AN ECONOMIC ANALYSIS OF THE EMISSION REDUCTION MARKET SYSTEM IN CHICAGO

by

Chao-Ning Liao and Hayri Onal *

Selected Paper, American Agricultural Economics Association Meeting,

Long Beach, California, July 28-31, 2002

An Economic Analysis of the Emission Reduction Market System in Chicago

CHAO-NING LIAO, HAYRI ONAL[1]

A mixed-integer programming model is used to investigate economic impacts of the permit trading market in Chicago and determine the equilibrium price. Unlike previous studies, the model determines unit pollution abatement cost endogenously depending on firms' technology adoption decisions. A sequential trading process is used to simulate firms' behavior under incomplete information. The results show that average shadow prices, a counterpart of conventional shadow prices in discrete problems, slightly underestimate the equilibrium prices. Moreover, the model predicts an over-supply of permits for the first two trading seasons.

Key words: mixed-integer programming, ERMS, average shadow price, pollution permit.

Introduction

The 1990 Clean Air Act Amendments require all severe non-attainment regions, including the Chicago area to lower their pollution levels to satisfy the federal ozone ambient concentration standard of 0.125 part per million by the year 2007. In response to meet the federal standards, the Illinois Environmental Protection Agency (IEPA) has developed a proposal for controlling Volatile Organic Materials (VOM) emission through an emission trading scheme named the Emissions Reduction Market System (ERMS).

Tradable permits systems have been shown to be economically more efficient than a command and control policy. (e.g. Atkinson, Lewis, Malonet, Yandle, Krupnik, Johnson and Pekelney). However, one important issue that was not properly dealt with in permit trading models is the fixed cost of technology adoption, which may be substantial as in the case of ERMS (Durham and Case). Most studies used the marginal analysis approach, that incorporates a constant variable cost (including the operating costs and annualized fixed costs) for each permit unit, assuming that each emission abatement equipment is used up to its full potential. When a particular technology is not used with its full potential or the life of permit trading program is shorter than the lifetime of emission reducing devices installed, the traditional marginal cost approach

[1] The authors are, respectively, assistant professor, Department of Economics, National Cheng-Kung University, Taiwan and associate professor, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

would underestimate both the cost and market price of permits.

Two studies have been conducted so far to investigate the feasibility and economic implications of the ERMS program. The first of these was done by the IEPA (1996b) and used the marginal cost approach described above. The firms were ranked according to their marginal cost of emission abatement. The equilibrium price was determined as the cutoff price at which the total demand of inefficient firms and the total supply by efficient firms are balanced. The second study was conducted by Evans (1999), who used a mixed integer programming model to determine the optimum choice of emission control technologies that minimizes the total industry cost. This study also incorporates annualized fixed costs as part of the variable operating costs for emission control technologies. Both the IEPA study and Evans ignore the firms' optimizing (cost-minimizing) behavior in a multi-period horizon. The IEPA study is a static simulation, where the intertemporal relations between firms' technology adoption and permit trading/saving decisions are not incorporated. The Evans study, on the other head, assumes a benevolent decision maker (social planner) acting on behalf of all firms to minimize the total emission cost to the industry as a whole. This is an important modeling deficiency since in most situations there will be discrepancies between the social planner's optimal strategy and individual firms' profit maximizing behavior. This study presents an appropriate methodology that considers a multi-period planning horizon and incorporates the independent, optimizing behavior of individual participants of ERMS. To accomplish this objective, a price endogenous dynamic mathematical programming model will be developed that simulates the firms' behavior under ERMS provisions and determines the market prices, optimal technology adoption and permit trading decisions. The model also incorporates the fixed costs of technology adoption when simulating firms' behavior.

ERMS

The ERMS is a "cap and trade" market regime that imposes a cap on the total emissions by its participants and requires that each participant must hold "trading units" for its actual emissions. Mandatory participants of this system are those firms with historical emissions of 10 tons or above during the critical ozone formation season, which is May 1 through September 30. This criterion covers about 250 firms with more than 4000 emission sources in the Chicago area. Each year, starting with the 2000 ozone season, the IEPA will issue emission permits called "allotment trading units" (ATU) to individual ERMS participants. Each ATU allows its holder the "right" to emit up 200 pounds of VOMs during the critical ozone formation season. The initial allocation of permits for each participant will be based on the average emission level during the period 1993-1995, which is called the source's emission baseline. In the first year of implementation of the ERMS program, the IEPA will reduce each participant's allotment by 12% of it's baseline emission level. A participant may use all of its permits in a season or bank some permits for use in the following season, or may sell them to other participants without the IEPA's approval. Banked ATUs will expire automatically after one year. At the end of each "reconciliation period", which is October 1 through December 31, all participants have to report their VOM emission levels and ATU allowance to the IEPA. During this period, each source must compile data on its actual emission level, check its ATU allowance, and purchase additional permits if necessary to assure that sufficient ATUs are held.

To meet the permit demand of such firms, a safety net will be established by the IEPA. This reserve of ATUs, called Alternative Compliance Market Account (ACMA), will start with an initial amount equivalent to 1% of the total baseline allotments of all participants and it will be managed by the IEPA. However, the price of ATUs purchased from the ACMA will be the minimum of $1,000 and 1.5 times the current market price.

The Model

In order to incorporate technology adoption as a decision variable and investigate possible impacts of the ERMS, two mixed-integer programming models are used in the study. The first model represents the perspective of a social planner who wants to achieve the targeted emission reduction levels in the most economical way and the second model represents the profit maximizing behavior of an individual firm participating in the ERMS.

The Social Planner's Model

The objective of the social planner's model is to minimize the total emission control cost including variable costs of technology use and fixed costs of installing equipments by producers. Each producer can either choose to install an expensive but more efficient technology to comply with its emission reduction requirement and sell excess ATUs or buy required ATUs from other participants in the permit market. The purpose here is to determine a socially optimum solution which provides a benchmark against other alternatives, particularly the market solution where individual producers act independently to minimize their compliance costs.

A mathematical representation of the social planner's model is given as follows:

$$\text{Min`} \sum_f \sum_y \sum_t \delta^y (vct_{ft} \cdot X_{fty}) + \sum_f \sum_y \sum_t \delta^Y (fc_t \cdot Z_{fyt} \cdot (N+1-y)) \qquad (1)$$

such that:

$$B_{fy} + H_{f,y-1} + \sum_t e_{ft} \cdot X_{fty} \geq S_{fy} + H_{fy} + el_{fy} \quad \text{for all } f, y \tag{2}$$

$$\sum_f B_{fy} = \sum_f S_{fy} \quad \text{for all } y \tag{3}$$

$$\sum_t e_{ft} \cdot X_{fty} \leq b_f \quad \text{for all } f \text{ and } y \tag{4}$$

$$X_{fty} \leq \mathrm{m} \cdot \sum_{y' \leq y} Z_{fyt} \quad \text{for all } f, y \text{ and } t \tag{5}$$

$$\sum_y Z_{fyt} \leq 1 \quad \text{for all } f \text{ and } t \tag{6}$$

where: *f, t, N, y* denote firm, technology, length of the planning horizon, and year, respectively; δ is the discount factor; vc_{ft} is the variable cost of installing technology *t* by firm *f;* fc_t is the fixed cost of installing technology *T;*

B_{fy}, H_{fy} and S_{fy}, are the amounts of ATUs bought, banked, and sold by firm *f* in year *y;*

el_{fy} is the required reduction of VOM by firm *f* in year *y*;

e_{ft} is the VOM reduction if technology *t* is used by firm *f;*

b_f is the baseline emission level of firm *f*;

X_{fty} is the utilization rate of technology *t* by firm *f* in year *y;*

Z_{fyt} is a binary variable indicating whether or not technology[2] t is adopted by firm *f* in year *y*;

m: is an arbitrarily selected large number that relates the binary variable Z_{fyt} and the utilization rate X_{fyt} to represent that an equipment can be used at an endogenous rate only if the related technology is adopted.

Equation (1) is the objective function and represents the total cost of emission control. The first part of the equation is the total variable costs resulting from the use of all technologies adopted by the firms, and the second part is the total fixed costs of installing required equipments during the planning horizon. Variable costs are defined as costs per ton of pollution reduction.

Equation (2) regulates the annual emission level for each firm. Each firm must have enough ATUs in hand to match its seasonal emission level. Besides saved ATUs from previous year (if any), ATUs can be generated by installing cleaner technology or

---

[2] According to the IEPA, Regenerative Thermal Oxidizer (RTO) is the most cost-effective equipment compared with other add-on equipment. Thus, RTO is the only equipment considered in the model.

by purchasing through market transactions. These three sources constitute the supply side of ATUs. The right hand side of equation (2) is the demand for ATUs. For any firm, it includes the amount of ATUs sold, banked for future use and used by the firm to cover the required emission reduction by the IEPA. If the total supply of ATUs is greater or equal to the total demand for ATUs, then the emission standard is met.

Equation (3) implies that the total demand and supply of ATUs have to be balanced. This constraint will be relaxed later to find the average shadow prices. Constraint (4) implies that producers cannot generate more ATUs than their baseline emission level, as required by the ERMS provisions. Equation (5) and (6) are technical constraints which ensure that an equipment can be used only after it is installed, and each technology can be installed only once during the planning horizon. Any equipment that has once been adopted can be used for the remaining years.

Results of the Social Planner's Model

The database required in the social planner's model and firm level model, including total and seasonal 1994 emissions inventory for projected ERMS participants among 97 different industries, technical description of the ERMS sources, their 8-digit Source Category (SCC) descriptions, the Source Industrial Category (SIC) description for firms and control efficiency of add-on control technologies available to these sources, is provided by the IEPA. 4,105 sources that belong to 244 firms are covered in this database. Other costs and engineering data used in the simulation come from engineering studies by the IEPA.

A 5-year social planner's model with 344 sources (77 firms) and a total allowance of 2,839 tons of seasonal VOM emission is considered in the present study. This emission level is approximately one third of the total emission level targeted by the ERMS for the entire region. Table 1 shows that the seasonal ATU trading volume is estimated as 3,189 units in the first year and is slightly higher in the following years, which corresponds to roughly about 10 percents of the total ATUs issued in the model [3]. Seventy firms would choose to be permit buyers while only seven firms would be sellers in the market. Two of those seven sellers would adopt new control equipments. These two firms both have large baseline emission levels and are from the primary metal and paper industries. The other five sellers would increase the control efficiency

[3] The slightly increasing trend in the trading volume should not be attributed any significant meaning. This is most likely a computational anomaly. During the branch and bound procedure, an LP problem is solved at each iteration and an upper bound on the objective value is determined. If an integer solution is obtained within a tolerance neighborhood of the most recent upper bound, it is reported as the optimum solution. Thus, slight derivations from the true optimum solution may occur.

Table 1: Results of the Social Planner's Model

	Year 1	Year 2	Year 3	Year 4	Year 5
Required VOM reduction(ton)	387	387	387	387	387
Total ATUs issued	28,390	28,390	28,390	28,390	28,390
# of ATUs traded	3,189	3,192	3,265	3,232	3,275
# of ATU banked	0	0	0	0	0
# of buyers in the market	70	70	70	70	70
# of sellers in the market	7	7	7	7	7
# of firms with RTO adoption	2	2	2	2	2
average shadow price ($/ATU)	$203	$191	$180	$170	$160

Total Costs of the program throughout year 1 to year 5= $2,508,957
Average control costs per ton: $1,297
Average annual abatement costs: $0.5 m

of their own existing equipment. The total abatement cost of the program for 5 years is about $2.5 million. Since the required reduction each year is constant throughout the 5-year planning horizon, the amount of banking is zero. The social planner's model assumes perfect information and full cooperation among the firms, therefore the $2.5 million cost corresponds to the minimum control cost for meeting the required VOM reduction.

The actual total emission level in the entire Chicago area is about 3 times[4] higher than the value used in this study (because the data was unavailable for those firms not included in the model). Extrapolating these results, the minimum total cost of the first five years of the program can be estimated approximately as $8.5 million with an annual average control cost of $1.7 million. Applying the same proportion, we may expect that about 3% of the ERMS participants would adopt new emission reduction technologies and 7% of the firms will increase their own control efficiency, while 90% would be permit buyers. About 11,000 units of ATU (11 % of the total ATUs issued by the IEPA) will be traded each year of the trading program.

This prediction of the model significantly overestimates the actual trading volume in the first year of the program (Oct.1-Dec.31, 2000), which was 1,643 ATUs.

[4] The actual number is 3.4.

One possible reason for this large discrepancy is that most firms had already adopted efficient emission equipments prior to the implementation of the ERMS, which is not considered in the model as the baseline emissions of all firms are set at their 1994-96 average levels. This possibility is seen clearly in the actual emission levels between 1996 and 1999. From the IEPA's estimation, total VOM emission is reduced by 51 tons per day (or 18,615 ton/year) during this period. Installing add-on technologies before the ERMS has begun may be influenced by the uncertainty of the new control program. Apparently many firms preferred to be on the safe side. This may explain why the actual trading volume in the first year of the program is so low when compared to the total emissions as well as the trading volume estimated by the model. Another important reason is that the social planner's model is based on full information and full cooperation assumptions. If the firms have misjudged possible market conditions, due to incomplete information, this may have caused an excessive emission reduction and therefore a higher total abatement cost than the one shown in Table 1.

Average Shadow Price and Equilibrium Price

It is a well-known result that in a market equilibrium model with differentiable objective function and constraints, the shadow prices associated with supply-demand balance constraints serve as market prices or equilibrium prices. Thus, in the case of permit trading, the market would be cleared (i.e., total demand = total supply) if the shadow price of the equilibrium constraint was announced as the price of tradable permits. If each individual firm makes its decisions based on the shadow price information, the entire system would achieve the socially optimum (economically efficient) allocation of resources automatically. This enables a social planner with full information to send right price signals to individual firms in advance to help and guide less informed firms in their decision making. However, the situation is different when working with integer programming models. Marginal analysis and shadow prices cannot be applied here because of non-differentiable functions and discontinuous (discrete) variables. This is because a marginal change in the availability of a resource (right hand side value) may not induce marginal changes in the model variables and the objective function.

Kim, Cho (1988) and later Crema (1995) proposed a new concept of shadow price, which is based on average rather than marginal values, in integer programming problems. They demonstrated the existence and uniqueness of this new concept, and showed that average shadow prices satisfy a version of the complementary slackness theorem in integer programming. As a counterpart of conventional shadow prices, the average shadow price associated with a resource constraint is interpreted as the maximum price a decision maker would be willing to pay for one additional unit of that resource. Although this interpretation is similar to that of conventional shadow prices, calculation of average shadow prices[5] is fundamentally different from conventional shadow prices which are obtained directly from the optimum solution of the “primal” problem. Furthermore, whether individual firms’ responses are consistent with the socially optimum solution when average shadow price is announced as market price is an issue that needs to be explored. These issues are discussed in the following.

To see whether the average shadow price can establish the market equilibrium, the firms’ responses are derived from a firm level optimization model and the aggregate supply and demand are generated assuming that the market price is given by the average shadow price. If a significant excess supply or excess demand occurs, this will be an indication that the average shadow price cannot be interpreted as the market equilibrium price. This is done by using the social planner’s model given above and calculating the average shadow prices as explained in Appendix. By announcing the average shadow price given in Table 1, we found that these prices cannot establish market equilibrium. Thus, we can conclude that unlike shadow prices in LP problems average shadow prices may not always be interpreted as market equilibrium prices when discrete choice variables are involved in the firm level decision making process.

Failure of the average shadow prices to serve as market equilibrium prices and absence of full information and full cooperation among the ERMS firms (assumed in the social planner’s model) calls for an alternative methodology to determine the market equilibrium. A sequential trading simulation models used for this purpose where the individual firms’ rational responses in an emerging market with uncertainties are derived from a firm-level optimization model that incorporates price expectations in each year of simulation. This procedure and the firm-level model are described below.

The Firm Level Model

The firms are assumed to be rational and minimize the cost of compliance by choosing optimum technology adoption and marketing decisions over a finite horizon. Using the same notation described in the social planner’s model, the decision model for firm F is described below.

$$\text{Min} \quad \begin{aligned} &\sum_t \sum_y \delta^y (vc_t \cdot X_{ty}) + \sum_t \sum_y \delta^y (fc_t \cdot Z_{ty} \cdot (N+1-y) \\ &+ \sum_y \delta^y (eprice_y \cdot (B_y - S_y)) \end{aligned} \tag{7}$$

such that

[5] Please refer to Appendix for further discussion.

$$B_y + H_{y-1} + \sum_t e_t \cdot X_{ty} \geq el_y + S_y + H_y \quad \text{for all y} \tag{8}$$

$$\sum_t e_t \cdot X_{ty} \leq b \quad \text{for all y} \tag{9}$$

$$X_{ty} \leq m \cdot \sum_{y' \leq y} Z_{y't} \quad \text{for all t} \tag{10}$$

$$\sum_y Z_{ty} \leq 1 \quad \text{for all t} \tag{11}$$

$$S_y,\ B_y,\ H_y \geq 0,\ Z_{ty} = 0, 1$$

where: $eprice_Y$ denotes firms' expectation of ATU prices each year and is updated each year when new information becomes available. Other symbols used in the above model are similar to those used in the social planner's model. Since the firm-level model focuses on the decisions of individual participants, the firm subscript *f* is removed in B, S, H and X variables.

The structure of the firm-level model is similar to the social planner's model except that the permit price and cost/benefit of ATU trading enter into the objective function. The price used here is the price "expected" by producers, which is based on past equilibrium prices but may or may not be the current year's equilibrium price. It is assumed that producers make their decisions on the basis of a price expectation every year. Since the ERMS introduces an entirely new market and there is no historical price information, it will be assumed here that decision making during the first year of the program will rely on the market price predicted by the IEPA's simulation[6]. However, in the following years, it is assumed that real transaction prices observed during the reconciliation periods of previous years will be used by the firms to form their price expectation for the future. The firm level model will be solved for a new price expectation considering a finite planning horizon that covers the remaining years of the initial planning horizon. When solving the model for each year, the optimum decisions made in previous years, in particular technology adoption and banking decisions are fixed at their respective levels. This dynamic price adjustment process continues until the trading program ends.

Instead of full cooperation among the firms as well as full cooperation between the firms and the social planner (IEPA), the simulation approach assumes that at any point in time individual firms determine their best course of action for themselves. This

[6] Before the ERMS, the IEPA estimated that the price per ATU would be $285.

determines the cost minimizing technology adoption and ATU generation decisions for each firm both for the current year and the remaining years of the planning horizon. In the simulation model, permit trading is assumed to be a bilateral and sequential process. After solving the firm level model that does not incorporate total permit supply and demand as a constraint, firms are selected randomly to allow permit trading transactions. In order to avoid possible biases in the selection procedure the simulation process is repeated several times (10 times in this particular application) for each trading season and the average volume of transactions and average market prices are obtained. The simulation results reported here are the averages of these multiple iterations. During each trading season, we assume that sellers' asking price of ATU will be the same as their average ATU costs plus a 6% fixed margin[7] even if they anticipate that buyers may be willing to pay more when the trading deadline approaches. It is assumed that they will not take advantage of this by raising their ATU price. However, the buyers' behavior in the simulation model follows two basic rules. First, firms that demand more ATUs are assumed to be willing to make their transactions earlier. Second, buyers' initial willingness to pay (WP) is based on their original anticipated prices for making production decisions. All potential buyers and sellers are matched randomly depending on their willingness to pay and reservation prices.

Simulation Results

Results of the sequential trading model are shown in Table 2. It is seen that if each participant relies on the $285 price expectation for decision-making in the first year, only 6% of the ATUs (1,694 out of 28,390) would be traded and the market is in a condition of excess supply during the first trading season. 8,076 units of those excess ATUs would be banked for the second year and the estimated first year's average transaction price would be $167 per ATU. Thus, the trading volume under incomplete information would be lower than the volume in the full information case discussed in the previous section. In the first season, 28 firms would be sellers and six out of those 28 sellers would adopt new equipment while the remaining 22 sellers would increase their present control efficiency. Firms adopting new technology operate in the rubber and plastic, fabricated metal, primal metal and paper industries. Baseline emission levels for all those firms are higher than 60 tons. Since another 28,390 units of ATU will be issued to firms in the second year and the firms would still expect a high price of

[7] 6% represents opportunity costs ATU sellers may earn from other assets such as certified deposit.

Table 2: Simulation Results of the Firm Level Model

	Year 1	Year 2	Year 3	Year 4	Year 5
Required VOM reduction (ton)	387	387	387	387	387
Total # of ATUs issued	28,390	28,390	28,390	28,390	28,390
ATU demand	1,694	1,694	3,263	3,380	3,380
ATU supply	9,771	7,883	2,226	2,839	2,849
# of ATUs traded in market	1,694	1,694	2,226	2,830	2,829
# of ATUs traded with ACMA	0	0	1,038	549	551
# of ATUs banked	8,076	1,802	0	9	20
# of expired ATUs	_	4,387	0	3	0
# of buyers in the market	49	49	73	74	74
# of sellers in the market	28	28	4	3	3
# of firms with RTO adoption	6	6	6	6	6
Simulated ATU Price	$167	$140	$196	$136	$136
Total Cost of Retired ATUs	_	$1 m	$0	$0	$0

Average annual abatement costs: $ 1.1 m
Average control costs per ton: $2,325
Average transaction price: $155/ATU

ATU (according to the simulation model assumptions) for the coming years[8], again there would be an excess supply of ATUs in the second trading season[9]. In response to the excess supply in the first trading season, it is natural to expect that some firms would cut back their ATU supply. To reflect this adaptive behavior, it is assumed that firms anticipate conservative ATU sales, instead of unlimited transaction amounts, and limit their sales in the current period to the average of planned and simulated sales in

[8] The new price expectation for year 2 to year 5 after observing a "real" transaction price in the first season is the average of $285 and $157.

[9] This excess supply phenomenon has also been observed in the real ATU market in year 2000.

previous period if the market is in an excess supply situation. After this modification, together with the banked ATUs from the first year, total ATU supply during the second reconciliation period would drop from 9,771 to 7,883 and the number of banked ATUs in the second year also decreases to 1,802 units. Excess supply of ATU also causes ATU price drop to $140 in the second year. Note that according to the ERMS provisions the life of banked ATUs is only one year. Therefore, some unsold ATUs from the first ozone season would have to be retired at the end of the second reconciliation period. The estimated loss of these ATUs is about $1 million. After the price drop in year-2, the number of buyers increases from 49 to 73. This phenomenon further eliminates the gap between total demand and supply. Because of the adaptive behavior and supply adjustment employed in the simulation procedure, the total supply in year-3 is lower than the total demand and the ATU price rises to $196. Consequently, some firms have to buy ATUs from the ACMA in year-3. After perceiving the high price, firms generate more ATUs in year-4. Even though the total supply is still lower than the total demand in year-4, the amount of ATU purchases from the ACMA decreases from 1,038 units to 549 units. The situation is similar in year-5, because of the stabilized price anticipation by the firms.

Estimated average annual abatement cost, including technology adoption costs and operating expenses, is $1.1 million. The average annual costs from the firm level model should be interpreted carefully since banking of ATUs gives the model a dynamic character and the abatement costs may not be distributed evenly throughout the 5-year horizon. The annual abatement costs from the firm level model is $0.6 million higher than the social planner's model[10] and estimated control cost per ton in the firm level model is almost $1,000 higher. This difference can be attributed to incomplete information and lack of cooperation[11].

Since firms have incomplete information about future price trends and other firms' behavior in a new market, they may over- comply with the environmental standards. The real ATU market partially reflects this phenomenon. Even though the system leads to a better air quality, it may not be economically efficient. This is the case

[10] Due to the oversupply of ATU in the first two trading seasons in the firm-level model, total VOM reduction under incomplete information is higher than the social planner's model.

[11] The model assumptions may also play a significant role here. The loss of retired ATUs may be overestimated due to the naïve price adjustment procedure used in the simulation. In reality, supplier firms would respond more quickly when dealing with excess supply of ATUs and prevent expiration of ATUs by lowering their willingness to accept. This would lower the overall cost of the trading program.

where the amount of pollution is under its socially optimal level. From Table 2, we find that only three firms in the paper and primary metal industries would be left as sellers in year-4. Since these sellers are the only ATU suppliers in the market, there is a potential that the firms could act as a monopoly. This may also occur in year-5. Since the data set consists of one third of the ERMS, it is possible that few firms control most of the ATU supply after a few trading seasons. If these firms cooperate with each other, this may increase the total control cost of the ERMS by raising ATU prices. Although, no abnormal trading activity was observed during the first trading season, the IEPA must be careful for preventing any illegal strategic behavior among firms by monitoring the market closely.

Actual ATU Prices vs. Model Predictions

Table 3 shows the actual transaction price of ATUs and the volume of trading during the first two ozone seasons (2000 and 2001). These values are far below the IEPA's estimation as well as the estimations of the present study (simulation results). One interesting phenomenon is that 60% of the total issued ATUs are used and only 2% of ATUs are actually traded in the market in year 2000 (the firms with excess ATU holdings, the remaining 38% are entitled to bank their unused ATUs for future use). As one would expect, more ATUs were traded (3,098 units) in year 2001 as a result of increased information available to the ERMS participants. The over-estimated ATU prices and low trading volume were found also in other related studies[12] of the ERMS.

By comparing the newly issued ATUs and the banked ATUs in the first year of the ERMS, we may expect a further ATU price decrease in the second year of the program (2001) because of the abundant ATU supply. The actual average transaction price of ATU in year 2001 has dropped to only $51.93, which is much lower than the model's prediction ($140). The gap between the estimations of this study and the real ATU prices may be due to the conservative learning behavior of firms or lack of information. Firms' concern about the expiration of banked ATU's may be another reason that explains the discrepancy. Permit holders cut their prices to avoid possible losses from expiration of banked ATUs. However, in the long term we might expect that the prediction ability of the social planner's model can be more reliable when the market reaches a stable condition. In contrast, the sequential trading model, where incomplete information is assumed, should be more closely representing the first few years of implementation of the ERMS.

[12] These studies were done by the IEPA (1996), Evans (1998), and Kosobud, Stokes and Tallarico (2001).

Table 3: Actual ATU Transactions During the First Ozone Season (2000)

	Actual ERMS Outcomes (Year 2000)	Actual ERMS Outcomes (Year 2001)
ATU average price	$75.87	$51.93
Average price per ton of emission	$759	$519
Number of ATUs traded	1,643	3,098
ATUs allocated	96,882	101,080
Actual reported emissions in ATU unit	60,164	N/A
Estimated banked ATUs	36,718	N/A
Number of participants	179	N/A
Seller participants	23	N/A
Buyer participants	34	N/A

Note: Actual Results taken from ANNUAL Performance Review Report-2000.
Bureau of Air, Environmental Policy and Science, Illinois EPA.

One interesting observation is that 36,718 units of ATU have been actually banked in the first year. Adding this number to the ATUs that will be issued at the beginning of the second season, a total of 133,600 ATUs (36,718+96,882) will be available during the second ozone season. If firms maintain their emissions at the same level (i.e., 60,164 units of ATU), it means that 73,446 ATUs would have to be banked at the end of the second year. This implies that 12,832 units of ATU (73446-60,164) would have to be expired. Assuming that the observed market price, $75.87 per ATU, represents the average cost of generating those extra ATUs, the total cost of these expired ATUs would be around $1 million. More ATUs would have to be abandoned later. The simulation model used in this study also predicts that a substantial number of ATUs would be expired (although the loss from retired ATUs is highly overestimated, about $3 million each year after extrapolating the results to the entire system). This is an alarming result that the IEPA has to take into account when making policy modifications in the near future.

Conclusions

An important feature that makes this study unique is the incorporation of discrete (binary) decision variables, namely technology adoption decisions, in an optimization model (a mixed integer program) that simulates the firms' decision-making behavior. This characteristic is important because in the case of ERMS the pollution control equipments are in general expensive and one-time fixed costs constitute an important component of the total costs and hence the firms' decision-making. Therefore, the model used in this study is a more realistic representation of the actual decision problem than the conventional modeling approaches seen in the permit trading literature where abatement costs involve variable costs only based on the simplifying assumption that once adopted the abatement technologies will be utilized at full capacity. In reality, the average cost of abatement under alternative technology options is endogenously determined depending on the firms' decisions regarding the number of permits generated, purchased or sold or banked, all of which are determined by permit prices over the duration of the emission trading program. When all decision variables are continuous and the model involves differentiable objective and constraint functions, shadow prices associated with demand-supply balance constraints determine the equilibrium prices in the permit market. When discrete variables are involved in the model, however, this convenience is lost and determining the market equilibrium becomes a difficult methodological problem. The concept of average shadow price, which is introduced as a counterpart of conventional shadow prices when working with mixed integer programming models, may offer a practical tool to resolve this problem. Although the two concepts have similar interpretation, no previous study has tested empirically whether or not average shadow prices can be viewed as equilibrium prices in a market equilibrium problem as in the case of convex programming problems. This would be the case if firms' responses lead to an equilibrium in the market, where aggregate supply and demand are equal, when the average shadow price is announced as the market price. The empirical results show that this is not the case, at least in the particular problem studied here, which is one of the main contributions of the present study.

For the first two years of implementation of the ERMS, the model results suggest that annual ATU supply would be enough to meet the ATU demand and no participant would need to buy permits from the ACMA. However, the simulation results show that some ATUs will expire in the first few trading season due to conservative behavior by firms and the loss of expired ATUs may be as high as $3.4 million. The IEPA may reconsider extending the life of banked ATUs at this moment.

References

Atkinson, S. E. and D. H. Lewis. “A Cost Effective Analysis of Alternative Air Quality Control Strategies.” *Journal of Environmental Economics and Management*. 1(1974):237-250.

Crema, A. “Average shadow price in a Mixed Integer Linear programming problem.” *European Journal of Operational Research*. 85(1995):625-635.

Dunham, S. and C. Case. “Emissions trading opportunities in Northeastern Illinois,” paper presented at the annual meeting of Illinois Economic Association, Chicago, IL, 1997.

Evans, D.A. <u>An Analysis of the Emissions Reduction Market System</u>. Unpublished Master’s Thesis, Department of Agricultural and Consumer Economics, University of Illinois, Urbana-Champaign, 1997.

ICF Resources Incorporated. <u>Economic Analysis of Title V(sic) (Acid Rain Provisions) of the Administration’s Proposed Clean Air Act Amendments (HR 3030/S 1490).</u> Prepared for the United States Environmental Protection Agency, 1989.

Illinois Environmental Protection Agency. 1996a <u>Emissions Reduction Market System Adoption of 35 III. Adm. Code 205 and Amendments to 35 Illinois Administrative Code 106: Statement of Reasons</u>. Springfield, IL.

Illinois Environmental Protection Agency. Technical Support Document for VOM Emissions Reduction Market System. Springfield, IL. Bureau of Air, IEPA. October. 1996.

Illinois Environmental Protection Agency. Annual Performance Review Report - 2000. Springfield, IL. Bureau of Air, IEPA. May, 2001.

Johnson, S.L. and D.M. Pekelney. “ Economic Assessment of the Regional Clean Air Incentives Market: A New Emissions Trading Program for Los Angeles.” *Land Economics*. 72(1996):277-297.

Kim, S. and S. Cho. “A shadow price in Integer Programming for management decision.” *European Journal of Operational Research*. 37(1988):328-335.

Krupnik,A.J. “Cost of Alternative Policies for the Control of Nitrogen Dioxide in Baltimore.” *Journal of Environmental Economics and Management.* 13(1986):189-197.

Liao, C.N. and H. Onal. “Is average shadow price equilibrium?” working paper, 2002.

Maloney, M.T. and B. Yandle. “Estimation of the Cost of Air Pollution Control Regulation.” *Journal of Environmental Economics and Management.* 11(1984):244-263.

U.S. Council on Environment Quality, “ Environmental Quality: The Ninth Annual Report of the Council of Environmental Quality.” U.S. Government Printing Office, Washington D.C., 1978.

United States Environmental Protection Agency, “Clean Air Market Programs: Acid Rain program SO2 Allowances Fact Sheet.” http://www.epa.gov/airmarkets/arp/allfact.html

Appendix: Derivation and Economic Interpretation of Average Shadow Prices

The general mixed integer linear programming (MILP) model can be defined as

$$Max \quad Q: cx \tag{A.1}$$
$$s.t. \ Ax \le b, \ x \in S$$

$$S = \{x : x = (x_i, x_j), Bx \le s, x \ge 0, x_i \text{ integer variables, } x_j \text{ real variables} \ \forall i, j \in I\}$$

where b, c and s are vectors, A and B are matrices with conformable dimensions and I represents the index set of integer variables.

Consider the following right hand side parametric programming problem:

$$Max \quad Q_\delta : cx \tag{A.2}$$
$$s.t. \quad Ax \le b + \delta d, \ x \in S$$

where δ is a scalar and $d \ge 0$ is a unit vector ($\|d\| = 1$) that has the same dimension as b.

Let H be an optimization problem, $F(H)$ represent the set of all feasible solutions, and $v(H)$ be the optimal solution value. Assume that $F(Q)$ is not empty and S is a bounded set. Define $f(\delta) = v(Q_\delta) - v(Q)$, $\forall \delta \ge 0$. Then, the ASP, denoted by q, relative to the direction d is defined by:

$$q = \inf\{p \ge 0 : f(\delta) - p\delta \le 0, \forall \delta \ge 0\} \tag{A.3}$$

It is shown that q has a finite value. Equation (A.3) is equivalent to

$$p = \frac{v(Q_\delta) - v(Q)}{\delta} \tag{A.4}$$

The value of p obtained from equation (A.4) is a measure of the average change in the objective value resulting from a small change in the right hand side.

For many economic questions, $Ax \le b$ represents the resource constraints such as total labor supply or capital availability. The decision maker may be interested in questions like: can the objective value be possibly increased by using more of these resources? If yes, what is the optimal resource quantity (δ) in MILP models? Crema defines the critical point of any given resource as:

$$C^* = \left\{\delta : \delta \succ 0 \quad and \quad \forall \delta_1, \delta_2 \quad such \quad that \quad 0 \le \delta_1 \le \delta \le \delta_2 : p_1 \succ p_2\right\}$$

where $p_1 = \dfrac{f(\delta) - f(\delta_1)}{\delta - \delta_1}$ and $p_2 = \dfrac{f(\delta_2) - f(\delta)}{\delta_2 - \delta}$. Because S is a bounded set, C^* is a finite set.

In order to find the ASP and δ, define a net profit function

$$e(p) = \sup\{f(\delta) - p\delta : \delta \ge 0\} \ \forall p \ge 0 .$$

e(p) measures the maximum additional profit one can get from buying an extra unit of the resource at price p. From this definition, we know that: (1) if $p \ge q$, $e(p)$ is

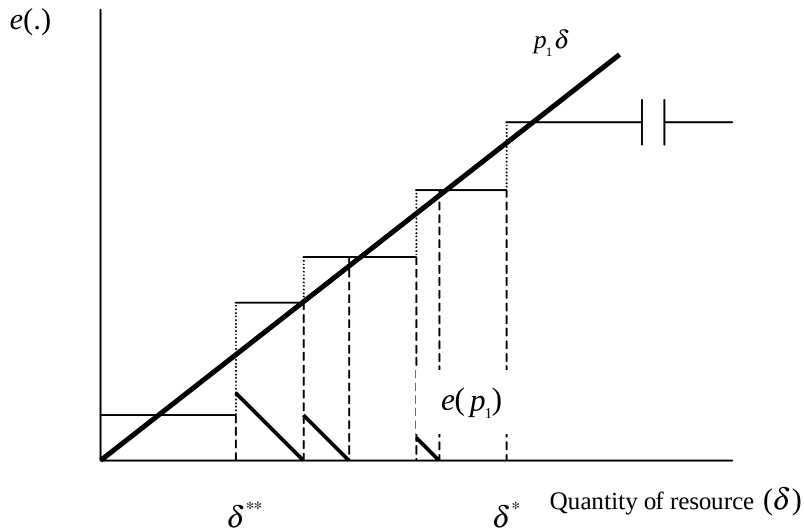

Figure A.1: Net Profit Function and Average Shadow Price

zero, and (2) For any non-negative p, q=0 if and only if $e(p)$=0. This net profit function, together with equation (A.3) give us the basic ideas of finding ASP. Crema suggests the following algorithm to find q by solving a finite sequence of MILPs.

The Algorithm

Step1: Find $e(0) = \sup\{f(\delta) : \delta \geq 0\}$.

Step2: If $e(0) = 0$, stop. $q=0$ is the solution.

Step3: Find $\delta_1 = \min\{\delta : \delta \geq 0, f(\delta) = e(0)\}$.

Step4: Let $p_1 = f(\delta_1)/\delta_1$ and r=1.

Step5: Find $e(p_r)$.

Step6: If $e(p_r)$=0, stop. $q = p_r$ is the solution.

Step7: Find $\delta_{r+1} = \min\{\delta : \delta \geq 0, e(p_r) = f(\delta) - p_r\delta\}$.

Step8: Let $p_{r+1} = f(\delta_{r+1})/\delta_{r+1}$, $r=r+1$and return to Step 5.

Figure A.1 illustrates the above algorithmic steps graphically. In the figure, the y-axis is the value of e when price is p and the x-axis is the quantity of the resource under consideration. $e(0)$ represents the net profit value when the market price for an additional unit of the resource is zero. Thus, the net profit function e at price zero becomes a step function. This value function reaches its maximum when the amount of the extra resource equals δ^*. It implies that any additional resource after δ^* will not increase the net profit under zero price. If the resource is not free, any point beyond δ^* will only hurt the net profit function *e(.)* by increasing the cost of purchasing that resource. If $e(0)=0$, it means that any additional amount of the resource cannot increase the net profit even if this resource is "free". The ASP under this case is zero. If $e(0)$ is greater than zero, like the case in Figure A.1, from Step 3 and the figure, we can get δ^* as the minimum amount of resource that maximizes the net profit function. Step 4 calculates the initial ASP by using the formula $p_1 = v(Q_{\delta^*}) - v(Q) / \delta^* = f(\delta^*) / \delta^*$.

After obtaining the initial ASP, we can draw a total cost line for purchasing the extra resource when price is p_1 and a new net profit function $e(p_1)$ required by Step 5. Unlike the previous case, producers now have to pay the price p_1 for extra units of the resource. Thus, the magnitudes of the steps in the step function *e(0)* and the total cost line $p_1\delta$ represent possible profits ($e(p_1)$ in Figure A.1). In the same way, a new minimum amount of the resource, which is δ^{**} in Figure A.1, can be found tomaximize $e(p_1) = f(\delta^{**}) - p_1\delta^{**}$. Then, starting with step 6 in the Algorithm, the ASP will be updated. This procedure will continue until we find $e(p_r)=0$ where p_r is the solution.