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CARBON PRICING IN DYNAMIC REGULATION AND CHANGING ECONOMIC ENVIRONMENT - AGENT BASED MODEL

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ABSTRACT

Like many industries, the financial services sector increasingly confronts a market environment in which both consumers and regulators are anxious to see organizations develop green products and services that hold the promise of mitigating environmental degradation and encouraging sustainable use of resources. Industry players must therefore be adept at reading demand signals from each of the primary financial services sectors (retail banking, corporate and investment banking, asset management, and insurance) while also keeping a sharp eye on evolving changes in these highly regulated businesses driven by proactive government policies (Porter and Kramer, 2006). Weather derivatives, energy trading and natural resource exploration are only few of the sustainability topics vital for the economic future of our province (Alberta), and the entire world. Our paper presents an overview of complex adaptive systems and the basics of building a model of CAS. We consider CAS to be well suited to the modeling of market behavior because it is robust to micro-level behavioral influences and allows the inclusion of heterogeneous agents. CAS also offers the possibility of capturing the dynamics of agents experience through features such as learning and memory. We present an agent-based model for pricing carbon emissions and results of simulations based on Alberta's current data of demand, supply, and regulation of carbon emissions. Pricing carbon drives innovation in technologies that improve efficiency, reduce pollution and recognize the social cost of business. We analyze the results of simulations in a dynamic framework of changing parameters and input variables.
Keywords: Agent Based Modeling, Carbon Market, Alberta Carbon Trading Scheme, Swarm software

INTRODUCTION

Global warming is a looming threat to our world today- a scary threat that our consumption and production habits over many years could doom the earth and make it uninhabitable in a few centuries to come. Sea levels are expected to rise, weather patterns are likely to change dramatically, frequent extreme weather occurrences will likely ensue, agricultural yield will necessarily drop, and some organisms in this ecosystem (including humans) are likely to be unable to adapt rapidly enough and go extinct. These are just a few of the consequences of unbridled global warming trends (*Houghton*, 1994). If our production and consumption processes remain ingrained with practices that heavily emit greenhouse gases, it is unlikely that they could be sustained for long. Worse still, by continuing on the current path, the world as we know it today may self-destruct.

The foregoing underlines the general need for a change in how we live, in order to preserve the earth. Practices in manufacturing, agriculture, exploration, and transportation especially need to be revised with the aim of reducing their current negative externalities. Since industries thrive on energy, this roughly translates to the development of alternative energy sources which shall reduce our dependence on fossil fuels. The burning of fossil fuels for energy has been identified as the heaviest culprit in green house gas emissions. Substituting other methods of energy generation should lead us to a cleaner and healthier world. However, this alone has proven an inadequate strategy due to limits to the development of technologies which efficiently harness these alternative sources.

Since energy-source substitution on a global scale cannot be an instantaneous occurrence, a major complementary strategy which is currently being given profuse attention is abatement; which entails the reduction of emissions by the establishment of projects which remove greenhouse gases from the atmosphere. The main focus of this approach is on carbon emissions which account for about 90% of total green house gas emissions (*US Gov*, 2006). These projects are expected to be paid for ultimately by emitters, who shall be required to buy up chunks of them in order to continue producing after exceeding their allotted emissions limit (*Stavins*, 2008). This added cost of production may itself discourage excessive emissions and encourage firms to develop better emissions-efficient processes and technology- thereby speeding up the process of achieving more sustainable habits in pursuit of an inhabitable future.

The strategy adumbrated on above is our broad concern in this study. In particular, how this framework that makes industry responsible for the social cost of its carbon emission-inefficient practices, can be optimally operationalized is our main focus. The current global trend is to execute this framework through markets where those chunks (defined as emissions credits) are sold at prices determined by market forces. These markets are burgeoning by the year, and starting to evolve from amorphous setups into more developed structures with the advent of stimulating global regulations and national policies (*Capoor and Ambrosi*, 2008). However, their form can hardly be understood through existing traditional market models given their evolutionary nature which evades the many assumptions intrinsic to traditional economic theory. Models imbued with more realism (perhaps at the cost of tractability) seem necessary if we are to understand the dynamic workings within these markets.

Our paper presents an overview of complex adaptive systems (CAS) and the basics of building a model of CAS. We present an agent-based model for pricing carbon emissions and results of simulations based on Alberta's current data of demand, supply, and regulation of carbon emissions. Pricing carbon drives innovation in technologies that improves efficiency and reduces pollution. We analyze the results of simulations in a dynamic framework of changing parameters and input variables. Agent-based modeling and complexity research methods aid in tackling problems related to economics and climate change, provide quantitative data for assessment of policy, and regulate intended results in a complex dynamic framework. We aim by this study, to provide a starting point in model building by constructing a simple model that captures some salient realities about the agents, environment and dynamics of interactions within the Alberta Carbon Market. We hope to have also built a model that shall be robust to mutations over time and that shall prove adaptable to other similar financial markets. In terms of practical gains, we also hope to have gained an understanding of what types of structures and regulatory policies could aid stability and healthy buoyancy of prices within this market.

In what follows, we give a brief background on agent based models, followed by a description of the Alberta carbon market. In the third section, we describe our proposed model and explicate on its peculiarities. We also discuss preliminary observations and our expectations from future simulations. The concluding section considers the gains, limitations to the study and areas in which the model could be improved in future studies.

MATERIALS AND METHODS

Agent based models

The modeling approach proposed for this study is one which is sensitive to the complexity inherent to the study of markets. Previously, economic researches of markets have been based on reductionist assumptions in pursuit of tractability. In particular, such models assume homogeneity of agents, i.e. *homo economicus* – the rational utility seeker – and thereby discount the full behavioral diversity of human motivation. While this has been helpful in gaining enlightenment on how diverse variables are related when isolated, the resultant theories have often been confounded by the realities suggested by empirical time-series data (*Campbell*, 2000). A very plausible explanation for these deviations may be that reductionism assumes away the complex realities of interactions among variables (in a model) and also ignores the underlying dynamics of interactions among economic units.

Based on this line of thought, a growing army of researchers have in more recent times turned attention to the study of complex systems. Fortunately, this school which embodies both a philosophy and specific techniques has been burgeoning with the development in sophistication of methods for exploring complex phenomena in other fields such as biology, computing and information technology. Today, these evolving methods which were born in other fields are being applied and adapted to the meaningful study of macroeconomic phenomena as well.

Agent based modeling is a technique for modeling complex phenomenon. Classical econometric models have failed over time to explain trends in real-world data (*Mitchell*, 2009; *Campbell*, 2000). Perhaps this stems from the fact that econometric models like most positivist models, assume a reductionist stance to problem solving (*Descartes*, 1637/2006). Econometric models assume macro-level behavior without consideration of how that behavior is generated. Such neglect may be trivial for static systems, but becomes costly when the system or unit being studied has a dynamic and adaptive nature.

Real economies are adaptive, and markets evolve over time. Classical economics (upon which econometric models are built) often attributes this evolution to exogenous factors. In reality, a market may evolve due to the interaction of factors within itself apart from exogenous influences. This is the logic underlying agent based modeling; the parts together may yield behavior that greatly differs from the anticipated behavior of their additive whole, and the explanation of macro-behavior may well be hidden within the dynamics of micro-level interactions of constituent units (*Beinhocker*, 2006). While this is true in most complex phenomenon, it is most obvious during bubbles and crashes.

Therefore, in order to capture the complexity of market behavior rather than making assumptions a priori, agent-based modeling simulates the behavior of many heterogeneous units which interact to define the market. This intuitively has a greater chance of achieving a tight fit with real world data than a simplistic model based on assumptions built on an ideal world (*Axelrod*, 1997). As outlined by *Bonabeau* (2002), agent based modeling yields promise when non-linear relationships are likely to subsist, agents are deemed heterogeneous in their interactions, averages are not reliable, and individual agents exhibit behavior such as memory, learning and adaptation in the system of interest. The Carbon trading market shows signs of all these features and so seems a great candidate for agent based modeling.

Carbon trading as a concept is relatively new. It dates only as far back as 1997 (*Kollmuss et al.*, 2010). Even so, the formal adoption of the Kyoto protocol subsequent to the Kyoto convention has been very slow. In Canada, it is still a very young and underdeveloped market. Thus, rich data such as time series or panel data are scarce. Due to the fact that many countries are yet to incorporate actual frameworks or policies, the market also does not exist in many countries. Thus, even cross-sectional data is scarce. This lack of data is one reason why agent based modeling is well suited for this study. By simulating data, it is hoped that we can understand the dynamics of the market despite not having had the market for an adequately long period of time and across diverse countries.

A related but equally compelling reason for employing this modeling technique is the evolutionary nature of the market. Agent-based modeling easily lends itself to simulations of evolutionary systems (*Axelrod*, 1986) due to its micro-level development. It allows for building in adaptive agents who themselves evolve to define a dynamically evolving market. It shall also illuminate our understanding of the relative importance of small differences in initial conditions on short, medium and long-run outcomes. Consequently, concepts such as information, memory and learning can be incorporated into micro-level behavior, and the effects of these on the quality of the market can be analyzed.

Past efforts in market modeling using an agent-based approach have mainly focused on the stock markets. Among these, the research styles range from purely analytic to heavily computational (*LeBaron*, 1995). Analytic studies such as *Kelley* (1956) and *Friedman* (1953) presented arguments which emphasized the role of agent heterogeneity in strategies and ultimate survival within an economic environment. *Figlewski* (1978) examined heterogeneity within the context of wealth dynamics and specifically considered how wealth dynamics affects the convergence of a market to efficiency. More recently, *Bossaerts* (1994) discovered that the speed of the learning process of different agents can have significant effects on the stationarity of financial time series data. All these demonstrate diverse aspects of the role that heterogeneity may play in market outcomes.

Computational models have witnessed an upsurge in numbers and variety in recent times. Drawing on recent developments in artificial intelligence and computing science, modern approaches such as genetic algorithms (GA), classifiers, and neural networks have been applied to financial problems in addition to more traditional methods such as least squares learning. *LeBaron* (1995) advocates that the main prerequisite to determining the appropriate computational technique for a given study is having precise knowledge of: "what domain the agents knowledge lies in; what types of equilibria lie in that domain; and how agents move in this domain by updating beliefs" (p. 2).

Lettau (1993), *Arifovic* (1996), and *Routledge* (1994), employ the use of well-defined simple economic models which focus on learning as a tool to explore both stability and evolution of markets within genetic algorithmic frameworks. These frameworks are generally less open in structure relative to neural networks such as that used by *Beltratti and Margarita* (1992), and classifier based systems used by *Marengo and Tordjman* (1995). In generally, these studies found scenarios in which the markets do not settle down to equilibrium for long due to agent heterogeneity in terms of risk-attitude, information quality and accessibility, network-types and memory.

Perhaps the most extensive agent-based market simulation to date, the Santa Fe Stock Market attempts to fuse a well-defined market trading mechanism structure with an inductive-learning oriented classifier based system (*Arthur et al*, 1997). This study shall lean on the logic of the techniques employed by the Santa Fe Stock Market in building a simple evolutionary model with specific applicability to the carbon-trading market.

The Alberta carbon market

Carbon-trading markets have recently sprung up in many developed countries- subsequent to the Kyoto protocol which enlists it as one of the major abatement strategies for economies. The Alberta emissions trading scheme is one of such responses which was effectively created in July 2007 by legislation (*Alberta Environment*, 2008). Its main objective is to regulate the emission of large emitters by determining an efficient price on emission, which will tend to reduce emissions without crippling the productivity of firms. The Large emitters- numbering about 100 corporations- are defined as those corporations which exceed 100,000mtCO_2e in emissions per annum (*Alberta Environment*, 2007). They are required by statute to reduce this by 12% every year from 2007 to 2014 calculated with a baseline of 2003-2005 (*Specified Gas Emitters Regulation*, 2003). The top 30 emitters were responsible for about 87 percent of total emissions in 2006 (*Goddard et al.*, 2008). This implies a non-normal distribution where the demand side in the market is likely to be dominated by a strong minority with very large demand size. This reality further justifies the adoption of a complexity-oriented methodology which makes no rigid assumptions about the underlying distributions in the market. With agent based modeling, the effect of power laws in ensuing interactions can also be recognized.

The Alberta scheme, while sharing many similarities with other emissions trading schemes, is different in a few ways. It is planned as a closed market. The market is administered by government with a stakeholder-based approach to decision-making and planning. Alberta statute recognizes only offset projects executed within Alberta (*Kollmuss et al*, 2010). Also, only Alberta-raised credits can be surrendered for compliance purposes by regulated Alberta companies. However, a leakage may exist in future if players from other markets are able to purchase credits from the market in order to meet compliance in their own environment. This may lead to an exogenous hike in the prices of credits. Currently, this is not the case. Non-Alberta corporations seem to be restrained from this incursion either because the markets are still emerging (information issues), compliance is yet to become strict, prices are not sufficiently low (especially when transaction costs are factored in), or because their own local regulations are still fuzzy.

There are two types of carbon credit recognized by the provincial government- Emissions performance credits, and Alberta-based offset credits (*Alberta Environment*, 2011). An alternative method with which a firm could buy up rights to pollute beyond stipulated thresholds include- Climate change and emissions management fund (CCEM). Also, corporations could improve their operations in order to consume within the statutory level stipulated.

MODEL SPECIFICATION AND DISCUSSION

Agents

By definition, agents in every market can be broadly classified into two groups; buyers (the demand side) and sellers (the supply side). The Alberta Carbon market, despite having several players active in it conforms to this functional classification. From the Specified Gas Emitters Regulation (*Alberta Environment*, 2011), we can clearly identify the buyers as including large regulated emitters who require the carbon credits for compliance. These large emitters are a hundred in number and they all fall into the regulation cadre due to their emissions being in excess of 100mtCO_2e per annum. In order to engender realism, the same numbers of large emitters are recognized in our model. It is noteworthy however, that this is not a homogenous group, since 30% of these large emitters is responsible for over 80% of total emissions (*Goddard et al*, 2008). The behavior of this top 30 is likely to be different from and have more impact on the market than that of the lower 70. Also there will be some of these emitters who will be able to develop emissions-efficient technology easier and thus save on cost of credits. These details on heterogeneity shall prove resourceful as the model gains sophistication.

In addition, apart from regulated firms, it is possible that traders will be allowed over time who intermediate in the market on behalf of investors and speculators (as is obtainable in stock markets). Their behavior is likely to differ meaningfully from that of large emitters who need credits as inputs for production. Our model includes 20 of such position traders who predict the medium to long term profitability of carbon credits based on adaptive expectations.

We start with a very simple premise that each agent has an objective function which it attempts to optimize subject to some constraint. From the preceding paragraph, we established the (non-exhaustive) existence of two major types of buyers- large emitters, and traders. We assume that they each attempt to optimize as follows; emitters minimize expenditure on credits subject to production targets while traders maximize profit gained by trading credits. The optimization task for traders will incorporate their forecasts and changing strategies due to learning and memory. The emitters in our model minimize their cost subject to their production function, that is;

$$\text{Minimize: } C = P_c\, C + P_e\, E \quad (1)$$

$$\text{Subject to: } Q = C^a\, E^b \quad (2)$$

Where C = Cost function
P_c = Price of a unit of carbon credit
P_e = Price of a unit of the CCEM
C = Quantity of credits used as inputs
E = Quantity of CCEM used as inputs
a & b = Elasticities of substitution for both inputs

We assume the Cobb-Douglas production function for simplicity. We also assume that emitters differ in their returns to scale based on size, with the largest 30 experiencing decreasing returns to scale ($a + b < 1$), while the remaining 70 enjoy increasing returns to scale ($a + b > 1$). Thus, as modeled, emitters buy just as much credits as necessary to produce their cost minimizing level of output. For example, if price of credits were to increase (ceteris paribus), they will choose to purchase more of CCEM to the extent that their cost minimizing goal is achieved. These functions feed into their individual demand functions to determine their behavior as the demand side of the market.

We use very simple heuristics to design traders assume for simplicity that only momentum traders exist within the market. They simply make their choice to buy when they foresee that prices will be higher in a future period by which they could sell and earn a profit. Specifically, momentum traders forecast of transaction price of credit in the next period is denoted as:

$$P_{t+1} = 1/N \left[\sum P_{t-n}(P_{t-n} / P_{t-n-1}) \right] \quad (3)$$

Where $n = 0,\ldots,4$ is the number of lags in periods
P_t = Price in the current period
N = number of items summed

As indicated, we allow n to vary between 0 and 4 while setting $N = 5$ thus keeping the forecast as a function of the 5 year moving average of credit prices.

Sellers on the other hand were indicated to include- the unregulated industrial sector (facilities emitting below 100mtCO_2e/yr), regulated corporations, the agricultural sector, and project developers (*Alberta Environment*, 2011). In order not to complicate the model excessively, we assume that regulated companies cannot sufficiently reduce their emissions to the level that they can earn credits which they resell. Companies within the unregulated industrial sector may raise credits by reducing their emissions for instance and sell those credits earned to the regulated corporations. Their goal will be to maximize earnings from sales of credits subject to the constraints of their costs and emissions-reduction capacity. In essence, unregulated firms have a carbon credit supply curve that is a function of changes in their scale of production, level of accessible technology, and the market price for credits.

That is;

$$QS_c = f(\Delta Q, T, P_c) \quad (4)$$

A firm which increases its scale of production for instance, has to either reduce its supply of credits to the carbon market or access a higher level of carbon efficient technology in order to maintain its previous supply levels. Similarly, the price of credits acts as an incentive to firms if by selling such credits, they are likely to make more profit than by increasing their production levels. Unregulated firms as designed in our model, adopt a very basic forecast and shortsighted heuristic; $P_{t+1} = P_t (P_t / P_{t-1})$ (where P_t = Price of credits in current period) in which price in the next period is a function of price in the current period and the previous period.

The agricultural sector and project developers which are directly involved in abatement projects (such as carbon sequestration) shall seek to maximize their earnings from credits subject to the cost of those abatement projects. Thus they face a supply curve of the form;

$$QS_c = f(P_{t+1}/ C_p) \quad (5)$$

Where C_p = Cost of the project per unit of realizable credit

QS_c = Quantity of carbon credits supplied to the market

If $P_{t+1} / C_p \leq 1$; No profit is made, no developer wants to participate in an ungainful market and supply $QS_c = 0$

If $P_{t+1} / C_p > 1$, Profit is made, and QS_c varies directly with the level of profit.

Their function is similar to that of traders but differs in that a 10 year moving average is used rather than the 5 year variant (i.e. N = 10). This follows intuitively from the fact that projects are often highly capital intensive and take a while to implement. Also, agricultural and project developers have a lower threshold for risk than traders, and so attempt to access more information by longer memory.

Finally as can be expected, traders also feature on the supply side by employing the previously discussed forecast heuristic; they take positions based on anticipated trends and sell to the market if they anticipate a possibility of making a spread or cutting a loss. Typically, traders in the model sell whenever current price exceeds the price at which they bought, provided prices are expected to take on a decline.

Our agents all exhibit behavior as defined by objective functions very much unlike the agents in *Gode and Sunder* (1993), which employ "zero intelligence" budget constrained agents because agents in their model are not capable of learning or adaptation (their study is more concerned with institutional dynamics). Other studies have modeled agents based on trading rules without any objective functions, but these achieve simplicity at the cost of stifling the evolution of new strategies. Agents in our model are more similar to those described by *Levy et al.* (1994), *Arifovic* (1996), and especially with *Arthur et al.* (1997) which incorporate forecasts of future prices into their agents' decision making framework. Future models are likely to improve on this agent specification by allowing for variability of inter-temporal optimization plans.

Trading Mechanism

In the absence of the convenience afforded by equilibrium modeling, it becomes necessary to specify the process through which trading occurs and by which the proposed market clears. Agent based markets mostly handle the clearing problem either; by assuming that price simply adjusts to excess demand, by constructing a market in which temporary equilibrium prices easily subsist or by explicitly modeling trading in a continuous form as prevalent in actual markets (*LeBaron*, 2001).

For our purpose, the second method seems most appropriate. Demand functions of agents are likely to be reasonably well behaved since the carbon market is unlikely to yield high-frequency price dynamics given its nature. The first method is fast and acknowledges perpetual disequilibrium in the market but requires the artificial inclusion of a market maker (*Farmer and Joshi*, 2001), while assuming constant market depth (*LeBaron*, 2001). The third method seems most appealing with respect to its high level of realism, but is unlikely to be worth the cost in efforts outside high-frequency market applications.

Traded Commodity

The Alberta provincial government recognizes two types of carbon credits- Emissions Performance Credits, and Alberta-based offset credits (*Alberta Environment,* 2011). In addition, firms could substitute the CCEM which is currently priced at a flat rate of $15 per unit of emissions. The pricing of the CCEM thus effectively functions as a price ceiling for credits.

Unlike stock market models which frequently have a risk-free commodity and a risky one between which traders choose, the carbon market necessarily incorporates this choice only for traders and project developers. The choice for regulated firms precludes this risk free option since they require the credits for compliance, but includes the CCEM. To enhance simplicity, we consider the two types of credits as one type from two sources. Therefore for the purpose of this study, we consider both performance credits and offset credits as identical commodities- simply called carbon credits.

Our commodities also differ from the stock market variants in their fundamental nature. Traders in the stock market often read signals from announcements regarding the fundamentals (such as dividends or earnings) of securities. In fact, their forecasts are mostly a function of these. Carbon credits lack this signaling facility from fundamentals. Thus price forecasts are likely to be made mostly based on expectations of demand for those credits by regulated firms, relative to supply.

Frugality in the number of included commodities is important because the heterogeneity of agents itself presents complexities (both analytical and computational) which may be difficult to study in the mire of many commodities.

Calibration/Validation

Validation of this simulation is likely to present certain hurdles which are likely to diminish over time. As suggested by *LeBaron* (2001), validation could be achieved through calibration of parameters with certain benchmark cases which converge into a well defined homogenous agent equilibrium. Unfortunately, this type of data is as yet unavailable in actual carbon markets which are quite new and just emerging. Over time, calibration will likely become feasible as the market matures.

Being an exploratory study of the carbon market, our main claim to validation is in avoiding the introduction of features which are not apparent or likely to be evident in the actual carbon market into our model. This representativeness, while not being adequate validation, does give some credibility to our findings. We expect that future studies will be better equipped with the relevant data sets for calibration.

Evolution

Evolution is at the core of agent based modeling. When agents interact among themselves in a market, each seeks to maximize certain objectives by using specific strategies. Strategies compete in the marketplace, and intuition suggests that over time the less-competitive strategies will be squeezed out. This means that agents will abandon those strategies and not necessarily that they will themselves be pushed out of the market. This seems a more realistic expectation than the argument by traditional economic theory (See *Friedman*, 1953) which focuses on the agents themselves rather than their strategies.

As these strategies interact in the marketplace and the less-competitive ones get weeded out, it is likely that the surviving ones may be combined and mixed in the bid for superior strategies. Once these hybrids are born, they again contest with existing strategies, and again the weaker strategies in the market get weeded out. The process continues over time and may be influenced by the intermittent entry of entirely new strategies which also strive for survival. This process describes the kind of evolution that exists in actual markets and is very likely to prevail in carbon markets.

This perspective of evolution as a mutation of strategies rather than in terms of rational/irrational traders allows for an intelligible representation of learning among agents (*LeBaron*, 2001). Perhaps within the stock markets, rationality may be fruitful bases for exploration. However since the agents in our model have heterogeneous goals and not all are traders (which are reasonably classified based on rationality), irrational agents are likely to exist. As such, "irrational" agents as described by *Blume and Easley* (1990) may be favored by the market, especially where power laws have a strong pull.

Our agents evolve their strategies based on risk attitudes and past performance of strategies. We make no prior assumptions about which strategies are rational and which are not. As identified by *Kyle and Wang* (1997), we also expect that certain evolutionary pressures may cause the market to favor agents that are excessively risk-seeking in the long run. We expect that changing the rate at which strategies are updated alone will significantly influence market mutations.

A key related concept is memory. Trading agents are modeled to vary in their memory lengths. Price forecasts which are a basis for strategies are made partly as a function of previous prices. Agents differ in the extent to which they remember prices-some have much longer memories than others. Some agents may also perceive only more recent information as being relevant to decision making. We incorporate this feature as well into our model to allow for an evolutionary market with realistic agents.

SOFTWARE

Due to its flexibility and accessibility, Netlogo 4.1.3 is the software chosen for the purpose of this study. Apart from being built to ease the technical difficulty inherent to simultaneous simulation of activities of agents within a system, it also affords a comprehensive user guide which most other relevant software such as Repast and Swarm lack. Thus, its codes are much more accessible and easier to learn. These advantages are further accentuated by the software's 2-Dimensional graphical interface.

Using Netlogo 4.1.3, we ran two separate preliminary simulations for this study; one representing the very tame market (without traders), and the second one with traders introduced. We also ran the simulations for 100 periods each. The primary aim of implementing two runs was to tease out the influence of traders on efficient price determination.

CONCLUSION

In this paper, we have explored issues relevant to building an agent based model of the nascent carbon market in Alberta. We have also specified some details about the proposed model. As the simulation aspect of the modeling progresses, we hope to uncover more pertinent issues. We hope that these shall prove useful in envisaging likely issues that may evolve in the carbon market in future.

One major finding in our preliminary simulation was that the inclusion of traders into the model prevented the market from reaching equilibrium during the 100- period span, while equilibrium was attained within the first 48 periods of the tame market. The traders being momentum traders by design kept the market spinning out of perceivable tendencies towards equilibrium with wild oscillations in price and traded volumes. Prices were almost always higher relative to the tame market, while a higher volume of credits were traded than in the tame model. Generally, while being very premature to conclude as yet, the trial runs suggest that traders may be a positive influence on the market in terms of price buoyancy, but may greatly increase volatility within the market. The increase in traded volumes may have been due to increased liquidity brought into the market by traders. The higher prices are likely indicative of noise brought by the traders into the market. However, more evidence is required before a conclusion can be reasonably drawn.

It shall also be useful to compare prices in subsequent runs in our simulation with equilibriums that could be expected given a rational expectations formulation of forecasts. It will be interesting for instance to know whether the wild market converges to a rational expectations equilibrium as similar to that reported by *Plott and Sunder* (1982), in their human experiment.

Subsequently, the software shall be used to run simulations in which the assumption that only momentum traders exist (implicit in the trader's forecast mechanism) is relaxed. Furthermore, future simulations shall vary the number and proportion of traders and also toggle the proportion relative to other supply side agents and emitters. Also an extension of periods beyond 100 may reveal eventual long-run equilibrium, even in the trader-inclusive model.

As yet, calibration of the model is a hurdle which we hope will become surmountable with the development of the market and growth of trade datasets; this will enable more rigorous empirical exploration. This does not however detract from the dividends that this analytical inquiry promises to regulators, and other stake holders.

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