Emissions Permits Auctions: an ABM Analysis

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Abstract. Since the "Kyoto Protocol" a milestone in worldwide efforts towards global warming abatement, many countries are due to design a proper trading of GHG emissions permits. Thus the analysis of the auction institution becomes a major issue. There have been a substantial analytical effort to understand the EPA emissions trading mechanism with very poor results even under extreme simplifying assumptions. EE has revealed why the EPA was to end up as a failure. Why not to take a further step and experiment with soft agents to engineer the appropriate trading system? After showing that we could have advanced the EPA's failure from an ABM approach we argue that the CDA is a suitable choice for the trading permits. We analyse the CDA under different strategic behaviour of buyers and sellers using the same ABM approach, extending previous works with evolutionary adaptation and learning.

1 Introduction

The Kyoto Protocol (1997), ratified later on by the EU, Japan and other countries set a target for collective GreenHouse Gas (GHG) emissions, which required a reduction of total emissions of 5,2 % below 1990 levels by 2010. Of course a major issue was that for the global reduction to be efficient the levels for each country should be at the same marginal reduction costs. This was unacceptable for some countries like the USA, and brings up the typical problems from asymmetric information. A possible way to avoid free riding is to allow GHG emissions to be traded: "emissions trading".

Although the option between a piguvian tax and emissions trading is always an open choice, (and this paper is not the proper place for arguments) many countries including Spain have decided to initiate an emission trading market. In the case of Spain, at the time of writing up this paper, the Socialist Government just approved the National Plan of Emissions Permits for the period 2005-2007. Germany has a tax programme, and the U.K adopted a mixed of tax and trading control. Many countries have now to decide about the proper market design.

The models of exchange traditionally used by economist in general equilibrium theory are simplified for the purposes of analytical tractability to the extreme that they are of scant relevance to guide the designer of real-world exchanges. Among other things, they ignore market power, assume many traders and do not accept strategic behaviour… but economics and trade is a matter of intentions.

An alternative approach is a micro-founded theory of marketplaces: auction theory, in which the rational behaviour of individual agents faced with different pricing and trading rules, is analyzed using game theory. There are analytical solutions only for very strong assumptions about agents rationality, because the dynamic and evolutionary nature of auctions. Apart from the lack of realism of this assumption [8], in the double sided auction (which is the central object of this paper) it is not possible to achieve allocative efficiency and budget balance under individually rational behaviour [10]. The problem is that each trader only knows their own reservation prices. Traders have not enough information to determine the market supply and demand curves.

In the absence of analytical tools to guide auction design, the analysis of these institutions has used computer simulation and laboratory experiments. Why don't we take a step further and experiment with soft agents that could allow us to control the experiment to engineer the trading institution [6, 7]? If the human traders are replaced by software agents, the modeller can control the agent strategies by specifying the decision rules.

In a typical exchange the market institution attempts to match offers to buy (bids) with offers to sell (asks). In the case of emission trading there is an interesting a valuable experience of wrong design: the EPA's annual sealed bid/offer asymmetric auction. It is interesting because the analytical game approach has been unable to explain its properties and because reality has proved the practical value of the predictions from Experimental Economics and the importance of emerging private markets to discipline and benchmark a particular public trading institution. We shall show that with our approach, using artificial agents, we could have predicted the EPA's failure. In this paper we compare two types of exchange:

-The EPA market in which we wait for all trades to place offers before clearing the market and

-A market in which trades are executed as new offers arrive. Following the terminology of [12], we refer this one as the Continuous Double Auction (CDA)

Although a computational analysis can be programmed in standard object oriented language, we use SDML as programming shell, a cognitive strictly declarative language, since the user of SMDL is forced to set up the simulation in terms of the environment (initial endorsements, preferences and transaction costs), the institution (the actual exchange rules and the way the contract is closed) and the agent behaviour.

These three dimensions are essential in the design of any market experiment [13]. A basic fact must be clear: that the institution is a container for the agents. It is important because the strategic agents' behaviour depends on the exchanges rules. In CDA markets traders face non-trivial decisions:

- How much should they bid or ask for their own tokens?
- How soon should they place a bid or ask?
- Under what circumstances should they accept an outstanding bid or ask of some other trader?

In the EPA market traders face only this one decision: How much should they bid or ask for their own emission permits?

We want to remark another aspect: traders must be agents, not objects. There are of course many different definitions of an agent. But in all of them it is necessary to be sure that the agent is autonomous, and consequently different from objects. The following statement can clarify the issue. *Objects do it for free, agents for money*. They, and not the institution, which may be an object, must make the decisions.

The paper is organized as follows. First the EPA's auction is considered. Previous analytical studies of this institution and experimental evidence are summarized. We show the results of our experiments with soft agents with strategic options, that confirm the EPA`s low efficiency. Then we consider the CDA, since for global GHG reduction and with the facilities offered by internet, it looks as a first choice for emissions trading. Finally we comment about the results and conclusions.

2 The EPA´s Experience

In 1990, the first emissions trading auction was introduced in the USA. It was applied to the SO2 emissions of electric utilities since 1993. From 2000 on, all electric utilities participated. Sulfur permits could be traded privately between utilities or in the annual auction in March organized by the EPA. After some years most of the trade was private and the EPA auction sold 2,8 % of the total amount of allowances. The revenues of the auctions were distributed among the allowances holders to encourage clean production activities.

The way in which the auction was organized was quite peculiar, and was not mandatory in the Clean Air Act Amendments (CAAA). The bids were ranked from high to low. The offered permits were sold to the highest bidders. The offers were ranked according to the increasing asking prices, from low to high. The lower asking price was matched with the highest remaining bidder, as long as the asking price was below a bid price. A successful bidder played his bid price to the seller to whom he was matched.

There was substantial analytical knowledge and experimental evidence about the uniform price auction [9, 13, 15] but the asymmetric EPA`s auction was quite an intellectual challenge. The analysis of this auction first made by [1] shows that market-clearing prices are too low and that not all the gains from the trade were obtained. The EPA´s rules could generate significant biased price signals and reduce the efficiency of the trading market. The sellers have incentives to offer units at prices below their marginal costs (or reservation prices). There was some laboratory evaluation by [2] that seemed to confirm his theoretical findings.

These results were soon questioned by further research. Apart from the extreme assumptions made by [1] for analytical tractability, he did not considered the unavoidable relation of the EPA´s market with private trading. He didn't consider the possibility that the participants could be selling and buying at the same time either, to say the least about trader's strategic behaviour. No wonder the EPA´s auction was a failure and a very instructing experience. It proved that the private market should always be allowed to co-exist with a public one to mutually discipline each other. It also proved once and again the scan value of game theory to help governments to decide on some type of emission trading auction. And once more, it called for experimental economics as the primary source to gain in our knowledge of auction design and performance.

It is a good opportunity as well for us to show in the following that we could have predicted the EPA´s failure using an ABM approach.

3 ABM Simulation of EPA Trading Emission Permits with Strategic Agents

In the works referred earlier on, the strategic behaviour of the agents was far too simple. We shall allow for richer strategies.

In a EPA auctions we consider four types of agents: the environment, the EPA institution, the buyers and the sellers. Participants are assigned a fixed role of either buyer (only submit bids) or seller (only submit asks). The assumptions of fixed roles conform to extensive prior studies, including experiments involving human subjects and software agents. The interactions between them are simple (Table 1).

Table 1. Interactions between agents of EPA model. Agents in rows send the information to agents in columns

Receive / Send	**Environment.**	**EPA**	**Buyer-$_j$**	**Buyer-$_k$**	**Seller-$_i$**	**Seller-$_k$**
Environment.	*efficiency*		*PR*	*PR*	*CMa*	*CMa*
EPA			*Price*	*Price*	*Price*	*Price*
Buyer-$_j$	*profit*	*bid*	*HMBid profit*			
Buyer-$_k$	*profit*	*bid*		*HMBid profit*		
Seller-$_i$	*profit*	*ask*			*HMAsk profit*	
Seller-$_k$	*profit*	*ask*				*HMAsk profit*

In our EPA model the reservation prices (*PR*) and the marginal costs (*CMa*) are generated randomly from a uniform distribution. These values are sent to traders (first row).

Each agent only faces the following decision: To think (*HMBid* or *HMAsk*) and to make an order (*bid* or *ask*, second column).

The EPA institution waits for all trades to place offers before clearing the market. It ranks the bids, from high to low, and the asks, from low to high. The lower asking price is matched with the highest remaining bidder by the institution, as long as the asking price is below a bid price. The *transaction price* is at the bid price. The matches are sent to the traders (second row).

Those agents that have traded calculate the profit (diagonal). At the end of the period, the *market efficiency* is calculated as the ratio of actual to theoretical populations surplus (first cell of first column).

The initial works to modeling agent behavior in auctions were published ten years ago [5, 6]. We use the GD strategy developed by [4] because it is in the line of analytical EPA models This strategy was developed for a CDA market, so we have done some modifications.

We use the ZIU strategy developed by [5] as a training strategy during the two first periods. A Zero Intelligence Unconstrained agent generates random order prices ignoring the state of the market and it is free to engage in money losing transactions.

Each GD buyer for each bid forms a subjective belief *q(b)* that some seller will accept the bid. GD agents use the history H_M of the recent market activity (the bids and asks leading to the last M traders: *ABL* accepted bid that are less than *b*, *AL* accepted bid and ask that are less than *b*, *RBG* rejected bid that are greater than *b*, etc.) to calculate this belief. Interpolation is used for prices at which no orders or traders are registered in H_M to calculate the belief function *Π*.

$$\hat{q}(b) = \frac{ABL(b) + AL(b)}{ABL(b) + AL(b) + RBG(b)} \,. \tag{1}$$

The buyer then chooses a bid *b* that maximizes its expected surplus, defined as the product of the gain from trade (equal to reservation price minus price *b*) and the probability for a bid *b* to be accepted Π_b.

$$\max \hat{B}(b) = \max \Pi_b \left(PR - p\right). \tag{2}$$

We have modified the original GD algorithm for sellers because in the EPA auction the transaction price is the bid price of the buyer to whom the seller is matched. The seller then chooses an ask *a* that maximizes its expected surplus, defined as the product of the gain from trade (equal to price *b* minus marginal Cost) and the probability for a ask *a* to be accepted Π_a.

$$\max \hat{B}(a) = \max \Pi_a \left(\hat{p} - CMa\right). \tag{3}$$

Each seller for each ask forms a subjective belief that some buyer will accept the ask like in [4]. We estimate the price as the average transaction price in H_M for each ask *a*. Interpolation is used for prices at which no traders are registered in H_M.

Twenty agents were used in the simulation of thirty runs and 15 periods per run. Simulations were run with one and ten emissions permits for each bidder/offer. In Fig.1 we show the results of our simulations with GD agents.

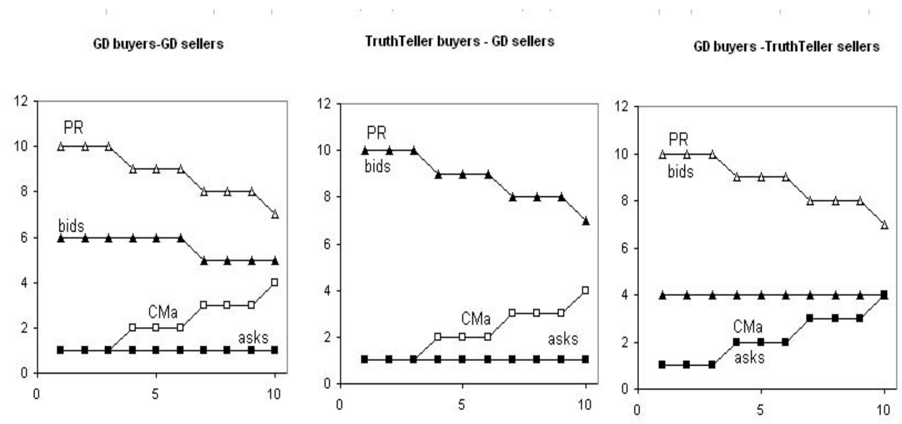

Fig. 1. EPA´s auction. Bids and asks behaviour after some learning

When the bidders are passive (truthteller) and the offers are strategic (GD), make offer to seller below their marginal costs. When the bidders are strategic (GD), and the sellers are passive (truthteller), the offers to buy are far less than the reservation prices, and near the low base of the price tunnel. When all the traders are GD intelligent after some initial periods they settle in a way that asks are always below bids, and these are very near the uniform clearing price as it could be expected.

The EPA auction created strong incentives for both buyers and sellers to underreport their true reservation values. In the extreme case where both behave strategically with learning from each other, the near uniform clearing price is reached to the advantage of the sellers…something that conventional Experimental Economics seemed to indicate and that theory could not prove. Yet it is very easy to simulate with our ABM approach. A kind of tacit collusion seems to occur within each group.

When we use more buyers than sellers (more contaminant industry) we obtain higher bids (and higher prices) than when there are the same number of buyers and sellers. No differences were visible when we variety the number of permits per agent.

3 CDA Market

Our goal is to design a highly efficient market for trading emission permits and to develop bidding agents who achieve high profit and whose performance should be robust with respect to various opponent strategies, potentially including copies of itself.

We choose the CDA institution is because it is the dominant institution for the real-world trading of equities, derivatives and commodities, and with the internet facilities looks like a first choice for global GHG reduction through trading emissions permits. Besides there is a substantial insight on CDA from Experimental Economics with humans agents [13].

We use one form of CDA, CDA *with order queue*, because the convergence to equilibrium is faster [13]. Under this market mechanism, a trader may make a bid or an ask at any time (round) during the trading period, but once it is made it will persist until the trader chooses to alter it, remove it or it is accepted. A trade takes place when any buyer accepts the ask of a seller or any seller accepts the bid of a buyer.

Although experiments directly reveal agents' behaviour, their decision rules and the impact of these rules on individual and aggregate performance are not directly revealed in experiments. However, CDA is a complex dynamic systems and we need a framework that captures the basic dynamics of the system.

Despite the fact that CDA is a complex dynamic system the interactions between agents are simple (Table 2).

Table 2. Interactions between agents of CDA model. Agents in rows send agents in columns the information

Receive / Send	**Environ-ment.**	**CDA**	**Buyer-$_j$**	**Buyer-$_k$**	**Seller-$_i$**	**Seller-$_k$**
Envi-ronment.	*efficiency*		*PR*	*PR*	*CMa*	*CMa*
CDA			*Price QueueBid QueueAsk cuBid cuAsk*	*Price QueueBid QueueAsk cuBid cuAsk*	*Price QueueBid QueueAsk cuBid cuAsk*	*Price QueueBid QueueAsk cuBid cuAsk*
Buyer-$_j$	*profit*	*bid*	*HMBid profit*		*acceptedAsk*	*acceptedAsk*
Buyer-$_k$	*profit*	*bid*		*HMBid profit*	*acceptedAsk*	*acceptedAsk*
Seller-$_i$	*profit*	*ask*	*acceptedBid*	*acceptedBid*	*HMAsk profit*	
Seller-$_k$	*profit*	*ask*	*acceptedBid*	*acceptedBid*		*HMAsk profit*

At the start of the simulation, buyers and sellers are given randomly a list of reservation prices or marginal costs (*PR* or *CMa*, first row). Each agent makes the following tree decisions:

- To think an order (*HMBid* or *HMAsk*, diagonal).
- To make an order (*bid* or *ask*, second column). All the agents have thought an order but only some of them actually make it in accordance with its strategy. We emulate asynchronous activity of making bid/ask through random activation of a subset of agents at each round. Each agent has a constant activation probability 25% per round like in [16]. The CDA institution ranks

the bids from high to low and the asks from low to high (*QueueBid* and *QueueAsk*, second row).

- To accept an open order. A seller issues an offer less than the best bid (*acceptedBid*) to accept an existing bid at the *currentBid* price. Similarly, if a buyer wishes to accept an existing ask at the best ask (*acceptedAsk*), the buyer issues a bid greater than the *currentAsk* price. Each transaction consists of one or more rounds of solicitations of bids and asks from traders. Orders placed at each round are processed by the traders to be exchange in a random sequence, using the opening order to set the trade price. Those agents that have traded in a round calculate the profit (diagonal).

On any subsequent round, an agent can update its order or accept an open order.

Software agents may achieve high allocative efficiency in CDA markets (near 100%). Although the Zero-Intelligence agents developed by [5]may achieve high market efficiency, intuitively it seems obvious that one should endorse the agents in a CDA with both, intelligence and adaptation. ZI agents perform poorly when they are competing with agents with learning capacity [14].

The GD agents learn very soon to trade at a price very close to the competitive equilibrium price (Fig.2). The transactions are made in the first rounds of each period. The CDA market efficiency is near 100%.

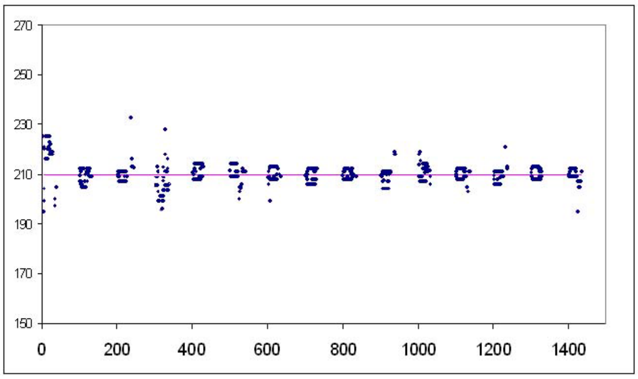

Fig. 2. Evolution price for a GD population in a CDA.

Other types agents developed for CDA markets are Kaplan and ZIP. In [16] these three types agents (GD, K and ZIP) rival each other.

The Kaplan strategy was the winner of the Santa Fe tournament [12]. The basic idea behind the Kaplan strategy can be summarized as: wait in the background and let others negotiate. When an order is interesting, jump in and steal the deal. An agent with a Kaplan strategy does not perform well against itself and to obtain profit it must be parasitic on the intelligent agents.

In [3] an agent with adaptive learning, the ZIP agent was proposed. Each agent has a mark up μ that determines the price at which it is willing to buy or sell. The agents learn to modify the profit margin during the auction using information about the last market activity. ZIP agents take more time than GD agents both to exchange and to learn. The market efficiency is between 80% and 100%.

Following [16] we have replicated their experiment. They found two Nash equilibria points for games with 16, 18 and 20 agents that are labeled NA (which assigns zero probability to the GD strategy choice) and NC (which assigns zero probability to the ZIP strategy choice), and the saddle point NB.

It was a surprise for us because GD agents learn very soon to trade at a price very close to the competitive equilibrium price. To explain it we allow our soft-agents to change their strategies in an autonomous process instead of fixing the agents strategies from the modeler like in [16].

4 Strategy Change in CDA Market

Our goal is to examine the emergence of Nash efficient solutions with a bottom-up approach and to develop bidding agents for CDA markets who achieve high profit whose performance should be robust with respect to various opponent strategies, potentially including copies of itself.

We endow the soft-agents with ZIP, Kaplan and GD ask-bidding strategies. But instead of fixing the agents strategies, we allow our soft-agents to change their strategies in an autonomous and evolutionary process. Thus, we extend previous works and we introduce evolutionary learning and adaptation.

Each agent chooses a strategy from a set of three alternatives (GD, K and ZIP) at the start of each period. The initial strategy is chosen randomly. On subsequent periods, an agent will consider to change its strategy if the profit is less than the profit from the previous period. The agent considers whether he could have reached higher profits following an alternative strategy. To this end he assesses the transactions he made in the past. He considers both the transactions in which he took an active ask-bid strategy and those where he passively accepted the bid-ask (Fig.3).

In the first case, there are three possible alternatives for the buyer.

1. The bid of the alternative strategy was lower than the minimum price of exchange for this period. In this case the buyer will assume that no seller would have accepted it.
2. The bid of the alternative strategy was lower than the realized bid, but greater than the minimum transaction price for that period. Then the buyer will consider that the bid would have been accepted and he could have obtained greater profits.
3. The bid of the alternative strategy was greater than the realized bid. Then, he could have obtained lower profits.

In the second case, above, there are only two possibilities:

1. The bid of the alternative strategy was lower than the seller's ask. The buyer would have rejected the ask with no profit.

2. The bid of the alternative strategy was greater than the seller's ask. Then he could have obtained the same profits whatever was the value of the bid.

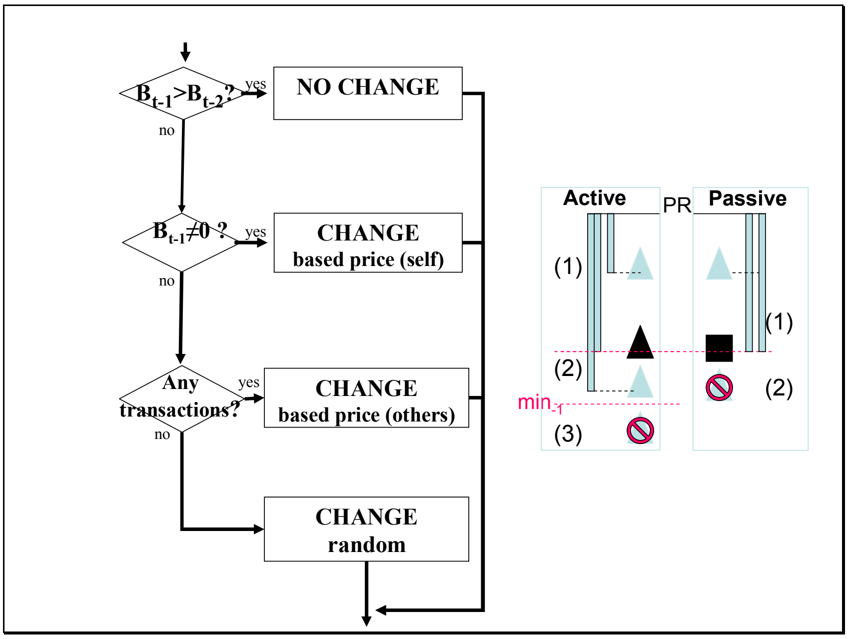

Fig. 3. Buyers algorithm to change the type of strategy for each trading period

If an agent has not traded yet, he will consider the transactions made by the other agents and he will proceed with the same criteria discussed above. If an agent has no information at all, and there are no open orders, he will change his strategies in a random way.

In Fig.4 we show the dynamics of the change in strategies for initial GD populations. Some GD agents consider whether they could have reached higher profit following a Kaplan strategy. But there is a maximum number of parasitic agents in the market.

In Fig.5 we show the evolution price during the strategy changes. The volatility of this price series is greater than the volatility of the price series from GD agents (to compare Fig.2 with Fig.5).

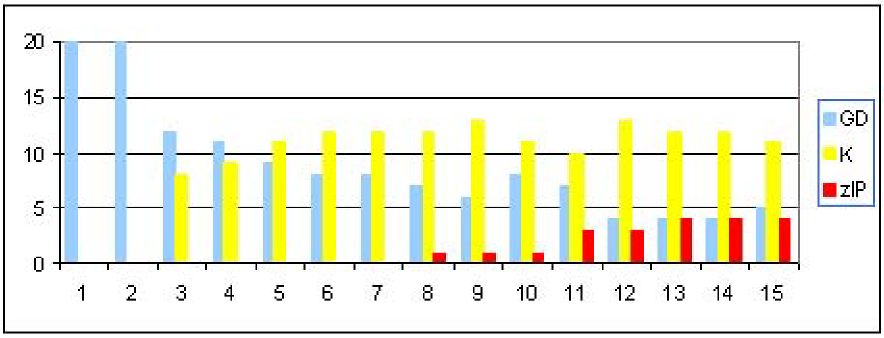

Fig. 4. Strategy change in initial GD population for CDA.

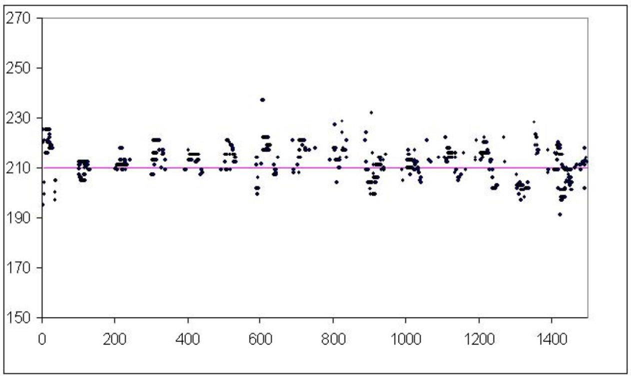

Fig. 5. Price Evolution when initially GD agents change its strategy in a CDA market.

We found that not only the proportion of strategies is relevant. It is important as well the proportion of buyers and sellers. An interesting case is that in which 50% are K agents because the agents can change the institution through its strategy if this 50% of K agents are all in one side of the market. We have simulated two scenarios.

In the first scenario the agents have fixed strategies. In Fig.6 we show the evolution price and the efficiency market. When this 50% of K agents are all buyers the transaction prices are below the competitive equilibrium price. On the contrary when they are all sellers the transaction prices are over the competitive equilibrium price. Our results reproduce those of [12]. When no side is silent there is an increase in efficiency and the transaction prices approach better the equilibrium. It is no a surprise since there is more information.

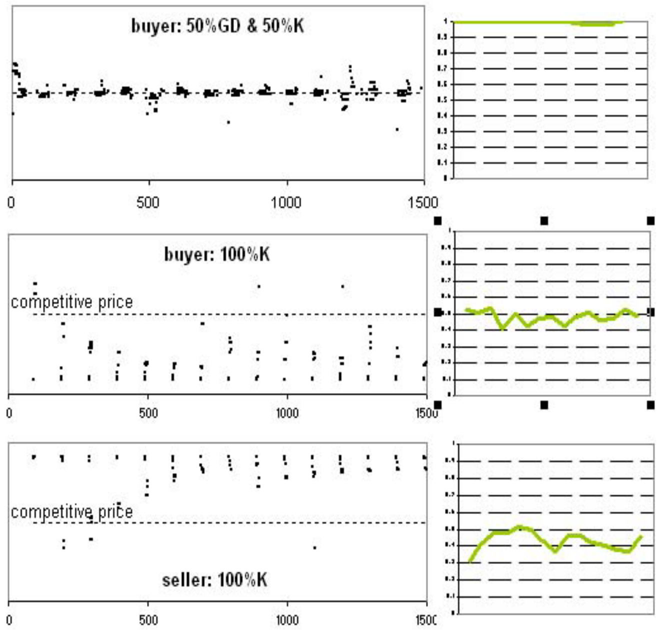

Fig. 6. Price dynamics and efficiency market when 50% are Kagents and 50% are GD agents in a CDA.

In the other scenario, assume that we start the simulation with a proportion of 50% of K agents but we allow them to change their strategies to increase its profit so that they can move to ZIP or GD all along the experimental run. As it can be seen from the Fig.7, the transaction prices are very near the competitive equilibrium price and there is an increase in market efficiency (near 100%) in all cases (to compare Fig.6 with Fig.7).

We have represented (not reproduce in here for space reasons) the strategy space by a two dimensional simplex grid with vertices corresponding to the pure strategies: all ZIP (point a), all GD (point d) and all K (point f). We have found that no matter what the initial population of agents is, the final composition of agents remains in a central region, where no strategy seems to dominate. Thus there are no attractors Nash equilibriums [11].

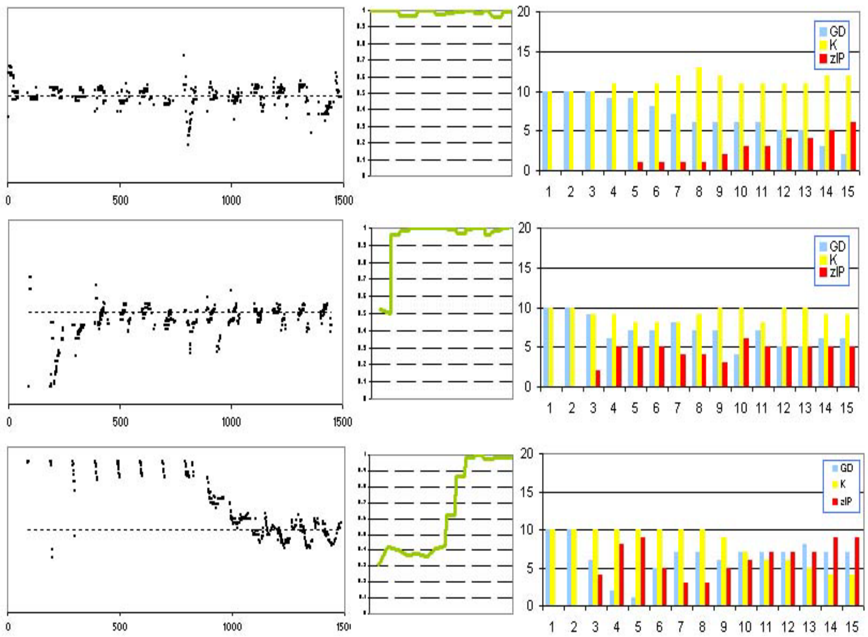

Fig. 7: Price dynamics and efficiency market when initially Kagents (50%) and GD agents (50%) change its strategy in a CDA market.

6 Conclusions

Auction engineering is of the most importance in economics, as auctions have been with us for ages. But unfortunately it is out of the conventional microeconomic textbooks with some exceptions that give this topic a brief and minor consideration. This importance has been enhanced with the use of internet, where many kinds of auctions and soft brokers can be designed. Yet there are very few founded results, in spite of the efforts of Vickery and other orthodox economists. The failure of the EPA´s emissions trading has shown that we need a better understanding of the way to achieve efficiency in auctions.

To this end models of exchange traditionally used by economists in general equilibrium theory are of little relevance for the designers of real-world emissions trading auctions, because they are drastically simplified for the purposes of analytical tractability. To allow for strategic behaviour among the traders game theory has been extensively used. But the dynamic nature of auctions defies mathematical game theory and ask for computational and laboratory experiments. Within this approach we claim that multi agent and bottom-up simulations where patterns and possible rules can emerge are very useful to design emission trading auctions.

We have shown that the failure and inefficiency of the EPA´s trading mechanism could have been predicted with our ABM simulation experiments. Since internet allows for a global emission trading a natural choice could be a CDA, since many real-world auctions are of this type.

The main problem to use conventional market theory with CDA markets is that the participants only know their reservation prices. Yet as the old Scottish philosophers advanced, coordination and market efficiency can be achieved in a generative and evolutionary mode. Although Experimental Economics has provided us with a lot of valuable knowledge, a simulation approach with soft agents is a very convenient alternative, since it allows the experimenter to calibrate the effects of different agent capabilities and the effects of institutional rules (norms).

In this paper we present results for CDA markets with different strategic behaviour, that are at odds with claimed experimental evidence from an up-bottom approach, which seemed to show the existence of Nash equilibrium. We do not find such results in our simulations if the auctions agents can adjust their strategies in an evolutionary way closer to the agents' behaviour in the real world. It seems that the final outcomes and the relative CDA efficiency strongly depend upon path, the types of agents and the initial composition of the population.

Many extensions to our analysis are possible. One could connect private and official markets. Allow for inter-temporal exchange (option strategies) and for the traders simultaneously to buy and sell, etc. Of course our evolutionary approach is a premier in the field, and more experience has to be gathered before we could claim both theoretical and practical value for the design and engineering of emissions trading auctions.

Acknowledgement

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