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Interaction and Market Structure

Essays on Heterogeneity in Economics

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Expectation Formation in a Cobweb Economy: Some One Person Experiments*

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Abstract. In economics expectations play an important role. In making decisions agents form expectations about future values of variables. Therefore, in any dynamic economic model, agents beliefs about the future have to be modeled. Do people form expectations using a simple rule of thumb or do they use a continually updated forecasting rule? Can people learn a *rational expectations equilibrium*? This paper describes experiments where we investigate how people form expectations in the simplest dynamic economic model, the cobweb model, without any knowledge of the underlying market equilibrium equations. We found that only about 35% of the subjects seemed to be able to learn the unique *rational expectations* equilibrium. We also found that many individuals deviate from *rational expectations* for long periods of time, sometimes with 'systematic forecasting errors'.

1 Introduction

In making optimal decisions agents often have to form expectations about future values of variables. Although much research has been done concerning theoretical models of expectation formation and learning, it is still not clear how agents form expectations in real markets. The currently leading paradigm in expectation formation in economics still seems to be the *Rational Expectations Hypothesis*, introduced by Muth [11]. However, this hypothesis has been criticized a lot in the last decade or so, especially in the *bounded rationality* literature; see for example, the surveys by Sargent [13] and Evans and Honkapohja [4]. One reason for the criticism is that rational expectations assumes unrealistic high computing powers of the agents within the model. Another critique is that rational expectations assumes perfect knowledge of underlying market equilibrium equations. As an alternative the rational agents may be replaced by boundedly rational agents who behave like

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econometricians using time series observations to form expectations. Boundedly rational agents use their own model of the world and they estimate the parameters as more observations become available.

The objective of this paper is to investigate how agents form expectations in an experimental cobweb economy, without knowledge of the underlying market equilibrium equations. In the experiment prices were generated by a non-linear cobweb model, with expectations formed by individual participants. In this experimental setting of what is perhaps the simplest dynamic economic model, we address the following questions: 'Do agents use simple habitual rule of thumbs or do they form expectations some other way?' and 'Do agents learn the unique *rational expectations equilibrium*?'.

The paper is organized as follows. Section 2 briefly recalls the price dynamics of the nonlinear cobweb model for different expectation schemes. In section 3 the experimental setting is explained, while section 4 gives a description of the results. Section 5 concludes and contains some remarks about future experimental work.

2 The Cobweb Model

In the thirties the cobweb model was introduced into economic theory, see for example Ezekiel [5]. Since then the cobweb model has been one of the benchmark models in economic dynamics. The cobweb model describes the price behavior in a single market with one non-storable good taking one unit of time to produce. The demand, q_t^d, for the produced good depends upon the price of the good, p_t. Since it takes one period to produce the good the production decision of the suppliers depends on the expected price, p_t^e, that will prevail in the market. The actual price is determined by market clearing, that is the equality of total supply and total demand. The model can thus be represented by the following three equations:

$$q_t^d = D(p_t) \tag{1}$$
$$q_t^s = S(p_t^e) \tag{2}$$
$$q_t^d = q_t^s. \tag{3}$$

Throughout this paper we will use the following specifications of demand and supply functions:

$$D(p_t) = a - bp_t \tag{4}$$
$$S(p_t^e) = tanh(\lambda(p_t^e - c)) + 1. \tag{5}$$

The demand curve is linear and decreasing in price, whereas the supply curve is non-linear and increasing in the expected price. Notice that a non-linear increasing supply curve is consistent with profit maximizing firms. The reason for choosing a non-linear supply curve is that, for instance with adaptive

expectations, the non-linear cobweb model can generate chaotic price fluctuations. An important question is whether in the corresponding experimental cobweb economy agents will be able to learn the (unstable) rational expectations steady state equilibrium price. From (1-3), using demand (4) and supply (5), one easily finds that the market equilibrium price p_t is given by:

$$p_t = \frac{1}{b}[a - tanh(\lambda(p_t^e - c)) - 1] \tag{6}$$

From this equation it is clear that the price, p_t, depends upon the expectations of the agents. In the experimental cobweb economy prices will be generated by the unknown market equilibrium equation (6), with expectations being formed by participants of the experiment. In the following we first recall how the dynamics depends upon the different kind of expectation schemes, studied in the literature.

Naive Expectations

The first expectation scheme we will consider is naive expectations. If producers have naive expectations then they expect today's price to be equal to yesterday's realized price, that is,

$$p_t^e = p_{t-1}$$

It is well known that the cobweb model with naive expectations and monotonic demand and supply curves yield only three types of long run dynamic behavior: (*i*) convergence to a stable steady state equilibrium, (*ii*) a (stable) period two cycle and (*iii*) unbounded price oscillations. In our setting, the latter possibility can not occur, since the supply curve (5) is bounded. Notice also that in the case of a 2-cycle, agents make 'systematic forecasting' errors, in the sense that the actual price will be high (low) when expected price is low (high).

Adaptive Expectations

Adaptive expectations means that the expected price is a weighted average of yesterday's price and yesterday's expected price, that is,

$$p_t^e = wp_{t-1} + (1-w)p_{t-1}^e$$

Nerlove [12] introduced adaptive expectations into the linear cobweb model and showed that it has a stabilizing effect on the price fluctuations. More recently Chiarella [3] and Hommes [7] investigated the cobweb model with adaptive expectations and a non-linear (but monotonically increasing) supply curve and found that price cycles of any period and even chaotic price fluctuations can arise. To show what happens we make use of a bifurcation diagram. A bifurcation diagram shows the long run price dynamics as a (multi-)

valued function of a parameter. In the bifurcation diagram, figure 1, below we see that a shift of the demand curve can result in a steady state price, a stable k-cycle ($k = 2, 4, ..$) or chaotic price oscillations.

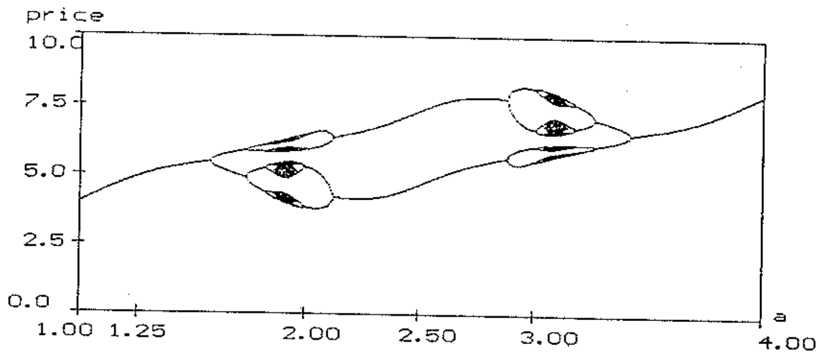

Fig. 1. Bifurcation diagram for cobweb economy with adaptive expectations w.r.t. shifting the demand curve upwards, other parameters are $\lambda = 2, b = 0.25, c = 6, w = 0.5$.

In figure 2 we see what will happen to the price dynamics if we change the weight factor, w, from zero to one.

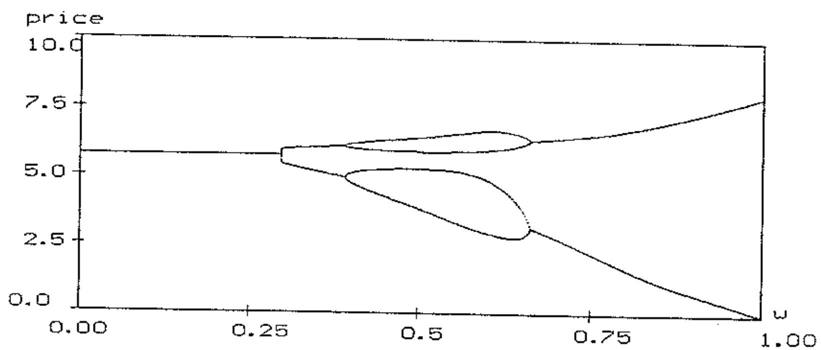

Fig. 2. Bifurcation diagram for cobweb economy with adaptive expectations w.r.t the expectations weight factor w, other parameters are $a = 2, \lambda = 2, b = 0.25, c = 6$

This figure demonstrates that the introduction of adaptive expectations into

the cobweb model has a stabilizing effect, it dampens the amplitude of the price oscillations. However adaptive expectations also introduces the posibility of chaotic or a-periodic price fluctuations.

Learning

In the theoretical bounded rationality literature, much attention has been paid to learning schemes where agents update parameters. There are different kind of expectations schemes that involve learning rules. A well-known example of a learning rule is Ordinary Least Squares-learning (OLS-learning). Bray and Savin [2] showed convergence to rational expectations in the cobweb model with OLS-learning. Another related adaptive learning rule, Sample AutoCorrelation-learning (SAC-learning) where agents constantly update the parameters of their forecasting function according to the sample average and the sample autocorrelation coefficient, was recently introcued by Hommes and Sorger [9]. Learning leads to convergence to the rational expectation equilibrium steady state price.

3 An Experimental Cobweb Economy

In this section we will describe the experiments. In the next section we will present the results of the experiments and we will show how these results fit the theoretical framework, presented above.

3.1 The Experimental Design

We conducted four experiments. The participants in experiments 1a and 1b had to predict a 'value' between zero and ten while participants in experiments 2a and 2b were asked to predict a 'price' between zero and ten. We started the experiment when everybody had finished reading their instructions. The experiments lasted 50 periods, every period lasted 30 seconds. We will call the participants predictions the *predicted value/price* and the realized value/price the *real value*. At the end of every period the participants were informed about the *real value*. Nothing was said about how this *real value* was calculated or if it was calculated. So the only information the participants had were the previous *real values* and that their prediction should lie between zero and ten. The better the participant predicted the more he would earn. Every period the participants could earn up to 1300 points[1]. At

[1] The payment of each prediction is based upon a quadratic payoff function $1300 - 260(X - Y)^2$ where Y is the predicted value and X is the real value. The expected value of this function is maximized by $Y = EX$. Negative payoffs were not used; earnings were 0 if $|X - Y| > \sqrt{5}$. At the end of the experiments the points were exchanged to Dutch guilders at a rate 1300 points = 1 guilder (is approximately \$0.50).

the end of every period the participants screen was updated. Figure 3 below shows a typical screen the participants saw during the experiment.

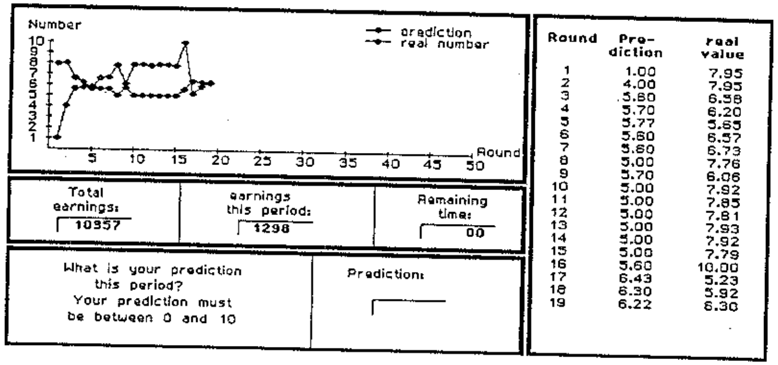

Fig. 3. Typical computerscreen of participants during the experiment

3.2 The Different Conditions

We report the findings from 4 experiments using the design parameters listed in Table 1.

Table 1. design parameters of the experiments

experi-ments	periods 1-15	16-28	29-40	41-50	shock (ϵ_t)
exp. 1a	$a_t = 2$	$a_t = 3$	$a_t = 1.25$	$a_t = 2.5$	U(-0.2,0.2)
exp. 1b	$a_t = 2.3$	$a_t = 2.3$	$a_t = 2.3$	$a_t = 2.3$	N(0,0.5)
exp. 2a	$a_t = 2$	$a_t = 3$	$a_t = 1.25$	$a_t = 2.5$	U(-0.2,0.2)
exp. 2b	$a_t = 2.3$	$a_t = 2.3$	$a_t = 2.3$	$a_t = 2.3$	N(0,0.5)

Participants were not informed about the market equilibrium equation which generated the price as a function of the expected price. The real value was generated to be the market equilibrium price in the cobweb economy in section 2, with expectations formed by a single participant, i.e.,

$$p_t = \frac{a_t - tanh(2(p_t^e - 6)) - 1}{0.25} + \epsilon_t, \tag{7}$$

where ϵ_t is an (unknown) exogenous shock. There are three main differences between the experiments. Firstly, as can be seen in Table 1, in experiments 1b and 2b the parameter a is the same for fifty periods, so that there are no large demand shocks. In contrast, in the other two experiments 1a and 2a four different values of the parameter a are used, implying that there are three (large) demand shocks (three shifts of the demand curve) within the 50 periods of the experiment. Participants have no information about any shocks occurring; in fact, as stated before, participants do not even know that the time series are generated by an underlying cobweb model with feedback from their own expectations. The second difference between the experiments is the difference between the permanent shocks (ϵ_t). In experiments 1a and 2a there are small permanent shocks, drawn from a uniform distribution. In experiments 1b and 2b there are medium size permanent shocks, drawn from a normal distribution. The third difference is that in experiments 1a and 1b the participants had no market information at all, but where simply asked to predict a 'value' or 'number' between 0 and 10. In contrast, in experiments 2a and 2b the participants had some general market information, and were asked to predict the price in a market. In the latter case, participants knew that they had to predict 'some kind of price sequence', but they were not informed that this price sequence was generated by a demand-supply model with feedback from their own expectations. The question now arises how these differences in the experiments affect the participants predictions.

4 The Results of the Experiments

In this section we will give the results of the experiments. We will show the differences and similarities of the results between the different experiments.

4.1 Experiments 1a and 2a: Three Large Exogenous Shocks

Large differences between the participants occured. Some of the participants earned up to 52000 points (40 guilders) while others earned nothing. An obvious reason for this is that participants used different kind of expectation rules. For a good examination of the results we categorized the participants into three categories by looking at their time series. The three categories we obtained are:

1. participants who seem to have some kind of adaptive expectations or AR(1) learning
2. participants who seem to have some special form of naive expectations, which we call markov expectations
3. participants who did not seem to use a systematic forecasting rule

Table 2 shows how the participants in experiments 1a and 2a are distributed over the different categories. The average amount of money in guilders earned

Table 2. earnings of participants of experiments 1a and 2a

experiment 1a	category 1	category 2	category 3	total
participants	8	5	7	20
average earn.	28.99	10.94	6.29	16.54
experiment 2a	category 1	category 2	category 3	total
participants	4	11	4	19
average earn.	25.85	8.97	9.33	12.60

by a subject in that category is also shown. From the table we see that participants in category 1 earned most money, while the difference between participants in categories 2 and 3 is less obvious. Even though the participants in experiment 2a had some general market information their average earnings are somewhat less than those of the participants in experiment 1a. Overall this suggests that general market information does not improve prediction performance. Note that the participants with naive expectations or markov expectations who according to the theory will always make systematic forecasting errors did earn some money. An explanation for this is that the theoretic cobweb model with naive expectations and parameters as in the experiment, leads to the stable equilibrium value in periods 29-40 .

Figure 4 shows the time series of participant 31 (experiment 1a), a typical example of category 1.

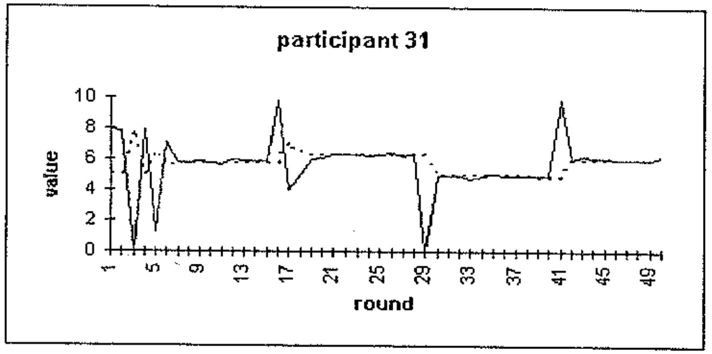

Fig. 4. time series of participant 31

The dotted line represents the participants' *predicted value* and the black line represents the *real value*. From figure 4 we see that around period eight

the participant predicted the equilibrium price. At period sixteen the (unexpected) exogenous shock takes place (the parameter a changes from 2 to 3) causing the *real value* to become almost ten. At period 17 the participant adapts his *predicted value* too much in the direction of the *real value* causing the *real value* to decline sharply. But from that moment on he adapts with smaller steps and within four periods he has found the new equilibrium again. After the second (period 29) and the third (period 41) exogenous shock he finds the equilibrium price/value even faster. Participant 31 is able to learn the unique rational expectations steady state within 8 periods, without any knowledge of the market equilibrium equations. After a large exogenous shock, participant 31 is able to find the new rational expectations steady state quickly.

Simulations with Experiment 1a and 2a

We did some simulations to show how our results relate to the theory. In figure 5 below we see that in the case the expectations or forecasting rule is adaptive expectations with weight factor $w = 0.2$, the generated time series is similar to the time series for participant 31 in the actual experiment. This suggests that participant 31 has been using some kind of adaptive expectations forecasting rule with a small weight factor.

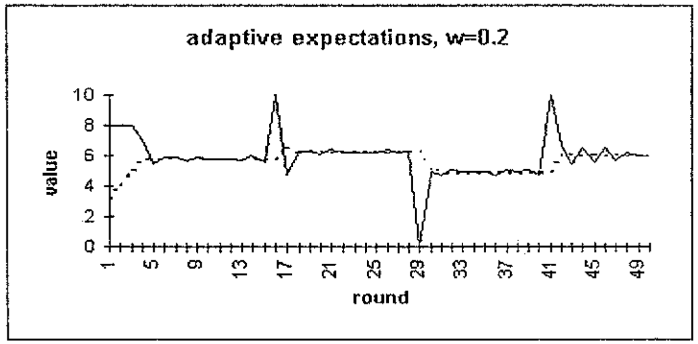

Fig. 5. simulated time series with adaptive expectations with expectations weight factor $w = 0.2$.

4.2 Experiments 1b and 2b: Permanent Medium Shocks

The difference between these experiments and the former experiments is that in this experiment there are no large shifts of the demand curve, but instead there are permanent medium exogenous shocks $\epsilon_t \sim N(0, 0.5)$. Table 3 shows the results for experiments 1b and 2b.

Table 3. earnings of participants of experiments 1b and 2b

experiment 1b	category 1	category 2	category 3	total
participants	7	9	6	22
average earn.	21.63	0	4.63	8.14
experiment 2b	category 1	category 2	category 3	total
participants	6	5	5	16
average earn.	29.18	0.32	6.96	13.22

Again we see that the participants who we put in category 1 earned the most money. Notice that in this case general market information does lead to some prediction improvement and therefore to higher average earnings. Figure 6 shows the time series of participant 102 (experiment 2b), a typical example of category 2.

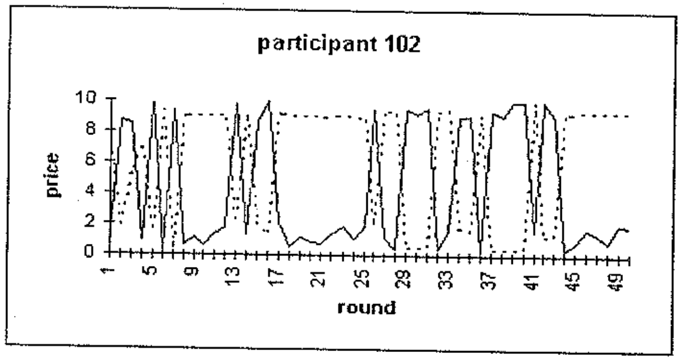

Fig. 6. time series of participant 102

It is easy to see that this participant only expected a high or a low price.

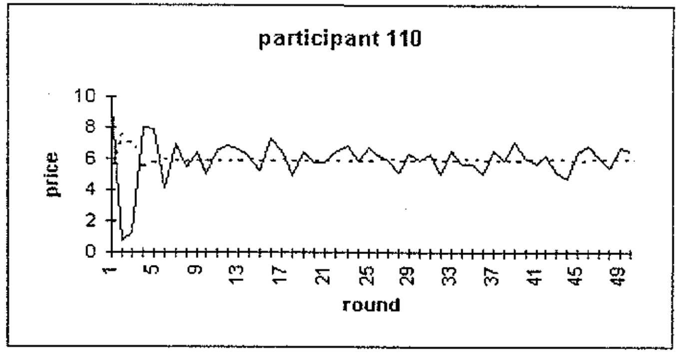

Fig. 7. time series of participant 110

Since in these experiments the equilibrium price was 5.92 this participant did not earn any points at all. On the other hand participant 110 from group 1 predicted the price very well as we can see in figure 7.

Simulations with Experiments 1b and 2b

We now present a simulation with markov expectations. Markov expectations means that a participants' *predicted value* is either his last *predicted value* or the last *real value*, with some probability of switching between these two. This leads to the following time series.

From a qualitative viewpoint, figure 8 is similar to the time series of participant 102. Some individuals in the experiments thus seem to use some kind of markov expectations rule.

Finally, Figure 9 shows the time series of a simulation with SAC-learning. Despite the medium sized permanent demand shocks, the learning algorithm converges to the unique steady state equilibrium. This time series is similar to the time series of participant 110 (category 1). SAC-learning thus seems to be a reasonable description of some of the individual forecasting rules.

5 Summary and Concluding Remarks

In this paper we have built an experimental environment to investigate expectation formation in a cobweb economy, and in particular to investigate

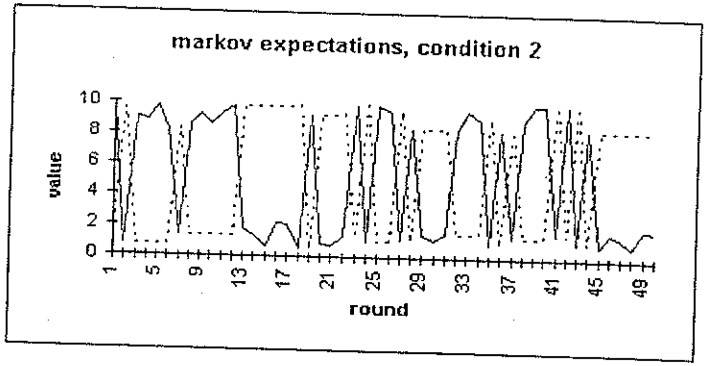

Fig. 8. simulated time series with markov expectations, transition probabilities of 0.25 and 0.75.

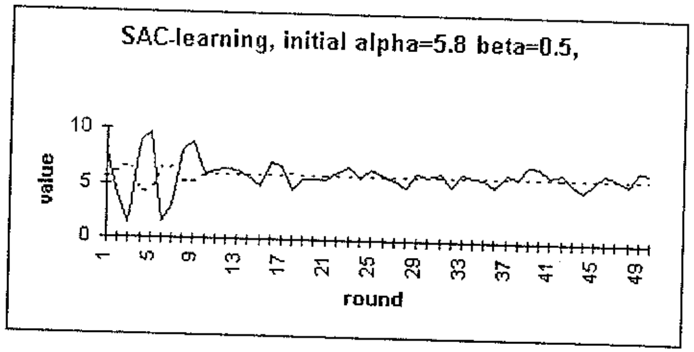

Fig. 9. simulated time series with SAC-learning, $\alpha = 5.8$ and $\beta = 0.5$.

whether agents are able to learn rational expectations in an unstable market when market equilibrium equations are not known. We found that around 35% of the participants was able to learn the rational expectations equilibrium price/value. These participants seemed to use adaptive expectations with a small weight factor w. They adapted their predictions with small steps into the direction of the realized price. Also in some cases SAC-learning or OLS-learning describes expectation formation reasonably well. In contrast, one of the main results of these individual experiments is that a large fraction of the participants was not able to learn the unique rational expectations equilibrium price/value, not even within 50 time periods. This result is remarkable since we are dealing with what is perhaps the simplest dynamic economic model. Although there is a unique rational expectations equilibrium many agents are not able to learn it when market equilibrium equations are unknown.

In order to get insight into expectations in real markets, much more work remains to be done. A controlled experimental environment seems to be very useful in addressing the problem of expectation formation. An important shortcoming of the present paper is that so far we have focussed entirely on individual experiments, that is, in all experiments described above the realized price/value is fully determined by the expected price of a single individual. It is much more interesting to consider group experiments, where the realized price/value will be determined by an equilbrium equation with simultaneous expectation feedback from many, different individuals. Does *aggregation* of expectations improve convergence to the rational expectations steady state, or is instability of rational expectations equilibria in a many agent world, with many different forecasting rules being used, even more likely? We intend to run such group experiments for the cobweb model in the CREED laboratory of the Unversity of Amsterdam in the near future. The individual experiments described in this paper should be useful as a benchmark to address the issue whether aggregation in expectations is stabilizing or destabilizing.

The market institution will also be important in determining whether aggregation of expectations will be stabilizing or not. In future work, we hope to consider different institutional settings, e.g. by applying our experimental setup to other underlying market equilibrium models such as financial asset pricing, exchange rate or inflation models.

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Fecund, Cheap and Out of Control: Heterogeneous Economic Agents as Flawed Computers vs. Markets as Evolving Computational Entities

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Abstract. Our objective in this paper is to try and clarify what we perceive to be two major approaches to the problem of heterogeneous interactive economic agents, and argue in favor of the option which we feel has suffered relative neglect. The first option, perhaps best represented by the work of Alan Kirman, but found throughout the avant garde of the profession, tends to characterize agents as flawed automata or limited computational entities. Exercises in this tradition tend to produce simulations of specific economic situations. While there is much to admire in this program, we maintain that invoking a gestalt reversal which regards markets as computational devices, or literal formal automata, would achieve many of the same goals as the former research program, but would foster a rich and viable evolutionary economics to boot, one which would encourage both mathematical rigor and historical relevance, while avoiding many of the mechanistic excesses of neoclassical theory. Because the second path is the road less traveled, we survey what we call a computational understanding of markets, in order to provide a framework for incorporation of automata theory into a consciously evolutionary approach. For after all, what is the purpose of acknowledging the heterogeneity of agents, if not to then subject them to some form of selection process? We work through an explicit example of the automata theory approach, using two papers by Gode & Sunder [1993, 1997] to illustrate how some recent literatures could be recast into this novel approach. We close with the suggestion that it is experience with real-time markets being run as automata on computers, and not just some academic simulations, which will induce both economists and market participants to come to an appreciation of this kind of evolutionary economics.

1. Waiting for a Little Spontaneous Order

The effect of the computer upon modern developments in economic theory is a topic still in its infancy. All manner of novel and imaginative research programs owe their genesis