An experimental approach to expectation formation in dynamic economic systems

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Chapter 9

Summary

Expectations play a key role in dynamic economic models. Many "theories of expectations" have been proposed in the literature, but these theories are hard to test on real data. The goal of this thesis is to get some insights in the way economic agents form expectations and to test different theories of expectations in the laboratory. We conducted experiments with two different types of dynamic economic models with expectations feedback, namely the cobweb model and an asset pricing model.

The first model corresponds to the classical cobweb or 'hog cycle' model. Participants of the experiments are asked to give a prediction of next periods price of some unspecified produced commodity. The market price is a function of his own expectation and of five other participants. Market equilibrium equations are unknown and subjects form expectations based upon time series observations. An important feature of the cobweb model is that it has a unique RE steady state.

The second model used in our experiments stems from the finance literature and is a standard asset pricing model. In these experiments participants give a prediction of the price of a risky asset two periods ahead and the market price is a function of the average prediction of six participants. In contrast to the cobweb model, the asset pricing model has multiple RE solutions: a constant RE fundamental price as well as infinitely many RE bubble solutions.

This thesis may be seen as an experimental testing of various expectations hypotheses proposed in the (theoretical) literature. In this chapter we summarize our main findings of the experiments with these two models. Section 9.1 discusses the main results from the cobweb experiments and Section 9.2 discusses the results from the asset pricing model. We conclude this thesis with some general remarks, comparing the results for both models.
9.1 Cobweb experiments

In Part I we study expectation formation in the cobweb model. Probably due to its simple structure, this model has played an important role in the literature on expectation formation. In particular, adaptive expectations (Nerlove (1958)) and rational expectations (Muth (1961)) were first introduced in the cobweb model. More recently, different boundedly rational learning models have been applied to this model (e.g. Bray (1982), Bray and Savin (1986), Arifovic (1994), Hommes and Sorger (1998) and Brock and Hommes (1997)).

In the instructions, at the beginning of the experiment, the participants are informed that they are an advisor to a producer, and that they have to predict next period's price for a certain produced commodity. The producer's production decision depends on the forecast of the price of the advisor (i.e. the participant). Participants are given some general market information. However, they are not explicitly informed about the price generating process, which among other things depends upon their own prediction, and have no exact knowledge of the market equilibrium equation. An important feature of the cobweb economy is that a high (low) prediction leads to a high (low) production and this results in a low (high) realized market price and therefore to a large forecast error.

We run experiments with the cobweb model with a number of different treatments. We distinguish between a stationary permanent shock treatment and a non-stationary treatment noise treatment. In the non-stationary treatment the demand curve is shifted three times during the 50 periods of the experiment. As a consequence, in different periods, participants face a different RE steady state equilibrium. In the stationary treatment the RE steady state equilibrium is constant over time. A second distinction is made between single-agent and multi-agent treatments. In the single-agent treatment the market price is a function only of the participants own prediction whereas in the multi-agent treatments the market price is a function of the prediction of six or twelve participants. The third distinction is made between a stable, unstable and strongly unstable treatment depending upon the ratio of marginal demand and supply at the RE steady state. We call the cobweb model stable if under naive expectations there is convergence to the RE steady state price.

Chapter 3 reports results on the strongly unstable single-agent treatment. The most striking result is that, even in this simple stationary environment, about 65% of all subjects is apparently unable to learn the unique RE steady state. Furthermore, a minority of the subjects that are able to learn the RE steady state seem to use some kind of adaptive strategy, i.e. they adapt their last prediction in the direction of the last realized market price. These kind of simple strategies work very well. However, a majority of the subjects
Summary

is unable to find such a simple strategy and does *not* learn the RE steady state.

For the multi-agent treatments discussed in Chapter 4 the amplitude of the price oscillations is smaller than in the single-agent treatment. For all the stationary treatments we *cannot* reject the null hypothesis that the sample mean of realized prices is equal to the RE steady state price. This means that participants are on average able to learn the correct price level. Secondly, in the strongly unstable multi-agent treatment we find significant excess volatility. Price fluctuations are significantly larger than under the RE benchmark. A final observation is that there is little linear predictability left in the realized prices.

The results for the non-stationary treatments are mixed. For half of the groups the null hypothesis that the sample mean is equal to the RE steady state price cannot be rejected, for the other half the null hypothesis is rejected. Also in this treatment we find excess volatility in market prices. In a non-stationary it is thus hard to learn the correct price level.

For the stationary treatments we investigated how robust our results are with respect to the group size and the stability of the cobweb model. Although excess volatility tends to decrease with group size, our experiments show strongly significant excess price volatility for all (strongly) unstable treatments with group sizes of one, six and twelve, respectively and the excess volatility result therefore seems to be robust with respect to the group size. The experimental outcome may thus be described as a *boundedly rational* heterogeneous expectations equilibrium where predictions are correct on average, prices converge to the RE steady state in the mean, but diversity of beliefs leads to excess price volatility. For the stable treatment the results are quite different and excess volatility disappears. If we account for a learning phase of 25 periods then the null of RE cannot be rejected for all 6 groups. Hence, even when agents have limited information and do not know market equilibrium equations the RE equilibrium concept may be a useful description.

The question of which expectations hypothesis is a good description of realized market price fluctuations in a cobweb economy thus depends crucially on market stability. In a stable market after a short learning phase RE is a fairly good description. In contrast, RE is not a good description of market fluctuations if the market is unstable because price volatility is higher than under RE.

In Chapter 5 we use the strategy approach to investigate expectation formation in the cobweb model. Participants in this experiment have to submit a prediction strategy, that is a complete representation of the subjects predictions in all possible states. We introduce a tournament incentive structure, i.e. the ranking is based upon the performance of the strategy measured by the average quadratic forecasting error. The winner is the strategy
with the smallest average quadratic forecasting error. A motivation for the strategy approach is that the behavior of the subjects in Chapter 4 is difficult to interpret since the learning possibilities are limited (only 50 periods). In particular, we study whether in the strongly unstable case convergence to RE occurs if the participants are given repeated possibilities to learn. The individuals in the strategy experiment have ample opportunity to learn and revise expectations in each of the 4 rounds. The submitted strategies differ a lot and tend to get more complicated over the rounds. Over the rounds the quadratic forecasting errors decrease and realized market prices move to a neighborhood of the RE steady state, but at the same time the complexity of the price fluctuations increases. Convergence to the unique RE steady state occurs in less than 10% of all cases. In the final round 60% of the price fluctuations appears to be chaotic. Strategy simulations with homogeneous agents typically show regular behavior, with prices converging to a steady state or to a ‘far from the steady state’ stable cycle with large amplitude. It seems that in a strongly unstable cobweb economy heterogenous interaction of simple prediction strategies is the main source of the endogenous price fluctuations, frequently leading to a boundedly rational equilibrium of ‘close to the steady state chaos’.

9.2 Asset pricing experiments

In the second part of the thesis we studied an asset pricing model with expectations feedback. The underlying equilibrium model is discussed in Chapter 6. Traders can invest in two assets: a risk free asset which gives a fixed return and a risky asset which pays a stream of uncertain dividends. The subjects in the experiment are informed that they are advisors to a pension fund and have to forecast the price of the risky asset. The investment decision of the pension fund depends upon the expected price of the risky asset: the higher the expected price, the higher the investment into the risky asset. Participants are informed about the mean dividend $\bar{y}$ and the interest rate $r$ and are thus able to compute the fundamental price ($p^f = \frac{\bar{y}}{r}$). An important feature of the asset pricing model is that it has a self-fulfilling or self-confirming expectations feedback mechanism: if agents forecast a high (low) price of the risky asset the demand for the risky asset will be high (low) and therefore the realized market price will be high (low). A high forecast thus leads to a high realized market price and hence expectations are confirmed. The asset pricing model has multiple RE solutions, a RE fundamental price will prevail when all participants predict the RE fundamental price and a bubble will emerge when all participants believe in the bubble.

In Chapter 7 we report the results of two treatments of the asset pricing experiments.
In the first treatment (NoRobot treatment) the asset market is populated by six subjects. In the second treatment (Robot treatment) the market is populated by six subjects and a robot trader who always predicts that the price of the risky asset is equal to the fundamental price. The robot trader may be seen as a 'stabilizing force', since its influence on the realized market price increases as the spread between the realized market price and the fundamental price increases. Another important difference between the two treatments is that in the NoRobot treatment the prices are restricted to be below a large upper bound of 1000 while in the Robot treatment prices are restricted to be below 100. We find some similarities and differences between the Robot and NoRobot treatment. Let us start with the similarities. In both treatments we find that participants seem to coordinate on a common prediction strategy. The predictions of the participants in the same group have the same structure and in particular the dispersion between individual predictions is on average smaller than the forecast errors the participants make. There are also some important differences. In the NoRobot treatment long lasting speculative bubbles occur to the upper bound of 1000 in 5 out of 6 groups. Notice that, for the RE benchmark prices are in 95% of the time in the interval [59,61]. On the other hand, in the Robot treatment we observe oscillating asset prices in some groups and (slow) convergence to the fundamental price in others. In both treatments we find that most participants make structural forecast errors. However, for the NoRobot treatment if only consider the observation until the bubble bursts we find almost no significant lags of the autocorrelation function of the excess returns. The asset market is in this sense informationally efficient. An econometric analysis suggests that participants, in the Robot treatment, learn to use simple linear prediction rules.

In Chapter 8 we report the results of a strategy experiment. The goal of this study is to investigate what kind of prediction strategies participants use in a laboratory experiment. The strategy experiment consists of an introductory experiment, where the subjects get experience in their forecasting task, a four round strategy experiment and one final laboratory experiment. In the short run, the first fifty periods, we do not observe any convergence to a steady state price. The distance of the price to the fundamental price in round 1 is fairly small while the distance in round 2 is very large. In rounds 3 and 4 this distance decreases again but is still larger than in round 1. An explanation for this would be that the strategies of the participants in round 1 are cautious but in round 2, while trying to improve prediction accuracy, the strategies become less cautious and there is overreaction. As a reaction of the bad performance in round 2 the strategies in round 3 and 4 become more cautious and the distance of the price to the fundamental price decreases again. However, over the rounds the percentage of convergence to a steady state
price increases in the long run (1000 periods). In round 2 after 1000 periods, the long run dynamics, we find that only around 17% of the simulations converged to a steady state far from the fundamental. The underlying dynamics may have a steady state far from the fundamental price. In the long run in round 4 only 40% of all simulations converged to the fundamental steady state while another 40% converged to a steady state price different from the fundamental. The other 20% of the simulations does not converge, neither to a steady state or to a periodic cycle. In a simple stationary asset pricing experiment participants have a hard time in learning the correct RE fundamental price level. The final laboratory experiment suggests that participants use their formulated strategy as a rule of thumb in the laboratory experiment.

9.3 General conclusions

We have used laboratory experiments to study expectation formation in two different dynamic economic models: the cobweb model and an asset pricing model. An important difference between these models is that the cobweb model has an expectations reversing (high forecast - high production - low realized market equilibrium price) whereas the asset pricing model has an expectation confirming (high forecast - high demand - high realized market equilibrium price) structure. When evaluating the results we should take this difference into account.

A first observation is that we find that, for all stationary cobweb model treatments, participants are on average able to learn the correct price level. However, there is excess volatility in the prices when the cobweb model is unstable under naive expectations. For a stable stationary cobweb model we do not observe excess volatility.

For the asset pricing experiments we find that it is hard to learn the 'correct' fundamental price level, even though the model is stable under naive expectations.

A third result is that in the asset pricing experiments we find that long lasting deviations from the RE fundamental price may occur. However, along such a temporary bubble we do not find significant structure in the forecasting errors. The asset market is in this sense (that participants do not make structural forecast errors) informationally efficient.

What have we learned from these experiments and what can we say about the real world? Is it possible to say something about stock prices in general given the results from our experiments? Since we use a somewhat 'abstract' dynamic financial environment for our experiments it is hard to derive exact conclusions about real financial markets. We find that in a very simple, stationary asset pricing laboratory environment it is hard to
learn the correct fundamental price level. Furthermore, we even observe non-rational large and long lasting deviations from the fundamental price. Based on our experiments one might draw the following tentative conclusion about real financial markets. In an uncertain world with little or diverse information about the fundamentals long lasting deviations from the fundamental may arise. Future experiments may reveal more insight into this problem.