_{\alpha j}\left[\sum_{i=1}^{I}\sigma_{ij}^{2} l_i^{2} + \varepsilon_j^{2}\right]^{0.5} - Q_j^{'}\right\} \tag{A.1}$$

$$\frac{\partial \mathscr{L}}{\partial l_{in}^{b}} = P_{in}^{b} - \pi_i - \theta_{in} + \phi_{in} \le 0 \tag{A.2a}$$

$$\frac{\partial \mathscr{L}}{\partial l_{in}^{b}} l_{in}^{b} = 0 \tag{A.2b}$$

$$(n = 1, \ldots, N)$$
$$(i = 1, \ldots, I)$$

$$\frac{\partial \mathscr{L}}{\partial l_i} = \pi_i - \sum_{j=1}^{J}\rho_j\left\{d_{ij}^{'} + \varphi_{\alpha j}\left[\sum_{i=1}^{I}\sigma_{ij}^{2} l_i^{2} + \varepsilon_{ij}^{2}\right]^{-0.5}\sigma_{ij}^{2} l_i^{2}\right\} - \psi \le 0 \tag{A.3a}$$

$$\frac{\partial L}{\partial l_i} = l_i = 0 \tag{A.3b}$$
$$(i = 1, \ldots, I)$$

Appendix B

The chance constraint (12) is stated as a quadratic equation. This precludes the possibility of solving the smart market model as a linear model, and it must be solved as a nonlinear programming model. Rahman and Bender [32], Olson and Swenseth [33], Segarra et al. [34], and Zare M and Daneshmand [35] along with Willett and Willett [36] show that for stochastic d_{ij} and Q_j^0, we can develop a linear approximation of the chance constraint Eq. (12) assuming that at least the target probability constraint is satisfied. Given that $\sigma_{ij}^2 > 0$ for all i and j, and $\varepsilon_j^2 > 0$ for all j, it follows that

$$\left[\sum_{i=1}^{I}\sigma_{ij}^{2} l_{ij}^{2} + \varepsilon_j^{2}\right]^{0.5} < \sum_{i=1}^{I}\sigma_{ij} l_j + \varepsilon_j \qquad (j = 1, \ldots, J) \tag{B.1}$$

The inequality (B.1) can be used to rewrite inequality (12) as follows:

$$\sum_{i=1}^{I}\left(d_{ij}^{'} + \varphi_{\alpha j}\sigma_{ij}\right) l_i + \varphi_{\alpha j}\varepsilon_j \le Q_j^{'} \tag{B.2}$$

Constraint (B.2) is used to replace constraint (12) in the smart market model.

The Lagrangian function and first-order conditions used to derive the pricing rules in the model with the linearized probability constraint are shown below:

$$\mathscr{L} = \sum_{i=1}^{I}\sum_{n=1}^{N} P_{in}^{b} l_{in}^{b} - \sum_{i=1}^{I}\pi_i\left(\sum_{n=1}^{N} P_{in}^{b} - l_{in}\right) - \sum_{i=1}^{I}\sum_{n=1}^{N}\theta_{in}\left(l_{in}^{b} - B_{in}\right) - \sum_{i=1}^{I}\sum_{n=1}^{N}\phi_{in}\left(-l_{in}^{b}\right) - \sum_{j=1}^{J} \rho_j\left\{\sum_{i=1}^{I}\left(d_{ij}^{'} + \varphi_j\sigma_{ij}\right) l_i + \varphi_{\alpha j}\varepsilon_j - Q_j^{'}\right\} \tag{B.3}$$

$$-\psi\left[\sum_{i=1}^{I} l_i - \bar{l}\right] \tag{B.4a}$$

$$\frac{\partial \mathscr{L}}{\partial l_{in}^{b}} = P_{in}^{b} - \pi_i - \theta_{in} + \phi_{in} \le 0 \tag{B.4b}$$

$$\frac{\partial \mathscr{L}}{\partial l_{in}^{b}} l_{in}^{b} = 0 \quad (n = 1, \ldots, N) \quad (i = 1, \ldots, I) \tag{B.5a}$$

$$\frac{\partial \mathscr{L}}{\partial l_i} = \pi_i - \sum_{j=1}^{J} \rho_j \left(d_{ij}^{'} + \varphi_j \sigma_{ij} \right) - \psi \le 0 \frac{\partial \mathscr{L}}{\partial l_i} = l_i = 0 (i = 1, \ldots, I) \tag{B.5b}$$

The marginal opportunity cost price adjusted for the health risk and uncertainty each firm pays for EDPs is represented as

$$\pi_i = \sum_{j=1}^{J} \rho_j \left(d_{ij}^{'} + \varphi_{\alpha j} \rho_j \right) + \psi \qquad (i = 1, \ldots, I) \tag{B.6}$$

The interpretation of Eq. (B.6) is similar to that of Eq. (17).

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