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Automated traders in commodities markets: Case of producer–consumer institution

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ABSTRACT

Automatizing commodities' price negotiation was hard to achieve in practice, mainly because of logistical complications. The purpose of our work is to show that it is possible to automatize thoroughly commodities' trading in the futures market by replacing human traders with artificial agents. As a starting step, we designed a market institution, called producer–consumer, where only an automated seller and an automated buyer can trade on behalf of the producer and consumer, respectively. The producer and consumer periodically feed their trading agents with supply and demand (S&D) forecasts. We suggested a parameterizable trading strategy, called bands and frequencies, for the agents. To measure the overall efficiency of this trading system in terms of price stability and liquidity, we made some hypotheses on the benchmark price curve and its linkages to S&D curves and other relevant market variables. Then we proposed analytical tools to measure strategy performance. Finally, we conducted some computer simulations to prove the workability of this approach.

1. Introduction

In the last two decades, internet advent has facilitated the emergence of electronic trading, gathering a lot of interest from both academic and professional organisms. The ultimate purposes were (a) creating stable and efficient trading platforms running on the internet and (b) designing autonomous agents able to trade on behalf of human buyers and sellers (Tesfatsion, 2003), the agents should be able to take decisions from market variables like S&D,[1] price history, etc. Furthermore, the generated price pattern should reflect the underlying S&D situation. Among the earliest experiments, the Santa Fe simulator was a typical computer model of the stock market allowing to carry out simulations and tests the effects of different trading scenarios on the price behavior (LeBaron, Arthur, & Palmer, 1999; Palmer, Arthur, Holland, LeBaron, & Tayler, 1994), leading the way to agent-based technology entering the arena of electronic trading. A genetic approach developed by Arthur, Holland, LeBaron, Palmer, and Tayler (1997) helped to clarify the links between fundamental and technical trading, this explained partially how bubbles and financial crushes occur (Levy, 2008; Roll, 1988). Automated trading had met success in several fields (Kearns & Ortiz, 2003), tough in the case of commodities the progress was hampered by some considerations, mainly logistical features and product characterizations (Arunachalam & Sadeh, 2005).

An automated agent is a software program which acts on behalf of its designer or owner to satisfy his/her interests. The owner delegates to his agent the authority to search opportunities and transact with other agents on his behalf. Preist (1999) has designed an agent-based technic for trading commodities via the Internet: the participants dictate to their automated agents rules like “if the price is $ *x* then buy or sell *y* units”. Agent-based were also used to evaluate the performance of trading strategies in heterogeneous populations of traders (Cai, Niu, & Parsons, 2008) and analyzing linkages between price and volumes (Chen & Liao, 2005). Automated traders with limited intelligence were tested by Gode and Sunder (1993), their setup achieved market price equilibrium. Shelton (1997) described an interesting trading strategy for the futures market in the context of stochastic games against nature.

The futures market is a major part of nowadays commercial exchanges, it is the place where *futures contracts* are traded. A futures contract is a binding agreement between a seller and a buyer, it is related to a specific commodity,[2] like crude oil, gold, metals, grains, oilseeds, etc. A typical feature of a futures transaction is that the price of the commodity is fixed at the present time, whereas the effective delivery of the merchandize, from the seller to the buyer, will occur at a future date, which could be several months or years later. The majority of raw commodities' producers, processors, consumers, and merchants buy and/or sell futures contracts in order to hedge their price risk, i.e. protect themselves against unforseen sharp price variations (Hull, 2002; Teweles & Jones, 1999).

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[1] S&D: abbreviation of supply and demand.

[2] There are also futures contracts on financial instruments like stocks, indexes, foreign currencies, etc.

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So far, automated trading in the futures market was limited to computerizing exchanges' platforms which once were operated by human pit brokers receiving orders, by telephone or other means, from external human traders, then proceed to their execution in an open outcry market. This first-step automatization process has met a great success with the advent of electronic platforms, consequently pit brokerage is progressively disappearing (Barcley, Hendershott, & McCormick, 2003; Weber, 2006). However, human traders, representing the interest of commercial companies (producers, farmers, refiners, consumers, etc.) are still operating. They constantly asses the market S&D balance as well as with their specific needs, then translate their judgments into sale or buy orders (CBOT, 1998). Our investigation is an attempt to expand the automatization process into a new border by eliminating human traders in the decision making process, and replace them by artificial agents who analyze the market fundamentals (supply and demand), then issue sale and buy orders to the exchange platform. Arunachalam and Sadeh (2005) enumerated the difficulties in automatizing commodities, markets. In earlier works, like Preist (1999), the decision process was directly supervised by human traders. In other setups (Cheng, 2008), only one automated trader is playing the market game with other human traders. In our setup, all traders are automatons, and the decision process is thoroughly in their hands. Furthermore, in contrast to several works where the purpose was maximizing the profit of participants, our work is rather focusing on market stability, that is designing a market institution with less crushes and bubbles.

Hereafter,[3] we create autonomous trading agents able to negotiate the price of futures contracts. The trading agents will be equipped with trading strategies reacting to S&D forecasts and other market data in order to generate sale and purchase orders. In turn, the interactions of these market orders will generate a price curve over the trading horizon. To measure the performance of the trading strategies, we propose to measure the *distance* between the generated price curve (or market price curve) compared to a benchmark price curve. For this reason, a discussion over the price's role in the market is necessary to establish some hypotheses on the properties of the benchmark price curve. Then we formulated the corresponding mathematical criteria allowing to measure the actual distance between the benchmark and market price curves. To show how this can work in practice, we suggested a framework of an artificial futures market composed from a seller agent and a buyer agent representing the interests of a producer and a consumer respectively. The agents are fed with a regular stream of forecasts on S&D levels over a trading horizon of m periods. The agents react first by adjusting their forecasts then they issue sale and purchase orders. To run the model, we suggested a parameterized trading strategy based upon the gap between S&D levels and price bands built around a *nominal price*. Finally, we used simulation to search for optimal parameters of the trading strategies by maximizing an aggregate performance function.

The next section is a discussion over the price's role in the market and its important link to the S&D balance. This will lead to formulating some hypotheses on the benchmark price curve, then deriving analytical measures to evaluate the performance of a given trading strategy. The third section describes the setup of the futures market adapted to the producer–consumer case. The forth section provides an example of a trading strategy for the autonomous trading agents. Illustrative tabular and graphical results are provided in the last section.

2. Measuring performance of a trading strategy

Price plays at least two important roles in the market. It could be seen as a thermostat measuring the pressure of the market, then taking the right decisions to equilibrate the market by regulating S&D levels.

In fact, if supply exceeds demand then the market is in a surplus status, leading generally to a price decline which in turn will be perceived as a buying opportunity by consumers, consequently consumption is encouraged to grow. Simultaneously, this price decline should be a signal towards the producers to reduce their output or momentarily halt it at all in order to erase the surplus status; consequently, this price decline has allowed to solve the prevailing surplus problem. Similarly, in a deficit market, the contrary of what was described heretofore should occur: the price should increase in order to reduce consumption and encourage production. If production capacity is insufficient to meet demand then producers will be attempted to invest more to raise their production capacities.

If the automated agents are to succeed in their trading mission then the price curve generated by their trading strategies needs to satisfy the spirit of the above discussion. In this optic, we suggested analytical tools to quantify and measure the degree of this satisfaction.

Our market institution is composed of an automated seller and an automated buyer. The trading game evolves over discrete periods $t_0, t_1, \ldots, t_m$. At the start of period t_j, the automatons get the following information:

- $S(t_j)$: the forecast available at instant t_j about the supply level; the final supply forecast, $S(t_m)$, will be the actual size of the crop. Set $\mathbf{S} = \{S(t_j),\ j = \overline{0,m}\}$ as the time series of supply forecasts.
- $D(t_j)$: the forecast available at instant t_j about demand level; the final demand forecast, $D(t_m)$, will be the actual size of demand. Set $\mathbf{D} = \{D(t_j),\ j = \overline{0,m}\}$ as the time series of demand forecasts.
- $p_N(t_j)$: nominal price of the commodity; it represents mainly production cost augmented by a profit margin. Nominal price is almost constant for long periods.

We assume the market is *transparent*, that is both automated traders have access simultaneously to the available information Φ:

$$\Phi(t_j) = \Phi(t_{j-1}) \cup \{S(t_j), D(t_j), p_N(t_j), U_1(t_j), U_2(t_j)\}, \tag{1}$$

where

- U_1 and U_2 are the market orders of the automated seller and automated buyer, respectively. At the initial period t_0, they issue no order.
- $\Phi(t_0) = \{S(t_0), D(t_0), p_N(t_0)\}$.

The agents build their market orders utilizing their trading strategies γ_1 and γ_2, respectively (Basar & Olsder, 1982):

$$U_1(t_j) = \gamma_1(\Phi(t_j)) \quad \text{and } U_2(t_j) = \gamma_2(\Phi(t_j)). \tag{2}$$

The interaction of these orders will generate:

- $p(t_j)$: transactional (or market) price of instant t_j, with $p(t_j) = f_1(U_1, U_2)$ where f_1 is the market mechanism allowing to build market price. We set $\mathbf{p} = \{p(t_j),\ j = \overline{0,m}\}$.
- $q(t_j)$: transactional quantity, this is the number of contracts sold by the seller to the buyer at instant t_j, with $q(t_j) = f_2(U_1, U_2)$ where f_2 is the market mechanism allowing to build market quantities.[4] We set $\mathbf{q} = \{q(t_j),\ j = \overline{0,m}\}$.

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[3] An initial version of this work was presented by the authors at the 7th workshop of International Society of Dynamic Games (ISDG), Djerba (Tunisia), July 2009.

[4] In case of the producer–consumer market institution, f_1 is given by relation (29) and f_2 by (30).