CYCLICAL BEHAVIOUR IN ELECTRICITY MARKETS: AN EXPERIMENTAL STUDY[1]

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> *"ALMOST ALL of the phenomena of economic life, like many other processes, social, meteorological, and others, occur in sequences of rising and falling movements, like waves. Just as waves following each other on the sea do not repeat each other perfectly, so economic cycles never repeat earlier ones exactly in duration or in amplitude. Nevertheless, in both cases, it is almost always possible to detect, even in the multitude of individual peculiarities of the phenomena, marks of certain approximate uniformities and regularities."*
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> (Slutsky 1937, p. 105)

ABSTRACT

This paper describes a laboratory experiment to study cyclical behaviour of electricity prices in deregulated electricity markets. We observe investment decisions in markets with five-producers, linear demand, and constant marginal costs. The experiment has a four year investment lag and the electricity generating capacity has a life time of 16 years. Oscillatory behaviour results in investment activity and prices. The cyclical tendency is stronger than in previous experimental studies with only one and two period investment lags. Average prices are closer to competitive equilibrium than in previous experiments. The results are consistent with bounded rationality theory; a simple heuristic produces fluctuations similar to those observed when applied in a simulation model. Hence, the results corroborate assumptions made in previous simulation studies.

KEY WORDS: *Electricity markets, Deregulation, Investor behaviour, experimental economics.*

JEL classification: *C9 - Design of Experiments; D01 - Microeconomic Behaviour: Underlying Principles; D43 - Oligopoly and Other Forms of Market Imperfection; D84 - Expectations; Speculations; L10 - Market Structure, Firm Strategy, and Market Performance.*

1 INTRODUCTION

Several authors have expressed a concern that cycles of over- and under-capacity may emerge in recently deregulated electricity markets (Ford, 1999 and 2000; IEA 1999, 2002, 2003; Bunn & Larsen 1992 and 1999; Larsen & Lomi, 1999). Such cycles are believed to represent a major threat to energy supply (IEA, 2002). This is so because electricity production cannot exceed capacity, demand is inflexible in the short run and there is barely any storage capacity. Regardless of these concerns, equilibrium is normally assumed in economic studies with little or no mention of market dynamics (Rothwell & Gómez, 2003; Kirschen & Strbac, 2004; Stoft, 2002). In fact, if the economist can show

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that there is a negative feeback loop, there would be a equilibrium and cyclical tendencies will be prevented by cyclical tendencies (Stoft, 2002). However, Stoft (2002) argues that an engineering view goes beyond traditional economic theories and considers whether an electricity market system will sustain cycles and analyse whether these cycles are over- or under-damped. Some of these engineering views are Ford (1999, 2000, and 2001) and Bunn & Larsen (1992 and 1999), they explore the occurrence of cycles in using of simulation models. In this paper, we employ an alternative method; a laboratory market experiment. Both cyclicality and efficiency are considered.

So far, the evolution of deregulated electricity markets does not present conclusive evidence of capacity cycles[3]; more data is needed to evaluate such behaviour (IEA, 1999 and 2003; Bunn & Larsen, 1992 and 1999). The concerns are based on the above simulation models (e.g. Ford, 1999; Bunn & Larsen, 1992; Arango, 2006c) and on analogies, such as real estate markets (IEA, 2002), and meat markets (Meadows, 1970).

Investor behaviour is one of the main concerns for regulators of electricity markets (IEA, 2002 and 2003). In regulated markets, one agency is responsible for the planning of total capacity expansions. Furthermore, the regulating agency may not have to carry the cost of overcapacity itself; and, it may act with caution to prevent shortages. In deregulated markets, individual suppliers make separate investment decisions. The individual suppliers are not responsible for market stability or reliability. If they were, they would have to forecast both electricity demand and the total supply of competitors in order to make a decision; a more complex task than that of the regulator. Efforts to coordinate investments adequately to stabilize the market would be contrary to competition legislation. Hence, market stability will depend on individual investment behaviour. Rational investment behaviour could lead to economical and minimal fluctuations, while myopic investors could concentrate investments during periods of relatively high electricity prices, causing pronounced cycles (Ford, 1999 and 2000; Bunn & Larsen, 1992; Gary & Larsen, 2000). Under these circumstances, experimental economics provide a methodological framework to test the rationality of subjects making isolated investment decisions in a deregulated electricity market.

Most experimental markets do not include dynamic structures and are reset each period (e.g. Plott, 1982; Smith, 1982). Simple dynamics have been introduced by lagged supply models (Carlson, 1967; Sonnemans *et al* 2004; Holt & Villamil, 1986; and Sutan & Willinger, 2004) and by repeated play Cournot models (Rassenti *et al* 2000; Huck *et al* 2002). While the predicted cycles of the Cobweb theory do not materialize in these experiments, some random fluctuations are sustained[4].

Arango (2006b) extends the simplest Cobweb market[5], step by step, by including a four period lifetime of production capacity and a two period investment lag. Certain cyclical tendencies are observed in the treatment with the two period investment lag. Arango (2006b) presents a continuation of the previous experiment replacing the linear demand by a constant elasticity demand. With these changes, the treatment with a two period investment lag produces stronger cyclical tendencies with asymmetries not observed in earlier experiments. The present experiment can also be seen as a continuation of Arango (2006b). The main difference is that the investment lag is now 4 periods (where each period is one year against 5 years in the previous experiments) and the lifetime of production is 16 years.

We formulate the null hypothesis based on the rational expectations hypothesis (Muth, 1961) and the standard assumption in neoclassical economics about optimal decision making. The null hypothesis is

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[3] After more than a decade, there are not significant cycles in UK and Norway (IEA, 2003). Colombia barely shows a first boom of investments after the high prices presented in 1997-1998 (Arango *et al* 2006), the same situation occurred in California with late investments (IEA, 2003).

[4] Previous applications of laboratory experiments in electricity markets have focused primarily on price institutions for market design (e.g. Rassenti *et al.*, 2002; Schaeffer & Sonnemans, 2000; Vogstad & Arango, 2005b).

[5] 5 players, constant marginal costs, and linear demand.

convergence to a stable Nash equilibrium; minor and seemingly random variations around the equilibrium value will be consistent with this hypothesis. Systematic cyclical tendencies are not consistent with this hypothesis. Fully rational agents could predict cycles and benefit from countercyclical investment decisions.

The alternative hypothesis is based on the bounded rationality theory (Simon, 1979), which assumes that complex dynamic problems are approached with heuristics (Tversky & Kahneman, 1987). There is much experimental support for bounded rationality theory in dynamic settings (Paich & Sterman, 1993; Diehl & Sterman, 1995; Kampmann, 1992; Smith *et al* 1988; Sterman, 1989; Moxnes, 2004). While heuristics could lead to near-to-optimal results for simple problems, the results are likely to deteriorate with complexity (Paich and Sterman, 1993; Diehl and Sterman, 1995; Kampmann 1992; Sterman 1989, Herrnstein and Prelect, 1991, Moxnes, 2004, Arango, 2006a and 2006b).

Regarding market efficiency, it is difficult to predict the outcome of bounded rationality (Conlisk, 1996; and Foss, 2003). While simplified heuristics may lead to biases relative to preferable individual outcomes, the bias may draw the market outcome in the directions of both monopoly and perfect competition. Thus, we consider the experiment exploratory in this regard.

Regarding cyclicality, we formulate a more precise hypothesis. We propose a heuristic that expresses the intended rationality of investors. Since the choice of heuristic is case dependent (Tversky & Kahneman, 1987; Conlisk, 1996), we select a heuristic based on the understanding of electricity market investment dynamics reported in the literature. The heuristic assumes that subjects form expectations about prices and profitability and use these expectations in a given investment strategy. The investment strategy assumes that profits drive the investment, which is key to the long term market equilibrium Stoft (2002, p. 114). Previous experimental support for the heuristic is presented in a number of one player experiments (Sterman, 1987a; Sterman, 1989; Bakken, 1993; Diehl & Sterman, 1995, Barlas & Günhan, 2004). The strategy tends to ignore the supply line of capacity under construction and to underestimate the investment lag (Sterman, 1989; Diehl & Sterman, 1995; Barlas & Günhan, 2004). Simulations with adaptive or myopic investors have shown cyclical behaviour (Ford, 1999; Bunn & Larsen, 1992).

Section 2 describes the experimental design. The design includes testable hypotheses based on rational expectations and bounded rationality. Section 3 presents the experimental results. Cyclical behaviour emerges, consistent with the bounded rationality hypothesis. Finally, we discuss and conclude.

2 EXPERIMENTAL DESIGN AND HYPOTHESES

We present the underlying model, procedures, hypotheses, heuristics and methods to test cyclicality.

2.1 Experimental economic model

We use a computerized experiment of a symmetrical five player market with linear demand. The marginal cost is constant and it includes both capital and operational costs. It takes four years before new production capacity is in place and capacity lasts for 16 years. Investment decisions are made each year. These are the main differences from the design in Arango (2006b), where the investment lag is one or two periods, capacity lasts four periods, and each period is five years long. The present experiment is more complicated than the previous one because now it takes four periods before an investment affects the production capacity. As in the previous experiment, full capacity utilization is assumed at all times. Thus, production equals the sum of the capacities of all vintages. Additionally, Arango (2006b) includes a profit calculator (to help the players to identify the Cournot-Nash equilibrium). The calculator is not part of this experiment.

This economic model is identical to Huck's standard conditions[6] for Cournot markets, except for the extra lags and the capacity vintages. Each subject decides freely on investments with the exceptions that its capacity must not exceed 36% of the total initial capacity (reflecting the maximum allowed market share) and that its investments must not be negative. The program gives an error message whenever subjects enter investments that are too high or negative. The market price is determined by a linear inverse demand function with a nonnegativity restriction. Information about the realized price and own profits is given each period. The market price in period *t* is

$$P_t = Max\ (6 - 0.1 * \sum_{i=1}^{5} q_{i,t}\ ,\ 0) \tag{1}$$

where $q_{i,t}$ is the production of subject *i* in period *t*. Given the investment lags and the vintages of capacity, production is given by

$$q_{i,t} = \sum_{j=t-19}^{j=t-4} x_{i,j} \tag{2}$$

where $x_{i,j}$ is the investment decision made in years $j=t-19$ to $j=t-4$. The profit function in experimental dollars (E$) for subject *i* in period *t* is,

$$\pi_{i,t} = (P_t - c)\ q_{i,t} \tag{3}$$

where the marginal cost *c* equals 1 *E$/Unit*. Subjects receive information about production and vintages of capacity (aggregates over four vintages) for themselves and for the total market (see Appendix 2). We use a time horizon of 70 years which should be large enough to allow learning and eventual convergence towards some equilibrium.

2.2 Experimental Procedure

The experiment follows the standard framework used in experimental economics. All subjects were recruited from the same population of last year students in the program "Energy and Environment" at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway in the autumn of 2004. There were a total of 6 markets. No subject had previous experience in any related experiment. Subjects were told they could earn between NOK 40 and NOK 120 (US$5 – US$20 at that time) in about one hour. They knew that rewards were contingent on performance, which was measured in cumulative profits.

Upon arrival, subjects were seated behind computers. Groups were formed in a random way, such that subjects could not identify rivals in the market. Instructions (see Appendix 1) were distributed and read aloud by the experimenter. The subjects were allowed to ask questions and test out the computer interface. All parameters of the experiment were common knowledge to all subjects, including the symmetry across firms. The initial condition was a total industry production of 55 units and individual productions of 11 units. Thus, the price started at 0.5 E$/unit. These initial values were identical across groups.

Each simulated year, the subjects were also asked to forecast the price at the time when new investments would be in place. Extra reward was given for good forecasting, measured by the

[6] Standard conditions (Huck, 2004, p.106): a. interaction takes place in fixed groups; b. interaction is repeated over a fixed number of periods; c. products are perfect substitutes; d. costs are symmetric; e. there is not communication between subjects; f. subjects have complete information about their own payoff functions; g. Subjects receive feedback about aggregated supply, the resulting price, and band their own individual profits.; h. the experimental instructions use an economic framework.

accumulated forecasting error. The extra revenues could vary from 0 for forecast errors above a given standard, to NOK 30 (around US$5) for perfect forecasts. Optimal performance regarding investments and forecasts would lead to a payoff slightly above the typical hourly wage for students.

The experiment was run in a computer network using the simulation software Powersim Constructor 2.51. The software ran automatically and kept record of all variables including the subjects' decisions. Still subjects were asked to write down their decisions on a sheet of paper to keep a memory of past decisions and to provide a backup of the experiment. The software interface is presented in Appendix 2 and the experiment is available upon request.

2.3 Testable Hypotheses

We first formulate null hypotheses based on the standard economic model with rational expectations. Thereafter, we present alternative hypotheses based on bounded rationality. In each case, we consider equilibrium and cyclicality.

2.3.1 Rational Expectations Hypothesis: Cournot Nash equilibrium

The economic model has a unique Cournot Nash equilibrium (CN).

Hypothesis 1: *Average prices are equal to Cournot Nash equilibrium predictions.*

Table 1 shows the numbers characterizing the CN equilibrium, which is derived in Appendix 3. Previous experiments have shown some biases (Huck, 2004; Huck, *et al* 2004, Arango. 2006b). To judge our results in this regard, Table 1 also presents the equilibrium values for perfect competition and joint maximization (Appendix 3).

Table 1. Equilibriums of the experimental markets

	Individual Investment [Units]	Market Production [Units]	Price [$/Unit]
Joint maximization	0.31	25.0	3.50
CN equilibrium	0.52	41.7	1.83
Competition	0.63	50.0	1.00

Neoclassical economic theory suggests no cyclical behaviour but stability. Any predictable cyclical tendency would lead to countercyclical investments and stabilisation. Accordingly, economic theory normally attributes cyclical behaviour to external shocks, particularly in commodity markets (e.g. Cuddington & Urzua, 1989; Cuddington, 1992; Cashin *et al* 2002; Reinhart & Wickham, 1994; and Cashin & Patillo, 2000). We consider random shocks generated within a market to be consistent with standard economic theory. Such random variations may occur for a number of reasons, such as discontinuous investments, learning, strategic moves, etc. Previously, experiments with Cournot markets have found that outputs and prices are not exactly equal to the CN equilibrium but close, typically closer than one standard deviation of the observed price fluctuations (Huck, 2004).

Hypothesis 2*. Market prices do not show cyclical tendencies, while random variations may occur.*

2.3.2 Bounded Rationality: Heuristics and cycles

The alternative hypotheses are based on bounded rationality theory. Individual investment decision can be seen as consisting of two steps. First, the subjects form expectations about future prices, and next they deliberate on the size of their investment. For instance, Nerlove (1958) assumes adaptive expectations and uses the inverted marginal cost curve to find the appropriate future supply (and implicit investment). Here we rely on the same assumption about adaptive expectations; however, we formulate an explicit investment function because we assume constant costs (implying zero or infinite capacity with Nerlove's procedure) and that investments accumulate in long lived capacity.

The investment function is inspired by the investment function formulated in Senge (1978) and the investment dynamics for electricity markets described in Stoft (2002). It is also consistent with the anchoring and adjustment heuristic, Tversky & Kahneman (1987). The formulation of the investment function is similar for both individual and aggregated investments, the difference is that the investment function for individuals includes individual capacity while aggregated investment function does not. It is also expected that there is some randomness because the decision making process deviates from the investment function. The function assumes that people use a feedback strategy to adjust their capacity towards a desired capacity indicated by the expected return on capital. The investment function is,

$$x_t = MAX\,(\,0,\, C_t/\tau + \alpha_C\,(C^*_t\; - C_t) + \alpha_{SC}\,(k/\tau\, C^*_t - SC_t)) \tag{4}$$

where the max function precludes negative investments, capacity C_t divided by the life time τ denotes a normal level of investments to replace depreciated capacity, α_C determines how fast capacity is adjusted towards the desired capacity C^*_t. Finally, α_{SC} determines how quickly the supply line is adjusted toward the desired supply line $k/\tau\, C^*_t$, where k equals the investment delay of four years. The desired capital

$$C^*_t = MAX\,(\,0,\, a + \left(\frac{q^e - a}{P^e}\right) P^*_t\,) \tag{5}$$

is a linear function of expected price P^*_t. When P^*_t equals the equilibrium price P^e, desired capacity C^*_t equals equilibrium production q^e. The parameter a denotes the intercept with the y-axes and influences the slope as well. We choose the simple linear model for desired capacity, even though many profit functions could lead to the same equilibrium, as argued by Stoft (2002). The parameter a is restricted to $a < q^e$ to avoid negative slopes. Note that C^*_t depends on P^*_t relative to P^e and not to the marginal cost c. Hence, the formulation could be used to test different assumptions about equilibrium. Finally, the expected price is given by

$$(P^*_{t+1} - P^*_t) = \beta\,(P_t - P^*_t) \tag{6}$$

which represents adaptive expectations, formulated initially by Nerlove (1958) and used in related economic experiments (e.g. Carlson, 1967; Sterman, 1987b and 1989; Frankel & Froot, 1987). The difference in this experiment is that we define P^* to be four years ahead. Note that this formulation considers the available information for subjects at time t to forecast the price, i. e. the current price P_t and the price forecasted for the current period P^*_t. The parameter β is called the coefficient of expectations. Following, we provide a simulation analysis of the proposed heuristic.

Initial conditions are the same as in the experiment. The coefficient of expectations is set to the average of the values estimated by Sterman (1989) and Carlson (1967), i.e., β=0.53. Given that we have limited knowledge of parameter values a priori, we hypothesise two sets of parameters and perform some sensitivity tests. Set 1 has α_{SC}=0.10 and α_C=0.26; and set 2 has α_{SC}=0.5 and α_C=0.5. Set 1 refers to values estimated by Sterman (1989) in an analogous heuristic for an inventory management problem, and set 2 has a more aggressive policy where half the adjustments take place within one year. Parameter a=38 is chosen through simulations with parameter set 1 as fallow: We introduce noise in the heuristic (the noise has the same average standard error for regression of the heuristic for all experimental markets) and then simulate for different values of a. Finally we select $a=38$ because the average standard deviation of experimental prices is similar to the standard deviation of simulated prices. The last condition is also true for parameter set 2. Thus, parameter a takes the same value for both parameters sets. Note that this value is considered for the aggregated market. Figure 1 shows simulated behaviour for both parameter sets. We observe that the heuristic leads to oscillatory behaviour in both cases. Set 1 produces one dominant cycle with increasing amplitudes over time. Set 2 shows a dominant cycle with a slightly shorter period than observation with set 1 and there also seems to be a minor cycles with about half the period length of the dominant cycle.

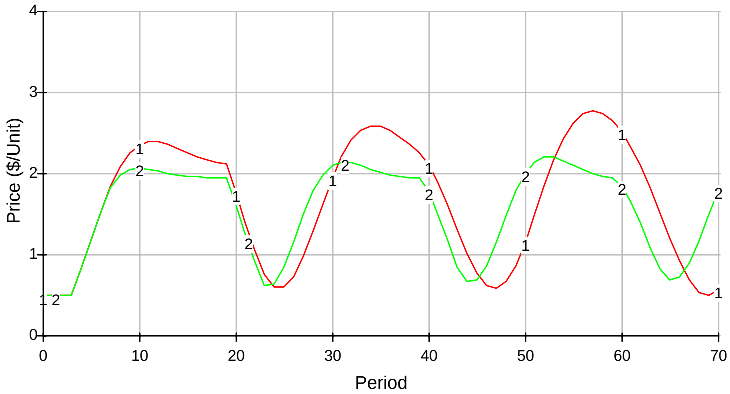
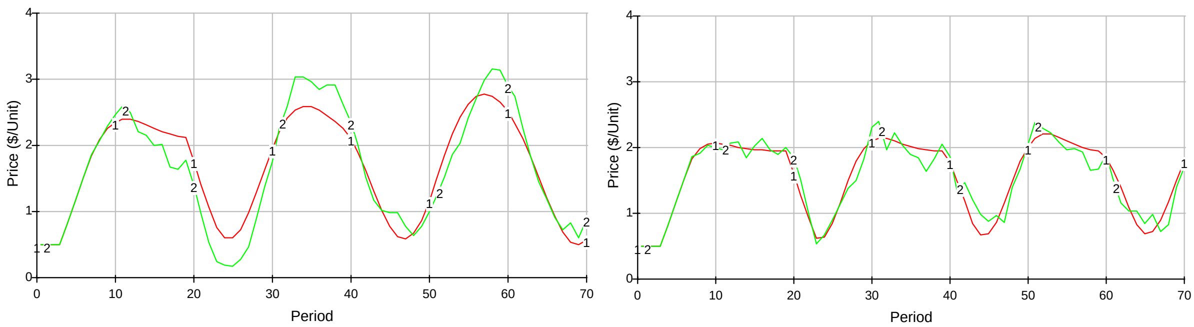


Figure 1. Simulated prices of the experimental market with the proposed heuristic. Numbers denote parameter sets 1 and 2

Sensitivity analysis of the hypothesised parameters for both sets shows a tendency towards price stabilization when *a* and α_C are reduced. Low values of α_{SC} lead to stronger instability, which indicates that ignoring capacity on order leads to greater oscillations. Behaviour is not very sensitive to reasonable changes in the parameter β.

The simulations in Figure 1 are deterministic. To study the effects of internally generated disturbances, we introduce an additive normally distributed noise u_t (*iid*) to investments, $u_t \sim N(0,S^2)$. *S* is set as the average standard error for regression of the heuristic for all experimental market. Figure 2 shows how randomness changes the previous deterministic behaviour. We observe that the main driving forces generating cycles are conserved, and that the noise does not affect the mode behaviour.



(a) (b)

Figure 2. Simulated prices of the experimental market without (line 1) and with noise (line 2). (a) represents set 1 and (b) set 2.

To summarize, we present the next formal hypothesis:

Hypothesis 3: *Price behaviour will be cyclical.*

2.4 Methods to test cyclicality

To test for cyclicality, we use spectral analysis, we calculate autocorrelations and we estimate investment functions. These methods are discussed below.

2.4.1 Methods to test behaviour

Regular cycles are characterized by their frequency or periodicity, amplitudes and attenuation. However, these measures are not easy to obtain for irregular cycles and visual inspections may be misleading. Estimates of variance measure the dispersion of any data around their average, and attenuation is indicated by showing variance for different time intervals. Nevertheless, variance does not say anything about frequencies or autocorrelation. To capture these aspects and to test for random and cyclical behaviour we turn to spectral analysis and autocorrelation.

Spectral analysis: The frequency decomposition of variance is called the autospectrum or the autospectral density function. Peaks in the autospectrum indicate that variance is concentrated at certain frequencies[7]. This allows detection of both cyclical tendencies and period lengths. For instance, white noise has a uniform autospectrum; a sine wave has an autospectrum totally concentrated at a single frequency (the period). When both processes are combined, the resulting autospectrum is the sum of the individual spectra.

Correlation analysis - autocorrelogram: Based on covariance, the autocorrelogram indicates cyclical behaviour and indicates both amplitude and periodicity. The autocorrelogram measures the correlation of the variable with itself, at different time lags. The autocorrelogram is most directly interpreted as a measure of how well future values can be predicted based on past observations. While random processes have autocorrelation functions rapidly diminishing to zero, cyclicality is observed when there are values significantly different from zero at different lags.

Ideally the above tests require infinite time series. To clarify what the implications are of limited data, we test a pure sine wave with a period of exactly 20 years and a series with *iid* random numbers ~U(0,1). Figure 3 shows the corresponding autospectra and autocorrelograms. When calculating the autospectrum we use only the last 64 data points, for the autocorrelograms we use the same number of data points as in the experiment, 70. The result is a spectrum for the sine function that is concentrated in the frequency 1/20years=0.05 per year; however, it is not a perfect peak but somewhat distributed peak because of the limited amount of information. The autospectrum for the white noise does not show noteworthy peaks. While the autocorrelogram for the white noise does not have any significant values, it shows the first four values positive and significant different than cero. Also note that the autocorrelogram for the sine function does not present the perfect value (-1) for the tenth lag, also because of the limited length of the time-series.

[7] Spectral analysis decomposes the time series in orthogonal components. Each component is associated with a particular frequency. The autospectrum shows the contribution of each frequency band to the total variance (details in Bendat & Piersol, 1980; Box *et al* 1994).

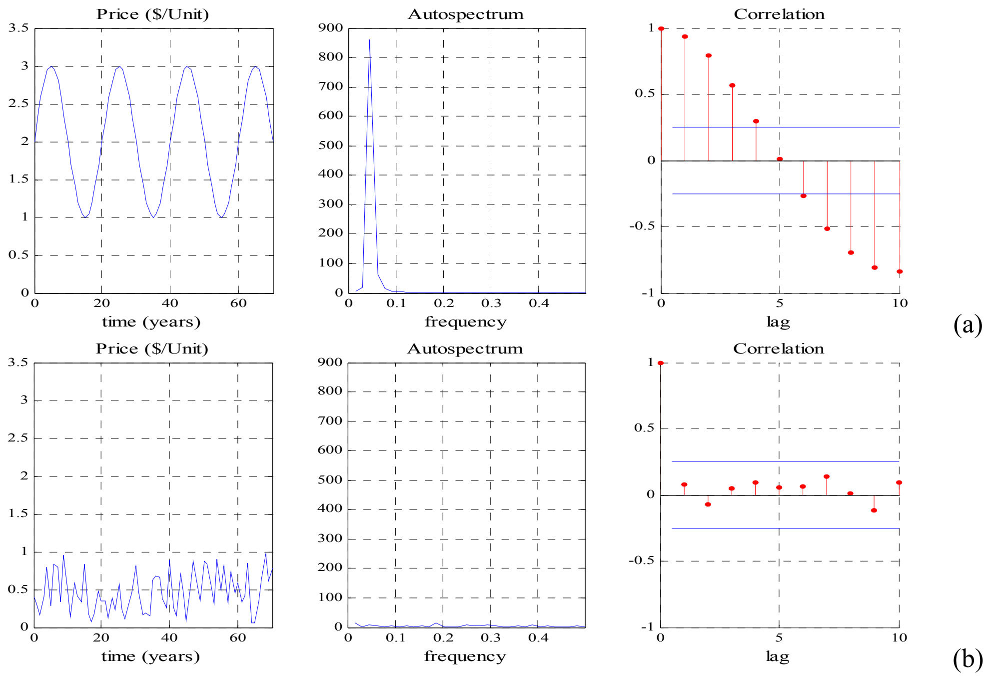


Figure 3. Time series for a pure sine wave (a) and for a series of random numbers ~U(0,1) (b). The autospectra are based on the last 64 data points and the autocorrelograms are shown with critical values at the 5 percent level.

Figure 4 shows the autospectra and autocorrelograms for the simulated market behaviours with parameter sets 1 and 2. Both cases include the previously described noise. Parameter set 1 shows a concentration around one frequency (20 year period). Parameter set 2 shows concentrations around the same frequencies. In addition it has more energy around the double frequency (10 year period). The higher frequency fluctuation leads to fewer significant correlations in the autocorrelogram for parameter set 2. The autocorrelograms also indicate sine-like fluctuations.

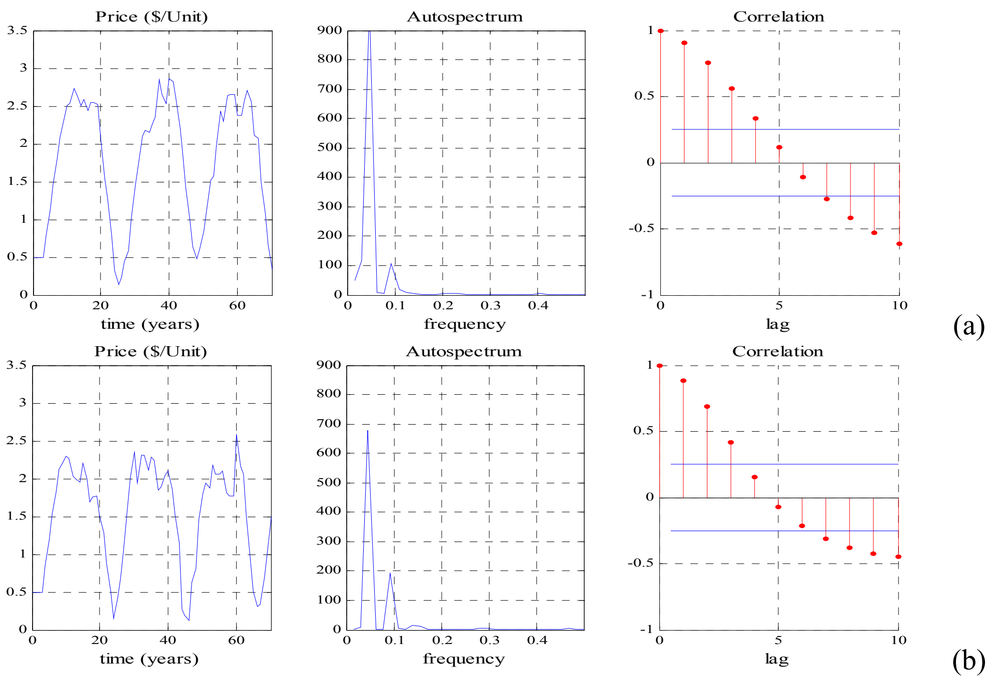


Figure 4. Simulated prices of the experimental market with noise for parameters set 1 (a) and set 2 (b). Both series have the autospectrum (performed with the last 64 data) and autocorrelogram (horizontal lines are the 95% confidence bounds).

2.4.2 Methods to test structure

We use regressions to test the proposed aggregate investment function. We regress on data produced by the simulation model. As long as this simulation model assumes one aggregate player, it is not possible to test the individual investment function for the aggregate market. Note that as long as the max-functions in equations 4 and 5 are not binding, the decision rule is linear. Hence, small price variations keep investments in the linear range of the investment function. However, the investment function most likely turns nonlinear for variations smaller than 0<P<6. The following simple linear form is an approximation of equations 4 and 5

$$x_t = m_3 P^*_t + m_2 P_t + m_1 SC_t + b + \varepsilon_t \qquad (7)$$

where m_i (i=1,2,3) and b are parameters to be estimated, and ε_t is *iid* random variable with zero mean and finite variance. We perform regressions for simulations with and without noise (see Table 2). For the case without noise, the r^2 values very close to but not quite equal to 1.0. Parameters come very close to theoretical values, with a certain deviation for m_3. As expected, the quality of the regression decreases after the introduction of noise with average values of r^2 around 0.6. The noise tends to lead to larger deviations from theoretical values, as expected. In particular m_3 for set 1 is sensitive. The parameter values in Table 3 will serve as references for comparison with the experimental results.

Table 2. Parameter estimates based on simulated data with parameter sets 1 and 2. The p-value of each coefficient is presented in parenthesis.

Simulation conditions	m_3 (*P**)	m_2(*P*)	m_1 (*SL*)	b	r^2
Set 1 – not noise	0,58 (0,00)	1,97 (0,00)	-0,10 (0,00)	-1,02 (0,00)	1,00
Set 1 – noise*	1,65	1,14	-0,16	-0,78	0,61
Theoretical values set 1	0,51	1,98	-0,10	-1,02	
Set 2 – not noise	1,26 (0,00)	4,37 (0,00)	-0,50 (0,00)	-2,50 (0,00)	1,00
Set 2 – noise*	1,30	3,68	-0,45	-1,63	0,57
Theoretical values set 2	1,12	4,38	-0,50	-2,50	

* Noise: we assume normally distributed noise with same average standard error for regression of the heuristic for all experimental markets $\sim N(0, 1.3^2)$. Values are averages of 10 simulations.

The linearity is the weakness of the regression model, i.e., the regression model fails whenever the non-negativity constraint of the investment function takes effect. of price This is revealed by varying parameter a. We consider a=35 (and a=37) for the case without noise and perform simulations with this condition with parameter set 1. Regressing on simulated behaviour we find m_3=-3.55 (and m_3=-1.35). These values deviate from the theoretical values (0.97 and 0.66 respectively); even the sign is incorrect. Thus, the greater the fluctuation in price and hence in investment, the greater biases we should expect in the estimated parameter because of the activations of the nonlinearities.

3 RESULTS

A summary of price statistics[8] is presented in Table 3. In all markets, we observe that average prices $\overline{X}$ are closer to the competitive price (1.00 \$/unit) than to the CN equilibrium price (1.83 \$/unit). The standard deviation, S, varies between 0.36 \$/unit and 0.75 \$/unit. Comparing prices from the first 35 periods with the rest, the average price increases in five of the six markets. To some extent this is expected due to the starting point with overcapacity. The average of standard deviations is slightly reduced from 0.44 to 0.41. The table shows high one-lag autocorrelation, on average 0.89, which constitutes the first indication of cycles.

[8] The analysis could be performed with a focus on prices or quantities. We have chosen prices since they are most easily observed and discussed in real markets.

Table 3. Summary statistics for the realized price.

	All periods			First 35 periods		Last 35 periods	
	$\overline{X}$ ($)	S ($)	α	$\overline{X}$ ($)	S ($)	$\overline{X}$ ($)	S ($)
Group 1	1.04	0.43	0.95	1.09	0.41	0.99	0.44
Group 2	1.05	0.37	0.86	1.01	0.30	1.09	0.44
Group 3	1.19	0.43	0.84	0.94	0.32	1.45	0.36
Group 4	1.29	0.36	0.93	1.11	0.39	1.46	0.20
Group 5	1.07	0.75	0.90	0.80	0.76	1.35	0.65
Group 6	1.15	0.44	0.87	1.01	0.45	1.30	0.38
Average	**1.12**	**0.47**	**0.89**	**0.99**	**0.44**	**1.27**	**0.41**

* $\overline{X}$: mean price; S : standard deviation; α : one lag autocorrelation.

Table 4 presents the limits for the 95% confidence interval for the average prices over time for all groups. The confidence intervals include the competitive equilibrium price for three of the markets. All markets have average prices significantly lower than 1.4 $/unit. These low average prices suggest that the markets are quite efficient. Table 4 also shows what the welfare loss would have been if prices had stayed constant at the observed average prices. Calculated losses are all close to zero (free competition) and far lower than the loss of $242 for CN equilibrium.

However, the fluctuations cause a welfare loss. Table 4 shows that losses for the actual and fluctuating price series are typically below one third of the loss for the CN equilibrium, with the exception of market 5.

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Table 4. 95 % confidence interval limits for average prices $\overline{X}$ and welfare lost of the experimental results.

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Lower bound [$/Unit]	0.905	0.937	1.062	1.175	0.842	1.019
Average [$/Unit]]	1.036	1.052	1.193	1.285	1.074	1.153
Upper bound [$/Unit]	1.167	1.167	1.325	1.395	1.306	1.287
Welfare lost (observed prices) [$]	62.88	50.15	75.43	74.40	196.97	73.74
Welfare lost (Constant average prices) [$]	0.01	0.01	0.18	0.42	0.03	0.12

We now look in more detail at the price development over time. Prices for the six markets are presented in Figure 5. Prices vary from zero to values close to the joint maximization level (3.5 $/unit). There are only few cases where price hits zero; therefore, prices are mostly in the linear range of the demand function. All the experiments begin with over-capacity and a price of 0.5 $/unit. Thereafter, a simple visual inspection suggests tendencies towards regular cycles.

The figure also shows autospectra[9] and autocorrelograms for all markets. The autospectra suggest cyclical tendencies rather than a flat distribution typical of random series. The autospectra tend to be concentrated at two frequencies: around 0.05 (period of 20 years) in 3 cases, and around 0.1 (period of 10 years) in 4 cases. This double-frequency behaviour is consistent with the simulations with parameter set 2 previously presented. The autocorrelograms show significant positive values for the first three or more lags for all cases, which is consistent with cyclical behaviour. Moreover, there is one market with significant negative values for the last four lags, which provide stronger indication of oscillations.

[9] When calculating the autospectra we use the last 64 out of 70 data points, since the Fourier transform works better with length series to the power of two (Bendat & Piersol, 1980). By removing the first data points we also reduce much of the effect of the initial disequilibrium for the case of perfect foresight and rapid convergence.

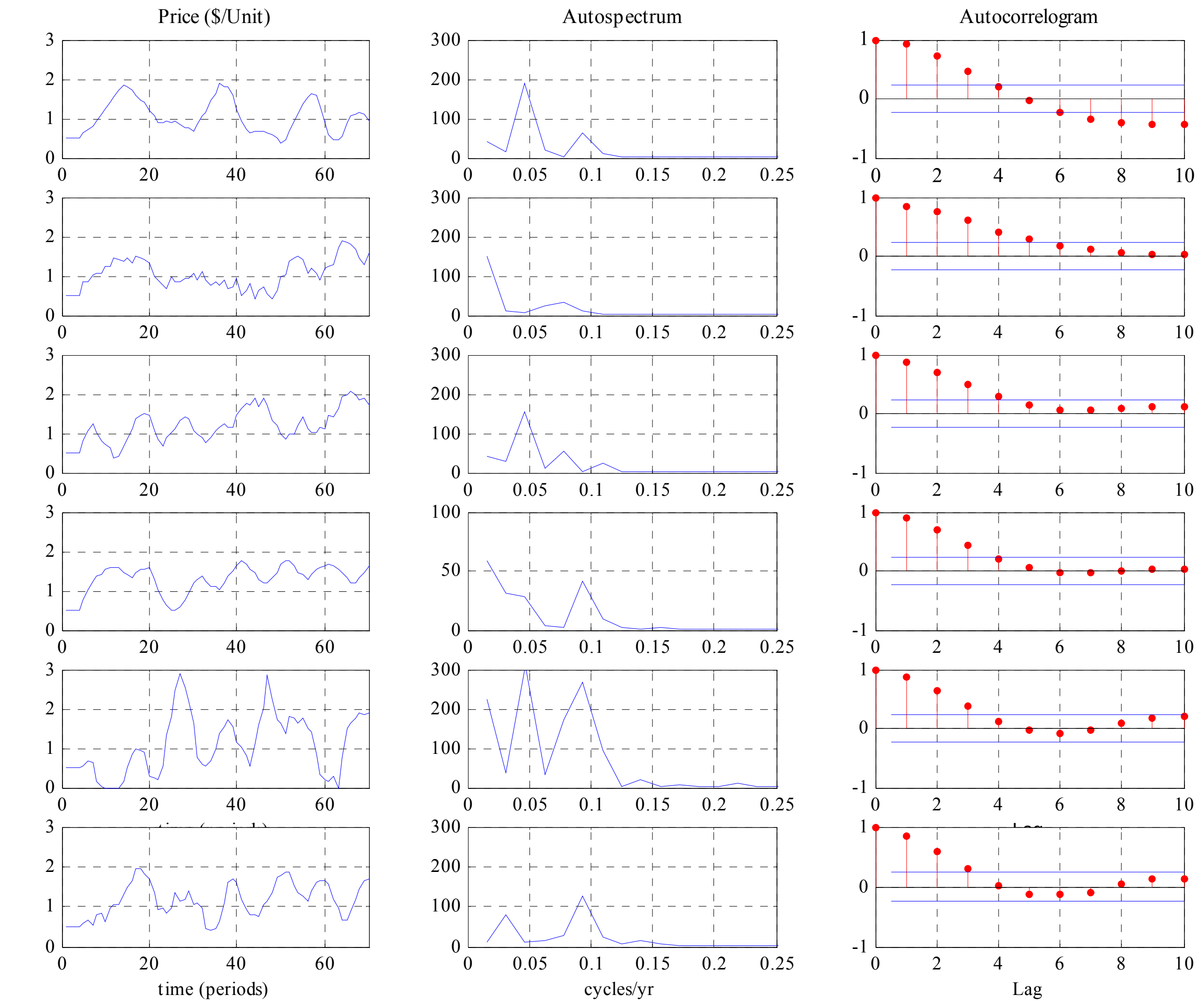

Figure 5. Realized prices in the six experimental markets, autospectrum and autocorrelograms. Autospectrums are based on the last 64 data points of the series, and autocorrelograms present the 95% confidence bounds (horizontal lines).

Figure 6 shows the average autospectrum and autocorrelogram with 2.5 and 97.5 percentiles for the six markets. The autospectrum shows significant peaks at frequencies of 0.05 per year (20 years) and 0.09 (11 years). The average autocorrelogram shows a typical shape of periodic time series with noise[10]; in particular, the four first lags are significantly greater than zero. Thus, visual inspections of the price series, the autospectra and the autocorrelograms, are all consistent with cyclical behaviour of price.

[10] See Bendat & Piersol (1980, p. 60) idealized autocorrelation functions.

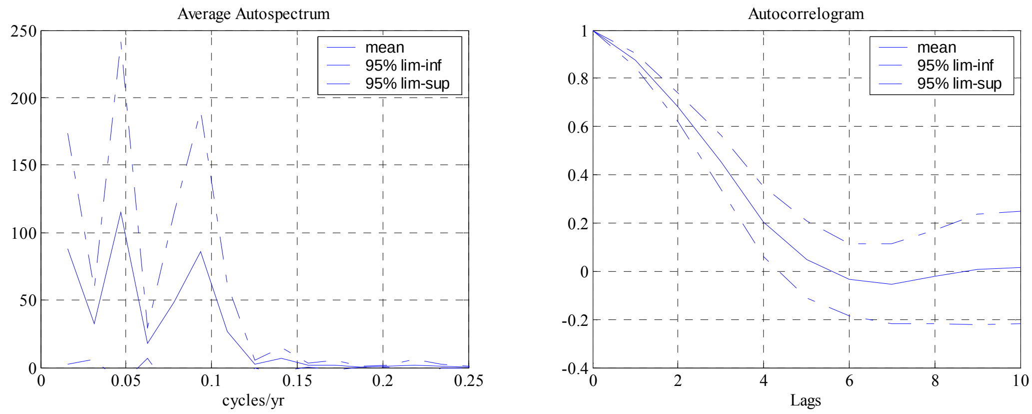

Figure 6. Average autospectrum and autocorrelogram across groups and the confidence interval with the 2.5 and 97.5 percentiles.

4 DISCUSSION

4.1 Testing the hypotheses

Following, we perform the formal tests of the hypotheses presented in section 2.

Hypothesis 1: *Average prices are equal to Cournot Nash equilibrium predictions.*

Table 4 shows that hypothesis 1 is rejected for all groups; the CN equilibrium does not fall within the confidence interval for average prices. Instead, average prices are close to competitive prices, only three out to the six groups have an average price significantly greater than the competitive price. All prices retain a bias towards competition. The bias towards competition is consistent with previous results of Cournot markets under standard conditions (see summary in Huck, 2004; and Huck *et al* 2004), where average prices tend to be between competition and CN equilibrium predictions. However, these experiments have neither the four period investment lag nor capacity vintages.

Now, we turn to the hypothesised cyclicality. We test hypothesis 2 and 3 simultaneously.

Hypothesis 2. *Market prices do not show cyclical tendencies, while random variations may occur.*
Hypothesis 3: *Price behaviour will be cyclical.*

In the results section, we observed enough evidence to reject hypothesis 2 and to favour hypothesis 3.

Previously we have argued that fluctuations could result from the use of a simple heuristic. The proposed heuristic (eq.6 and 7) was built on the assumption that subjects first form adaptive expectations about future prices, and next they deliberate on the size of their investment. First we test the adaptive expectations and then the investment function.

Test of the adaptive expectation hypothesis
The adaptive expectations hypothesis presented in *eq. (6)*, is a linear equation restricted to pass trough the origin of the 2D space (P_{t-1} - P^*_{t-1} , P^*_t - P^*_{t-1}). We have relaxed this constraint by postulating a linear function of the form

$$(P^*_{t+1} - P^*_t) = \alpha + \beta (P_t - P^*_t)) - \varepsilon_t \qquad (8)$$

where ε_t is an *iid* random variable with zero mean and finite variance. The term α can be interpreted as a bias parameter; and the subject that uses adaptive expectations could retain either an optimistic or a pessimistic bias. Note that in this experiment we define P^* to be four years ahead. The results of estimating α and β are presented in Table 5, for individuals and aggregated markets. We define the expected price for aggregated markets to be the average of the expected prices reported by the individuals.

Table 5. Parameter estimation for the adaptive expectations hypothesis for individuals and aggregated markets corresponding to *eq.(8)*.

Mkt/Player	α (p-value)	β (p-value)	r^2
1/1	0.01 (0.65)	0.03 (0.79)	0.00
1/2	0.06 (0.20)	0.16 (0.12)	0.04
1/3	-0.06 (0.56)	0.19 (0.01)	0.10
1/4	0.02 (0.51)	0.23 (0.01)	0.10
1/5	0.03 (0.33)	0.24 (0.09)	0.05
2/1	0.03 (0.21)	0.22 (0.04)	0.07
2/2	0.06 (0.04)	0.27 (0.00)	0.15
2/3	-0.01 (0.54)	0.06 (0.07)	0.05
2/4	0.02 (0.51)	0.34 (0.04)	0.07
2/5	0.03 (0.25)	0.47 (0.00)	0.21
3/1	0.03 (0.41)	0.17 (0.05)	0.06
3/2	-0.01 (0.86)	-0.04 (0.65)	0.00
3/3	-0.01 (0.70)	0.13 (0.09)	0.05
3/4	0.00 (0.98)	0.06 (0.56)	0.01
3/5	0.00 (0.89)	0.11 (0.11)	0.04

Mkt/Player	α (p-value)	β (p-value)	r^2
4/1	0.05 (0.21)	0.16 (0.18)	0.03
4/2	0.03 (0.47)	0.19 (0.07)	0.05
4/3	0.00 (0.98)	0.10 (0.32)	0.02
4/4	0.01 (0.50)	0.02 (0.75)	0.00
4/5	0.01 (0.64)	-0.09 (0.43)	0.01
5/1	0.00 (0.90)	0.27 (0.00)	0.14
5/2	0.01 (0.70)	0.00 (0.98)	0.00
5/3	0.05 (0.54)	0.22 (0.02)	0.08
5/4	0.01 (0.92)	0.14 (0.08)	0.05
5/5	0.03 (0.58)	0.02 (0.79)	0.00
6/1	-0.15 (0.07)	0.37 (0.00)	0.12
6/2	0.02 (0.37)	0.09 (0.13)	0.04
6/3	0.15 (0.06)	0.53 (0.00)	0.23
6/4	0.01 (0.57)	-0.03 (0.49)	0.01
6/5	0.03 (0.60)	0.08 (0.52)	0.01
Average	**0.015**	**0.157**	

Markets	α (p-value)	β (p-value)	r^2
Mkt 1	0.02 (0.37)	0.32 (0.00)	0.19
Mkt 2	0.00 (0.72)	0.32 (0.00)	0.40
Mkt 3	0.01 (0.77)	0.08 (0.16)	0.03
Mkt 4	0.00 (0.99)	0.46 (0.00)	0.27
Mkt 5	0.01 (0.82)	0.14 (0.01)	0.11
Mkt 6	0.00 (0.91)	0.54 (0.00)	0.40
Average	**0.067**	**0.31**	

The coefficient of expectations β is postulated to be in a range from zero to one. All β estimates from aggregate markets fall in this range, and only one is not significant. At the individual level, only three coefficients fall outside the postulated range, none of them significant. The average values of β are 0.015 for individuals and 0.067 for the average markets. It implies and average smoothing time T, $T= -1/ln(1-\beta)$, of 6 years for individuals and 3 years for average markets. The coefficient α is not significant at individual and aggregate level. Note that values of r^2 are very low compared with other estimations of adaptative expectation (e.g. Arango 2006a). A comparison of the two experiments implies that the lower r^2 values must be due to the shorter decision periods and therefore to the longer time horizon (in terms of the number of time steps) of the forecasts (four periods ahead). The average r^2 is higher for aggregate markets than for individuals. This makes sense if each player, making a unique investment decision, erroneously assumes that everybody else thinks similarly. Thus the average forecast of players would come to reflect more information about the market and be more correct. Less randomness would then make it easier to get support for the adaptive expectation hypothesis in the aggregate case than in the individual case, given that adaptive expectations have some merit. On the other hand, the rather low r^2 values signal a need for further investigations of expectation formation in this case.

Test of the heuristic

We explore the aggregated investment behaviour by performing regressions of the heuristic in *eq. (7)*, where the expected price P^* is taken as the average of individual price expectations each year. Regressions are presented in Table 6. The table provides estimates of m_1, m_2, m_3 and b from regressions on the observed results as well as theoretical values for two different parameter sets from Table 2. We observe that five out of the six markets present significant values for m_3, while only two for m_2 and only one for m_1. Thus, P^* is clearly the most interesting explanatory variable. The average value of m_3 is closer to the theoretical value for parameters set 2 than parameter set 1.

Table 6. Parameter estimates for aggregated markets using *eq.(7)*.

	m_3 *(P*)*	$m_2(P)$	m_1 *(SC)*	*b*	r^2
Market 1	0.86*	1.25**	0.07	0.07	0.53
Market 2	-1.37	1.38	0.11	1.97**	0.08
Market 3	2.33**	-0.11	0.05	-0.09	0.16
Market 4	2.86***	-1.29***	0.04	0.51	0.48
Market 5	2.07*	0.03	0.05	0.27	0.15
Market 6	1.78**	0.18	0.09*	-0.35	0.28
Average	**1.42**	**0.24**	**0.07**	**0.40**	
Theoretical# Set 1	0,51	1,98	-0,10	-1,02	
Theoretical# Set 2	1.12	4.38	-0.50	-2.5	

* significance at 10%; ** significance at 5%; *** significance at 1% (2 tailed t-tests).

\# Theoretical parameters from Table 2.

We also explore the individual investment behaviour. The proposed investment function for individuals is

$$x^i_t = m_4 P^{*\,i}_{t}, + m_3 P_t + m_2 SC^i_t, + m_1 C^i_t + b + \varepsilon_t \qquad (9)$$

where m_j (j=1, … ,4) and b are parameters to be estimated, and ε_t is *iid* random variable with zero mean and finite variance. The index *i* represents individuals and the variables conserve the previous names. Table 7 shows the regressions of *eq.(9)* for all individuals across markets. We observe 16, 15, 13, and 10 significant values out of maximum 30 for m_4, m_3, m_2, and m_1 respectively (significance at 10%). This is considerable given large variations of investment decisions. We also observe that r^2 is on average 0.33, which is actually larger than average r^2 for aggregate markets (r^2=0.28). This is not necessarily surprising since individual investments are likely to reflect individual price expectations. Still, further research could contribute to a better understanding of individual behaviour.

Table 7. Parameter estimation for the proposed heuristic for individuals (standard errors).

	m$_4$ (*P)**	**m$_3$ (*P*)**	**m$_2$ (*SL*)**	**m$_1$ (*C*)**	**b**	**R²**
Market 1						
P 1	0.242 (0.117) **	0.037 (0.157)	0.01 (0.069)	-0.03 (0.021)	0.27 (0.191)	0.29
P 2	0.23 (0.05) ***	-0.013 (0.063)	0.095 (0.032) ***	-0.025 (0.011) **	0.211 (0.121) *	0.74
P 3	0.101 (0.064)	0.685 (0.244) ***	-0.032 (0.059)	-0.074 (0.051)	0.457 (0.657)	0.36
P 4	0.221 (0.121) *	-0.177 (0.142)	0.103 (0.055) *	-0.02 (0.023)	0.475 (0.299)	0.15
P 5	-0.276 (0.269)	0.577 (0.33) *	0.198 (0.04) ***	-0.029 (0.018)	0.624 (0.378)	0.55
Market 2						
P 1	0.26 (0.898)	-0.379 (0.747)	-0.009 (0.09)	0.047 (0.041)	0.251 (1)	0.06
P 2	-0.007 (0.151)	-0.012 (0.152)	0.237 (0.059) ***	0 (0.023)	0.163 (0.31)	0.26
P 3	-0.072 (0.129)	-0.094 (0.106)	0.294 (0.034) ***	-0.008 (0.008)	0.248 (0.131) *	0.63
P 4	0.247 (0.237)	1.187 (0.287) ***	0.01 (0.046)	-0.022 (0.016)	-0.832 (0.232) ***	0.59
P 5	-0.043 (0.113)	0.175 (0.107)	0.074 (0.055)	-0.013 (0.024)	0.497 (0.246) **	0.18
Market 3						
P 1	0.832 (0.301) ***	-0.071 (0.306)	-0.072 (0.07)	-0.044 (0.046)	-0.392 (0.552)	0.15
P 2	0.805 (0.231) ***	0.348 (0.182) *	-0.069 (0.07)	0.096 (0.048) *	-1.654 (0.655) **	0.23
P 3	0.152 (0.11)	0.042 (0.086)	-0.285 (0.09) ***	0.007 (0.016)	0.23 (0.191)	0.16
P 4	0.058 (0.123)	0.052 (0.089)	0.143 (0.052) ***	-0.014 (0.018)	0.561 (0.266) **	0.11
P 5	2.573 (0.414) ***	-0.749 (0.259) ***	-0.032 (0.056)	-0.089 (0.04) **	0.627 (0.826)	0.39
Market 4						
P 1	-0.006 (0.092)	0.252 (0.133) *	0.134 (0.044) ***	-0.022 (0.019)	-0.04 (0.217)	0.51
P 2	0.052 (0.02) ***	-0.068 (0.036) *	0.047 (0.039)	-0.039 (0.008) ***	0.6 (0.107) ***	0.57
P 3	0.261 (0.153) *	-0.042 (0.134)	0.048 (0.048)	-0.085 (0.026) ***	0.913 (0.312) ***	0.33
P 4	0.249 (0.099) **	-0.165 (0.084) *	0.189 (0.046) ***	-0.034 (0.022)	0.637 (0.275) **	0.26
P 5	1.493 (0.353) ***	-1.073 (0.304) ***	0.063 (0.051)	-0.04 (0.025)	0.856 (0.502) *	0.41
Market 5						
P 1	-0.126 (0.396)	0.557 (0.316) *	0.041 (0.051)	-0.012 (0.038)	0.088 (0.621)	0.18
P 2	0.268 (0.443)	-0.091 (0.249)	-0.043 (0.07)	-0.042 (0.086)	1.013 (1.281)	0.02
P 3	0.665 (0.16) ***	-0.164 (0.155)	-0.052 (0.062)	-0.015 (0.03)	0.476 (0.529)	0.23
P 4	1.728 (0.281) ***	-0.569 (0.2) ***	-0.108 (0.057) *	-0.105 (0.049) **	0.458 (0.688)	0.43
P 5	0.006 (0.051)	0.207 (0.051) ***	0.023 (0.046)	-0.022 (0.014)	0.221 (0.116) *	0.49
Market 6						
P 1	0.33 (0.094) ***	0.345 (0.202) *	-0.183 (0.07) **	-0.057 (0.031) *	0.349 (0.358)	0.38
P 2	-0.173 (0.144)	0.391 (0.123) ***	0.087 (0.061)	0.064 (0.036) *	-0.447 (0.454)	0.23
P 3	0.206 (0.091) **	-0.075 (0.228)	0.158 (0.059) ***	-0.069 (0.026) ***	0.766 (0.524)	0.36
P 4	1.997 (0.416) ***	-0.615 (0.221) ***	0.076 (0.056)	-0.046 (0.025) *	-0.682 (0.433)	0.37
P 5	0.498 (0.213) **	-0.198 (0.229)	0.168 (0.049) ***	-0.087 (0.053)	1.012 (0.828)	0.46

* significance at 10%; ** significance at 5%; *** significance at 1% (2 tailed t-tests).

4.2 Behavioural implications of the estimated heuristic

Now, we compare previous simulations with a new one where we use the linear regression model with averages of the estimated parameters for aggregates. Figure 8 shows quite similar cycles, except that the new simulation has a longer period and it has a tendency towards exploding oscillations. A clearer picture about this is presented in Figure 7, where all individual markets except one presents cycles with small variations among them. Hence this test can not be used to discard hypothesis 3. However, the accuracy of the test is reduced by the rather poor results of the regressions.

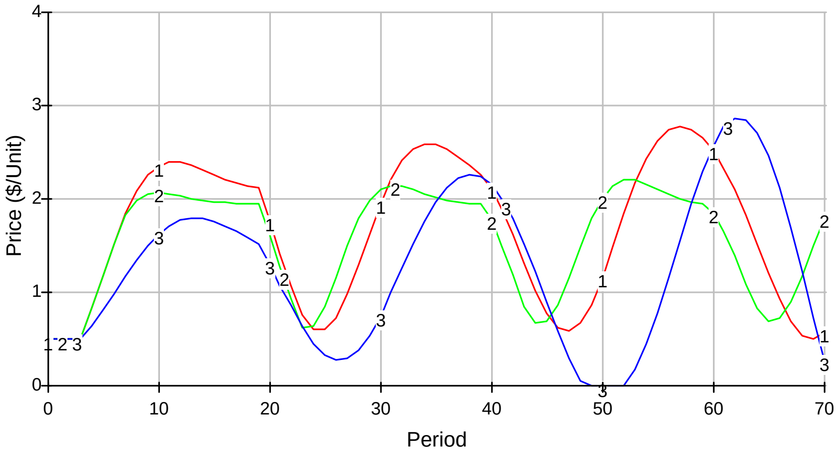

Figure 7. Simulation of investment rule with parameters' set 1 (line 1), set 2 (line 2), and average estimates from experimental results (line 3).

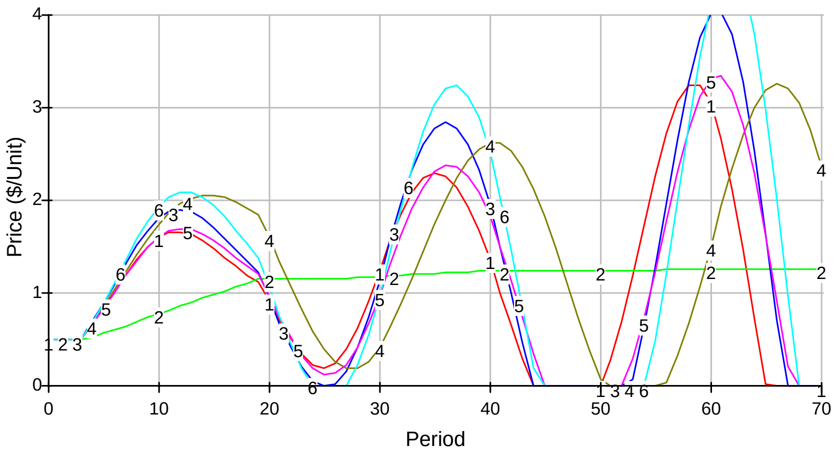

Figure 8. Simulations with estimates from the individual market (line number represents the number of the market).

Random investments?

Rather than taking the regression model at face value, one could also go to the other extreme and assume that decisions are entirely random. We do this and perform a simulation where investments are given by a normally distributed variable (iid). The expected value is set equal to the average investment over all markets in the experiment, and the variance is the average variance over all markets. Figure 9 presents some typical developments. By visual inspection we observe price patterns that differ from those of previous simulations and from the experimental results. Simulations with random investments show price variations closer to pink noise rather than periodic oscillations, while in Arango (2006b) the difference was not so clear. From this test we conclude that the players' heuristics play a vital role for the observed cyclical tendencies.

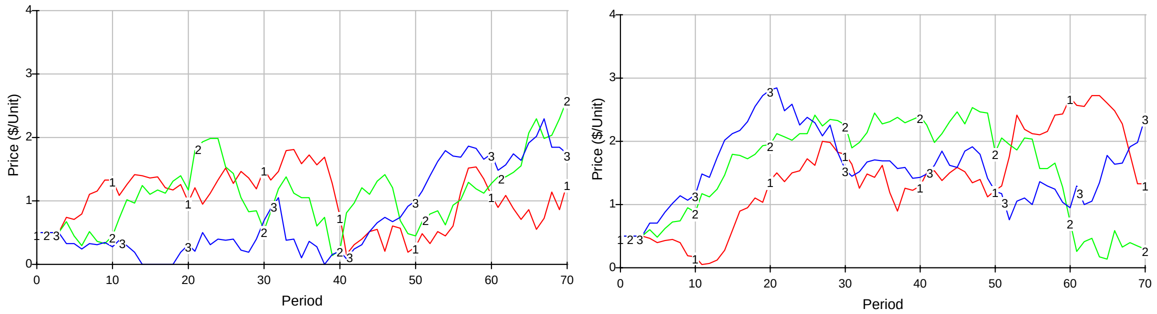

Figure 9. Stochastic simulations with normally distributed investments ~N(2.858, 1.557²).

4.3 Importance of the frequency of decisions

This experiment is an extension of the complex treatment (T3) of Arango (2006b). In Arango's experiment decisions were made each fifth year. This was a compromise not to depart too much from the simple Cobweb design and still have a reasonably correct representation of the long lifetimes of production capacity in electricity markets. The current experiment is more realistic because investment decisions to adjust capital are likely to be more frequent than each fifth year, perhaps yearly as assumed here. The lifetime of capacity is nearly the same in both experiments, four periods of five years (20 years altogether) in Arango and 16 years in this experiment.

Arango found that autocorrelated instabilities occur when the time lag between investment decisions and capacity expansion is increased from one to two periods. However, while Arango was not able to reject the importance of player heuristics, he did not produce strong evidence in favour of this hypothesis either. The present experiment shows more well defined cycles and heuristics seem to play a vital role. Since the frequency of decisions is the major design difference between the two experiments it seems safe to conclude that the frequency matters. [11] What are the likely reasons for this effect? More frequent decisions imply that much more information has to be kept track of. This point is weakened by the fact that the player interface had information about current capacity and capacity on order organised as in Arango in age classes (4 year long compared to 5 years in Arango). A minor difference in this regard is that Arango showed this information in graphical form and not just in a table. No such organising of data was available for prices, forecasts and market shares. Hence in this regard the present experiment was more complicated. This increase in complexity may have called for the use of simplifying heuristics for year to year decisions, rather than for heuristics to transform the decision problem to mimic that in Arango, which could be seen as an easier task. With a year to year investment heuristic, feedback from decisions already taken is slower in the present experiment than in Arango. The result is not surprising if one sees the present experiment as a further extension of what was started in Arango, where one extra investment lag lead to stronger fluctuations. Neither is the result surprising in light of the literature which has identified misperceptions of delays (Sterman, 1989; Brehmer, 1993).

4.4 External validity

The demand in the experiment does not present dynamic adjustment or demand growth, both factors being more realistic than the current assumptions. Both factors have implications for market stability. Demand growth may create an effect of amplifications of cycles as shown by Ford (1999) through simulations. Constant price elasticity and demand dynamics contribute to asymmetries in price distributions as shown by experiments in Arango (2006a). Thus, investigations of these aspects of demand would complement this experiment.

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[11] There is one alternative explanation, Arango provided the players with a profit calculator, we did not do that. However, it seems unlikely that the profit calculator should have an effect on anything but the average price over time. As reported earlier, the average price was on average higher in Arango's T3: 1.42 $/Unit. The profit calculator does not help players decide when to invest.

Capacity utilization is assumed constant and equal to one. This assumption allows isolating the investment decision from the strategic bidding behaviour. If subjects were allowed to make changes in capacity utilization, they may get more stable price behaviour. Relaxing this assumption should be considered together with changes in the demand formulation in future studies.

5 CONCLUSIONS

This paper presents an experimental study of construction cycles as a potentially serious problem for deregulated electricity markets. Simulation models have suggested the potential occurrence of cycles (Ford, 1999; Bunn & Larsen, 1999). However, the evolution of deregulated electricity markets does not present conclusive evidence of capacity cycles; more data is needed to evaluate such behaviour (IEA, 1999 and 2003; Bunn & Larsen, 1992 and 1999). Market stability depends on individual investment behaviour. Rational investment behaviour could lead to economical and minimal fluctuations, while myopic investors could concentrate investments during periods of relatively high electricity prices, causing pronounced cycles (Ford, 1999 and 2000; Bunn & Larsen, 1992; Gary & Larsen, 2000). We isolate investment decision to study directly the rationality of investors in a laboratory experiment.

Our results support the hypothesis of cyclical tendencies in electricity markets, as suggested by behavioural simulation models (Ford, 1999 and 2000; Bunn & Larsen, 1992 and 1999) and economic analysis (IEA, 1999, 2002 and 2003; Stoft, 2002). We find indications of cyclical behaviour by: visual inspection, spectral analysis, autocorrelograms and simulation tests. All observations are consistent with cyclicality.

Investors face a difficult dynamic decision problem that includes long time delays and accumulations, where bounded rationality is more likely to explain the behaviour than perfect rationality. We investigated a hypothesis that people use a simple investment heuristic consistent with bounded rationality theory. A statistical test of the heuristic suggests that investments are positively related to reported price expectations, which in turn may be explained as adaptive expectations with average smoothing times of around 3 years. The other explanatory variables come out mostly insignificant. Interesting to note though is that simulations with the estimated heuristic shows cyclical behaviour of the type observed in the experiment, while simulations with purely random investments show quite different price behaviour. Hence, it seems clear that the observed price cycles are related to player decisions. For most markets and individuals we cannot reject a hypothesis saying that expectations are adaptive and unbiased. However, low r^2 values indicate that the expectation formation is more complicated than assumed here. Hence, the search for better models to explain expectation formation, as well as investments, are interesting topics for further research.

We observe that subjects have the tendency to initiate new projects when they perceive high prices, while they tend to ignore capacity under construction and the involved delivery delay. Once new capacity is in place, the market has surplus capacity and therefore prices fall. There are no external disturbances in the experiment, hence this often quoted cause of fluctuations can be ruled out in this experiment. The players generate sufficient disturbances themselves to keep the cycles alive over time. Hence, our findings should serve as a motivation for further search for and analysis of stabilising policies in newly deregulated electricity markets.

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Appendix 1. Instructions for the experiment

INSTRUCTIONS

WARNING: ***DO NOT TOUCH THE COMPUTER UNTIL YOU ARE TOLD TO!!!***

INTRODUCTION

Thanks for show up and we hope you enjoy this part of the course. This is an experiment in the economics of decision making, the case is a deregulated electricity market. Various foundations have provided funds for the conduct of this experiment. The instructions are simple, and if you follow them carefully and make good decisions you might earn a considerable amount of money. The money will be paid to you in cash after the experiment. In this experiment you are going to play the role of an electricity producer who sells electricity in a market. Each period you will make investment decisions that influence your future production capacity. Your target is to maximize the profits over all periods of the experiment. **The larger your total profits, the larger the payoff.**

MARKET STRUCTURE

You are one among five electricity producers in a market. You do not know who the other players in your market are and how they perform individually. Your profits are estimated as:

Profits = your production * (Price – Cost)

Your production can not be negative and must always be below **20 Units in total**, which is an upper limit ensuring a minimum of competition. The cost is **1 $/Unit** (think of it as a leasing cost). The electricity price is set to equilibrate the total supply and the demand. The total supply is the sum of the production of the five players. It is assumed that the short and long run elasticities are the same. Demand is price sensitive and is given by the following function:

Price = A – B*Q, where Q is the total supply, A = 6, B = 0.1 (see Figure 1)

To summarize, **the larger the total electricity production is, the lower the price.** Respectively, the lower the total electricity production is, the higher the price. There is no economic growth, which means that demand only changes due to price changes.

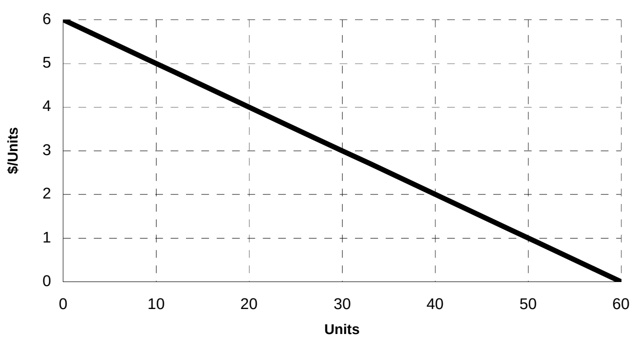


Figure 2. Demand curve

THE PRODUCTION

Your production will always be equal to your production capacity, you cannot reduce capacity utilisation. Each year you make investment decision in new capacity (**you can decide 0 Units**). Important characteristics of the electricity generators are:

Construction delay = 4 years

Life time of capacity = 16 years

This means that if you decide to invest in an additional capacity of **0.8 Units** in year 6, this capacity will be under construction for 4 years and will add **0.8 Units** to your capacity in year 10. This additional capacity will last until year 26.

INITIAL CONDITION
When the experiment starts, the previous managers of the firm have invested a constant amount of **11 Units / Life time = 0.69 Units/year** for a long time. Consequently, you start with a total production capacity of **11 Units**. Thus, if you want to keep the same production, you will have to invest in **0.69 Units** every year. All firms are identical, they have the same costs and the same initial capacity. The system start in equilibrium with an initial total capacity of **11 Units * 5 firms = 55 Units**. For a total supply of **55 Units**, the price is **0.5 $/Unit**. This means that **initially you are all operating with prices lower than your costs**.

PAYOFF
You will receive payoffs according to your performance. Your performance is measured by your cumulative profits. The higher the cumulative profits, the higher the payoff. The payoff will be in the range from **0 to 150 NOK**.

In each year, you are also asked to forecast the price ***in four years***. You will earn an **extra payment depending on the precision of your forecasting**. If you make a perfect forecast in each and every period you get an additional **25 NOK**.

RUNNING THE EXPERIMENT:

BE CAREFUL NOT TO PRESS **"Accept Decisions"** UNLESS YOU REALLY MEAN IT. After having pressed **"Accept Decisions"** your decision cannot be changed

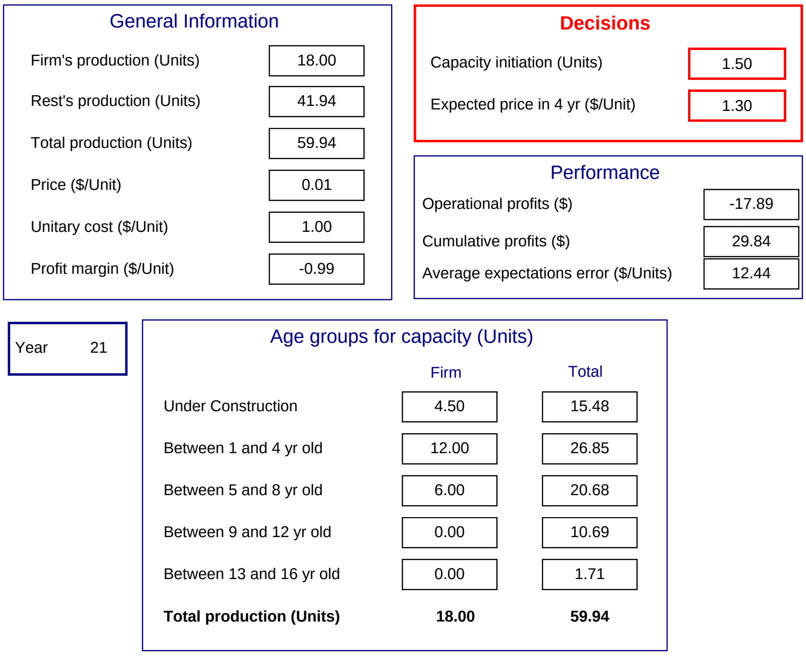
Look at the market and firm information available and make investment decisions and state your price expectations
Write your decisions in the given sheet of paper (this is our receipt for the payment to you, and your decisions have to be filled in), and press "Accept Decisions"
Wait until all the participants in your market have made their decisions
The window "Accept Decisions" appears again, the game has advanced to the next year. The information is updated and it is time to make decisions again.
The simulation will run for an undefined number of years. When the experiment leader stops the game , you must write down your payoff in the given sheet of paper and ask for your payment. Payments will be made privately, one by one.

NOTE
According to the purpose of the experiment it is required not to share any kind of information (verbal, written, gestures, etc.). Please, respect these rules because they are important for the scientific value of the experiment. Breaking the rules implies that the involved group is nullified and the group participants will receive no payment.

Thank you for joining this experiment and do your best!!!

Appendix 2. User interface and Code for the experiment (The software and the rest of the material is available upon request to the author).

User Interface



Code (from Powersim Constructur 2.51).

```
dim     Acum_Difference = (Players)
init    Acum_Difference = 0
flow    Acum_Difference = +dt*Difference
dim     C_Online_1 = (Players)
init    C_Online_1 = Initial_Capacity_per_yr
flow    C_Online_1 = -dt*Rate_21
        +dt*Rate_19
dim     C_Online_10 = (Players)
init    C_Online_10 = Initial_Capacity_per_yr
flow    C_Online_10 = -dt*Rate_31
        +dt*Rate_30
dim     C_Online_11 = (Players)
init    C_Online_11 = Initial_Capacity_per_yr
flow    C_Online_11 = +dt*Rate_31
        -dt*Rate_28
dim     C_Online_12 = (Players)
init    C_Online_12 = Initial_Capacity_per_yr
flow    C_Online_12 = -dt*Rate_29
        +dt*Rate_28
dim     C_Online_13 = (Players)
init    C_Online_13 = Initial_Capacity_per_yr
flow    C_Online_13 = -dt*Rate_34
        +dt*Rate_29
dim     C_Online_14 = (Players)
init    C_Online_14 = Initial_Capacity_per_yr
flow    C_Online_14 = -dt*Rate_35
        +dt*Rate_34
dim     C_Online_15 = (Players)
init    C_Online_15 = Initial_Capacity_per_yr
flow    C_Online_15 = +dt*Rate_35
        -dt*Rate_32
dim     C_Online_16 = (Players)
init    C_Online_16 = Initial_Capacity_per_yr
flow    C_Online_16 = -dt*Rate_33
        +dt*Rate_32
dim     C_Online_2 = (Players)
```

```
init    C_Online_2 = Initial_Capacity_per_yr
flow    C_Online_2 = +dt*Rate_21
        -dt*Rate_20
dim     C_Online_3 = (Players)
init    C_Online_3 = Initial_Capacity_per_yr
flow    C_Online_3 = -dt*Rate_22
        +dt*Rate_20
dim     C_Online_4 = (Players)
init    C_Online_4 = Initial_Capacity_per_yr
flow    C_Online_4 = -dt*Rate_23
        +dt*Rate_22
dim     C_Online_5 = (Players)
init    C_Online_5 = Initial_Capacity_per_yr
flow    C_Online_5 = -dt*Rate_26
        +dt*Rate_23
dim     C_Online_6 = (Players)
init    C_Online_6 = Initial_Capacity_per_yr
flow    C_Online_6 = -dt*Rate_27
        +dt*Rate_26
dim     C_Online_7 = (Players)
init    C_Online_7 = Initial_Capacity_per_yr
flow    C_Online_7 = +dt*Rate_27
        -dt*Rate_24
dim     C_Online_8 = (Players)
init    C_Online_8 = Initial_Capacity_per_yr
flow    C_Online_8 = -dt*Rate_25
        +dt*Rate_24
dim     C_Online_9 = (Players)
init    C_Online_9 = Initial_Capacity_per_yr
flow    C_Online_9 = -dt*Rate_30
        +dt*Rate_25
dim     C_under_contr_2 = (Players)
init    C_under_contr_2 = Initial_Capacity_per_yr
flow    C_under_contr_2 = +dt*Investment
        -dt*Rate_17
dim     C_under_contr_3 = (Players)
init    C_under_contr_3 = Initial_Capacity_per_yr
flow    C_under_contr_3 = -dt*Rate_18
        +dt*Rate_17
dim     C_under_contr_4 = (Players)
init    C_under_contr_4 = Initial_Capacity_per_yr
flow    C_under_contr_4 = -dt*Rate_19
        +dt*Rate_18
dim     Cumulative_profits = (Players)
init    Cumulative_profits = 0
flow    Cumulative_profits = +dt*Net_profit
dim     Difference = (Players)
aux     Difference = ABS(EP_minus_CP)
dim     Investment = (p=Players)
aux     Investment =
SELECTDECISION(INDEX(p),Investment_Decisions,Simulated,Simulated,Simulated)+IF(TIME=0,Initial_Capacity_per_yr,0)
doc     Investment =  AND INDEX(p)=p
dim     Net_profit = (Players)
aux     Net_profit = Revenues-Operational_Cost
dim     Rate_17 = (i=Players)
aux     Rate_17 = DELAYPPL(Investment(i),1,Investment(i))
dim     Rate_18 = (i=Players)
aux     Rate_18 = DELAYPPL(Rate_17(i),1,Rate_17(i))
dim     Rate_19 = (i=Players)
aux     Rate_19 = DELAYPPL(Rate_18(i),1,Rate_18(i))
dim     Rate_20 = (i=Players)
aux     Rate_20 = DELAYPPL(Rate_21(i),1,Rate_21(i))
dim     Rate_21 = (i=Players)
aux     Rate_21 = DELAYPPL(Rate_19(i),1,Rate_19(i))
dim     Rate_22 = (i=Players)
aux     Rate_22 = DELAYPPL(Rate_20(i),1,Rate_20(i))
dim     Rate_23 = (i=Players)
aux     Rate_23 = DELAYPPL(Rate_22(i),1,Rate_22(i))
dim     Rate_24 = (i=Players)
aux     Rate_24 = DELAYPPL(Rate_27(i),1,Rate_27(i))
dim     Rate_25 = (i=Players)
aux     Rate_25 = DELAYPPL(Rate_24(i),1,Rate_24(i))
dim     Rate_26 = (i=Players)
aux     Rate_26 = DELAYPPL(Rate_23(i),1,Rate_23(i))
dim     Rate_27 = (i=Players)
aux     Rate_27 = DELAYPPL(Rate_26(i),1,Rate_26(i))
```

```
dim     Rate_28 = (i=Players)
aux     Rate_28 = DELAYPPL(Rate_31(i),1,Rate_31(i))
dim     Rate_29 = (i=Players)
aux     Rate_29 = DELAYPPL(Rate_28(i),1,Rate_28(i))
dim     Rate_30 = (i=Players)
aux     Rate_30 = DELAYPPL(Rate_25(i),1,Rate_25(i))
dim     Rate_31 = (i=Players)
aux     Rate_31 = DELAYPPL(Rate_30(i),1,Rate_30(i))
dim     Rate_32 = (i=Players)
aux     Rate_32 = DELAYPPL(Rate_35(i),1,Rate_35(i))
dim     Rate_33 = (i=Players)
aux     Rate_33 = DELAYPPL(Rate_32(i),1,Rate_32(i))
dim     Rate_34 = (i=Players)
aux     Rate_34 = DELAYPPL(Rate_29(i),1,Rate_29(i))
dim     Rate_35 = (i=Players)
aux     Rate_35 = DELAYPPL(Rate_34(i),1,Rate_34(i))
dim     Age_between_1_and__4_yr = (Players)
aux     Age_between_1_and__4_yr = C_Online_1+C_Online_2+C_Online_3+C_Online_4
dim     Age_between_5_and_8_yr = (Players)
aux     Age_between_5_and_8_yr = C_Online_5+C_Online_6+C_Online_7+C_Online_8
dim     Age_between_9_and_12_yr = (Players)
aux     Age_between_9_and_12_yr = C_Online_10+C_Online_11+C_Online_12+C_Online_9
dim     Age_more_than_13_yr = (Players)
aux     Age_more_than_13_yr = C_Online_13+C_Online_14+C_Online_15+C_Online_16
dim     Auxiliary_149 = (Players)
aux     Auxiliary_149 =
Investment+C_under_contr_2+C_under_contr_3+C_under_contr_4+C_Online_1+C_Online_2+C_Online_3+C_Online_4+C_Online_5+C_
Online_6+C_Online_7+C_Online_8+C_Online_9+C_Online_10+C_Online_11+C_Online_12
dim     Average_error = (Players)
aux     Average_error = Acum_Difference DIVZ0 TIME
dim     Capacity = (Players)
aux     Capacity = Age_between_1_and__4_yr+Age_between_5_and_8_yr+Age_between_9_and_12_yr+Age_more_than_13_yr
dim     Capacity_Rest = (Players)
aux     Capacity_Rest = ARRSUM(Capacity)-Capacity(1)
dim     Capacity_Under_Construction = (Players)
aux     Capacity_Under_Construction = C_under_contr_2+C_under_contr_3+C_under_contr_4
aux     Consumption = ARRSUM(Capacity)
dim     EP_minus_CP = (i=Players)
aux     EP_minus_CP = DELAYPPL(Expected_Price(i), 4,Price)-Price
dim     Expected_Price = (p=Players)
aux     Expected_Price = SELECTDECISION(INDEX(p),
Decided_Expected_price,Simulated_Expected_price,Simulated_Expected_price,Simulated_Expected_price)+IF(TIME=0,Price,0)
aux     Margin = Price-Variable_O_and_M_costs
dim     Operational_Cost = (Players)
aux     Operational_Cost = Capacity*Variable_O_and_M_costs
aux     Precio_retardado = DELAYPPL(Price, 4,Price)
aux     Price = MAX(A-B*Consumption,0)
dim     Revenues = (Players)
aux     Revenues = Capacity*Price
dim     Simulated = (Players)
aux     Simulated = IF(TIME=0,0,Investment_Decisions(1))*0 + IF(TIME=0,0,Initial_Capacity_per_yr)
aux     T_13_and_16_yr = ARRSUM(Age_more_than_13_yr)
aux     T_C_Under = ARRSUM(Capacity_Under_Construction)
aux     Tot_1_and_4_yr = ARRSUM(Age_between_1_and__4_yr)
aux     Tot_5_and_8_yr = ARRSUM(Age_between_5_and_8_yr)
aux     Tot_9_and_12_yr = ARRSUM(Age_between_9_and_12_yr)
aux     total_invesment = ARRSUM(Investment)
aux     Total_profits = ARRSUM(Cumulative_profits)
dim     Warning_Botton = (Players)
aux     Warning_Botton = IF(Investment_Decisions<0,1,0)
dim     Warning_Top = (i=Players)
aux     Warning_Top = IF(Auxiliary_149(i)>Upper_limit_additional_production,1,0)
doc     Warning_Top = IF(Auxiliary_100(i,2)>Upper_limit_additional_production,1,0)*0
const   A = 6
const   B = 1/10
dim     Decided_Expected_price = (Players)
const   Decided_Expected_price = 0
const   Initial_Capacity_per_yr = (55/16)/5
dim     Investment_Decisions = (Players)
const   Investment_Decisions = 0
dim     Simulated_Expected_price = (Players)
const   Simulated_Expected_price = 0
const   Upper_limit_additional_production = 20
const   Variable_O_and_M_costs = 1
```

Appendix 3. Estimative of the equilibrium points in the market

Following is the notation for the market equilibrium points. Some variables are time dependent, which will be notified if needed.

P: market price
C: marginal cost
c: total cost
S: total supply
q_i: production of the player i
A, B: parameters of the demand curve.
π: profits

Competitive equilibrium
The competitive equilibrium price is the price that equates the quantity demanded and the quantity supplied, with neither surplus nor shortage. The competitive equilibrium is reached when the marginal cost equals the price. The competitive price equilibrium is:

$$P = C = 1 \quad \$/Unid.$$

The total supply is the sum of individual production ($S_t = \sum q_i,\ i = 1,2,...,5$), and there is symmetry across players in the market. Therefore, the total production of competitive equilibrium is distributed symmetrically among players ($S = 5q_i$), given by:

$$S = \frac{A-P}{B} \quad \therefore \quad q_i = \frac{S}{5} \quad \therefore \quad q_i = \frac{A-P}{5 \cdot B} \quad \therefore \quad q_i = 10\, Unid.$$

Cournot Nash Equilibrium
According to the Cournot Nash model, an oligopolistic market is in equilibrium if each firm produces the same expected production of the other, under conditions of profits maximization. The profit function for each firm is:

$$\pi_i = (P - C) \cdot q_i \quad and \quad P = A - B \cdot S$$
$$\pi_i = (A - B \cdot S - C) \cdot q_i$$

Every player assumes that the rest of players will produce the same as her/him. The quantity is the result of profit maximization assuming that the other's production q_i for $j \neq i$, is constant, and in the equilibrium the quantity is time independent. The following expression provides the first-order condition for the production q_i (Martin, 2002):

$$\frac{\partial \pi_i}{\partial q_i} = P + q_i \cdot \frac{dP}{dS} - \frac{d\, c(q_i)}{dq_i} \equiv 0$$

Given that $c(q_i) = C\, q_i$, $S = 5q_i$, the first order conditions becomes:

$$\frac{\partial \pi_i}{\partial q_i} = A - 5 \cdot B \cdot q_i p + q_i \cdot (-B) - C \equiv 0$$
$$q_i = \frac{A-C}{6 \cdot B} \quad \because \quad q_i = 8{,}33\, Unid.; \quad and \quad P = 1{,}83\ \$/Unid.$$

Joint maximization
The joint maximization equilibrium is estimated by assuming that each firm (subject) seeks to maximize the total industry profits and divided the joint profits equally. Since all firms are symmetric, it is equivalent to the

monopoly equilibrium. Thus, the industry maximizes its total profits with respect to the overall production and divides the profits among firms. The profit function for the total industry is given by:

$$\pi = (P - C) \cdot S$$
$$\pi = (A - B \cdot S - C) \cdot S$$

The first-order condition for the production S is:

$$\frac{d\pi}{dS} = (A - B \cdot S - C) + S \cdot (-B) \equiv 0$$
$$S = \frac{A - C}{2B} = 25\, Unid. \quad \because \quad q_i = 5\, Unid. \quad \because \quad P = 3{,}5\ \$/Unid.$$

Appendix 4. Derivation of the linear part of the decision rule with the set 1 and 2 of parameters for simulations.

We re-state the decision rule with the following equations:

$x_t = \text{MAX}(0, C_t/\tau + \alpha_C (C^*_t - C_t) + \alpha_{SC} (k/\tau\, C^*_t - SC_t))$
$C_t = 60 - 10\, P_t$
$C^*_t = \text{MAX}\left(0, a + \left(\frac{q^e - a}{P^e}\right) P^*_t\right) \cong a + Y\, P^*_t$
$Y = \left(\frac{q^e - a}{P^e}\right)$
$P^*_t = \beta\, P_{t-1} + (1-\beta)\, P^*_{t-1}$

To shorten the presentation, we neglect the variable *t* in the bold variables. We also take the linear part of the function and the new decision rule is

$x = \mathbf{C}/\tau + \alpha_C (\mathbf{C}^* - \mathbf{C}) + \alpha_{SC} (k/\tau\, \mathbf{C}^* - \mathbf{SC})$
$\mathbf{C}^* = a + Y\, \mathbf{P}^*$
$\mathbf{C} = 60 - 10\, \mathbf{P}$

Grouping and simplifying:
$x = \mathbf{C}/\tau + \alpha_C \mathbf{C}^* - \alpha_C \mathbf{C} + \alpha_{SC} k/\tau\, \mathbf{C}^* - \alpha_{SC} \mathbf{SC}$
$x = 60/\tau - 10\, \mathbf{P}/\tau + \alpha_C (a + Y\, \mathbf{P}^*) - \alpha_C (60 - 10\, \mathbf{P}) + \alpha_{SC} k/\tau (a + Y\, \mathbf{P}^*) - \alpha_{SC} \mathbf{SC}$
$x = 60/\tau - 10\, \mathbf{P}/\tau + \alpha_C a + \alpha_C Y\, \mathbf{P}^* - \alpha_C 60 + \alpha_C 10\, \mathbf{P} + a\, \alpha_{SC} k/\tau + Y\, \alpha_{SC} k/\tau\, \mathbf{P}^* - \alpha_{SC} \mathbf{SC}$
$x = \mathbf{P}^* [Y\, \alpha_C + Y\, \alpha_{SC} k/\tau] + \mathbf{P} [\alpha_C 10 - 10/\tau] + [-\alpha_{SC}]\mathbf{SC} + [60/\tau + a\, \alpha_C - 60\alpha_C + a\, \alpha_{SC} k/\tau]$

The parameters values are:
a= 38
qe = 41.33
pe = 1.87
α_C = 0.26 (set 1) 0.5 (set 2)
α_{SC} = 0.10 (set 1) 0.5 (set 2)
k = 4
τ = 16

We get the following expression
$\mathbf{x} = \mathbf{P}^* [Y\, \alpha_C + Y\, \alpha_{SC} k/\tau] + \mathbf{P} [\alpha_C 10 - 10/\tau] + \mathbf{SC} [-\alpha_{SC}] + [60/\tau + a\, \alpha_C - 60\alpha_C + a\, \alpha_{SC} k/\tau]$
which is analogous to the expression needed:
$x_t = m_3 P^*_t + m_2 P_t + m_1 SC_t + b$

Finally, the coefficient values are

Coeficient	Expression	Set of parameters 1	Set of parameters 2
m_3	$Y\, \alpha_C + Y\, \alpha_{SC} k/\tau$	0.51	1.12
m_2	$\alpha_C 10 - 10/\tau$	1.98	4.38
m_1	$-\alpha_{SC}$	-0.10	-0.50
b	$60/\tau + a\, \alpha_C - 60\alpha_C + a\, \alpha_{SC} k/\tau$	-1.02	-2.50