An experimental approach to expectation formation in dynamic economic systems

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Chapter 1

Introduction

Expectations play an important role in economics. Many decisions by economic agents are based on expectations or beliefs about the future state of the market. Expectations about economic variables feed back into the actual realization of these same variables and these realizations affect agents expectations.

The following example about the unexpected death of a famous Dutch painter illustrates how expectations matter. After his passing away the demand for his paintings went up and as a result the prices of his paintings increased enormously. How can we explain this sudden rise in prices? A pure economic explanation would be that because of a change in the underlying fundamentals, the death of the artist, the demand increases while supply remains fixed. Overoptimistic beliefs about a price increase may reinforce the increase in prices and in this way a speculative bubble may arise. An important question is whether prices in financial markets are also driven, at least partly, by market psychology.

In general, if traders expect the price of an asset to rise in the future, demand for that asset increases and as a result, by the law of supply and demand the price of the asset will then also increase. A good example nowadays are stocks of the ICT industry. New information- and communication technologies will lead to economic growth in this sector. Due to economic fundamentals, the price of ICT stocks will therefore increase. Many people may have been overoptimistic about the growth of the ICT industry. This optimism resulted in an excessively rapid growth of stock prices and market indices and resulted in an overvaluation of the ICT stock prices. However, recently the prices have decreased sharply. It seems that this rise and fall in the ICT stock prices cannot be explained by changes in the fundamental values alone, but that the “psychology of the market” is an important factor as well. From these examples it should be clear that the interaction between the actual development of economic variables and the beliefs and expectations
of economic agents plays an important role in economic modeling. In fact, any dynamic economic system is an *expectations feedback system*: expectations affect market outcome and these outcomes lead to new expectations etc. A theory of expectation formation is therefore a crucial part of economic theory. In this thesis we will address the issue of expectation formation in dynamic economic systems, in a laboratory setting. The thesis may be seen as an *experimental testing of different expectation hypotheses*.

This introduction is organized as follows. The next section delves deeper into the problem of expectation formation in economics. Section 1.2 briefly reviews the history of experimental economics and reports on some earlier work on expectation formation. Finally, Section 1.3 provides an outline of the thesis.

### 1.1 Expectation formation

Let us start with a simple economic example from labor economics to illustrate the role expectations play in economics. We consider labor supply of engineers and assume that the demand for engineers is fixed. The wage of engineers depends on the total supply of engineers. If there are many engineers their wage will not be high; if there are few engineers wages will be high. It takes four years to graduate from engineering school. The number of students entering engineering school depends upon the wage expectation. If the current wages are high and students expect them to remain high, many students will enter engineering school, because they expect the future perspectives to be good. By the time they graduate there is excessive supply and realized wages will be low. Few students will therefore at that time enter engineering school and after a couple of years there is again a shortage of engineers and as a result wages will go up again. If people expect the wage in 4 years (the minimum number of years to graduate) to be equal to the wage today, cycles in wages, as discussed above, will emerge. On the other hand, if people understand this mechanism they may base their decisions on this and adapt their behavior, which might dampen the wage oscillations. From this simple example it is obvious that expectations are crucial in economic markets. Figure 1.1 represents a dynamic economic expectation feedback system. On the left side of Figure 1.1 we see the economic system, for example the model of labor supply as explained above. On the right side are the beliefs of the economic agents in the model. The economic agents have to make decisions concerning the future. From observing the economic system the agents "learn" and update their beliefs or expectations about the relevant variables in the economic system. These beliefs about the variables of the economic system affect the realizations and market outcomes, i.e. the beliefs feedback into the system. The whole
dynamic environment may thus be viewed as an expectations feedback system.

\[ x_t = T(E_{t-1} x_t), \] (1.1)

where \( x_t \) represents the economic variable of interest at time \( t \), let us say a price. The price in period \( t \) is some decreasing function \( T(\cdot) \) of the expectations about this periods price, \( E_{t-1} x_t \) formed at time \( t - 1 \). A high expected price now will lead to a low price next period (like the model of labor supply of engineers, explained above) and vice versa. We will refer to this kind of feedback systems as an expectations reversing feedback system.

For analyzing models with expectations feedback we need to make assumptions about the expectations of the agents in the model. Agents form expectations given the available information. In the model of type (1.1) beliefs have the following general structure:

\[ E_{t-1} x_t = F(x_{t-1}, x_{t-2}, \ldots, E_{t-2} x_{t-1}, E_{t-3} x_{t-2}, \ldots). \] (1.2)

The information set of the agents contains all his previous predictions and all the past prices upto period \( t - 1 \).

The second type of expectation feedback system we study in this thesis, the dynamic asset pricing model, is of the form:

\[ x_t = T(E_{t-1} x_{t+1}), \] (1.3)

again \( x_t \) represents the economic variable of interest at time \( t \), again, e.g. a price. However, the price in period \( t \) is now an increasing function \( T(\cdot) \) of the expectations about the
price in period \( t + 1 \), \( E_{t-1}x_{t+1} \) formed at time \( t - 1 \). This is a self-confirming expectations feedback system since a high expectation will result in a high realization. Notice that the information set of agents in models of form (1.3) differs from the agents in models of form (1.1). The agents in the dynamic asset pricing models form expectations for the price at \( t \) given all previous predictions up to \( t - 1 \) and all previous realized prices up to period \( t - 2 \), that is

\[
E_{t-1}x_{t+1} = F(x_{t-1}, x_{t-2}, \ldots, E_{t-2}x_t, E_{t-3}x_{t-1}, \ldots). \tag{1.4}
\]

Assumptions have to be made about how people use the available information and reach their predictions. Until the sixties it was common practice to use simple habitual rule of thumb predictors in modeling expectations. For example, agents with naive expectations expect the price for tomorrow to equal today’s price, \( E_{t-1}x_t = x_{t-1} \). Agents with naive expectations in a simple model like (1.1) make systematic forecast errors as discussed in the model for the supply of engineers discussed above. Another simple expectations rule which was quite popular in the sixties is adaptive expectations, \( E_{t-1}x_t = (1-w)E_{t-2}x_{t-1} + wx_{t-1} \), where \( 0 < w \leq 1 \). This is a weighted average of the last observed price, \( x_{t-1} \), and the last expected price \( E_{t-2}x_{t-1} \). Agents with adaptive expectations adapt their expectations in the direction of the latest observed value. Notice that naive expectations is a special form of adaptive expectations (i.e. where \( w = 1 \)). An important (theoretical) criticism against simple forecasting rules such as adaptive or naive expectations has been that agents make systematic forecast errors and do not learn from their mistakes. This criticism motivated Muth (1961) to introduce a more sophisticated form of expectations: Rational Expectations (RE). Since the pioneering work of Muth (1961) and Lucas (1971) the rational expectations hypothesis (REH) has become (and currently still is) the dominating paradigm in expectation formation in economics and finance. Muth (1961, p. 316) stated that:

Expectations of firms (or, more generally, the subjective probability distribution of outcomes) tend to be distributed, for the same information set, about the prediction of the theory (or the “objective” probability distribution of outcomes).

According to the REH agents use all available information and their subjective expectation equals the mathematical expectation conditional upon available information. In implementing the REH in dynamic economic models it is usually assumed that agents have perfect knowledge about market equilibrium equations, i.e. the theory. The agents in the model use these equations to compute their optimal predictions of future variables.
Under rational expectations equilibrium forecasts coincide (on average) with realizations and rational agents therefore make no systematic forecast errors.

The rational expectations equilibrium price can be derived easily, when demand and supply curves are known to the agents (and are linear). There seems to be general agreement among economists that the REH assumes too much knowledge of the agents. In particular, the assumption that agents have perfect knowledge of underlying market equilibrium equations is at odds with practice in real markets. In the last decade much theoretical work has been done on bounded rationality, in an attempt to back off from rational expectations. In the bounded rationality framework agents are assumed to form expectations based upon time series observations. Recent surveys on bounded rationality in expectation formation include Sargent (1993, 1999), Evans and Honkapohja (2001) and Marimon (1997). Sargent (1993, p. 3) writes:

I interpret a proposal to build models with ‘boundedly rational’ agents as a call to retreat from the second piece of rational expectations (mutual consistency of perceptions) by expelling rational agents from our model environments and replacing them with ‘artificially intelligent’ agents who behave like econometricians.

Bounded rational agents have some simple model of the world, the perceived law of motion, and try to learn or optimize the parameters of their perceived law of motion, e.g. by an econometric technique such as ordinary least squares, as additional observations become available.

A number of papers have argued that simple learning rules based upon observations may enforce convergence to the unique RE steady state. If convergence occurs, RE would be the market equilibrium outcome, at least in the long run, and this RE outcome could be attained without any knowledge of market equilibrium equations. Bray and Savin (1986) show that if agents, in a cobweb framework, employ ordinary least squares (OLS) learning, prices converge to the RE steady state. Bray (1982) shows that OLS-learning enforces RE in an asset pricing framework. Hommes and Sörger (1998), for the cobweb model, and Pötzelberger and Sögnér (2001), for an asset pricing model, have recently shown that, if agents simply learn the sample average and the first order sample autocorrelations in observed past prices, convergence to the RE steady state occurs. These theoretical papers suggest that learning simple forecasting rules may stabilize price fluctuations and enforce convergence to the RE steady state. Theoretical work on bounded rationality thus seems to support the RE as a reasonable outcome, even when market equilibrium equations are unknown.
In contrast, there is also theoretical work, e.g. in overlapping generations models, showing that learning schemes do not necessarily enforce convergence to a RE steady state but may lead to periodic (Bullard, 1994) or even chaotic price fluctuations (Schönhofer, 2000). Another example is Brock and Hommes (1997, 1998) who show for a heterogeneous beliefs cobweb model and a heterogeneous beliefs asset pricing model that evolutionary learning in general need not converge to a RE steady state but may lead to endogenous fluctuations. Apparently both stable and unstable outcomes are possible in models with boundedly rational agents. But which of the learning rules or expectations hypotheses is an accurate description of how people behave in real markets? Lucas (1986) proposed an experiment to investigate how people behave. This thesis uses an experimental approach to investigate which theory of expectations yields the ‘best’ description of agents’ forecasts in dynamic economic systems.

1.2 Expectations in the laboratory

It is hard to observe or obtain detailed information about individual expectations in real markets. One approach to obtain data on expectations is by survey data analysis, as done for example by Turnovsky (1970) on expectations about the Consumers’ Price Index and the unemployment rate during the post-Korean war period. Frankel and Froot (1987) did a survey on exchange rate expectations and Shiller (1989, 2000) on stock market data. However, since in survey data research one can not control the underlying economic fundamentals it is hard to measure the expectation rules in different circumstances. Another approach is to study expectation formation in an experimental setting. We report the findings of several laboratory experiments about expectation formation. In these experiments we ask the participants to give their expectation about next period’s price of an unspecified good. This experimental approach has two main advantages over survey data research. The first advantage is that the experimenters have control over the underlying fundamentals. Uncertainty about economic fundamentals affects expectations of agents in real markets. In the experiment we can control the economic environment and the information subjects have about this environment. A second advantage is that we get explicit information about individual expectations. Since in our setup there is no trade, our data is not disturbed by speculative trading behavior of the participants. Prior to the experiment the only unknown to the experimenters is the way subjects form expectations. Hence, our experimental approach provides us with relatively ‘clean’ data on expectations.
History of experimental economics

In this section we give a short overview of the history of experimental economics (see Davis and Holt (1993) and Kagel and Roth (1995) for a more elaborate overview). One of the main advantages of experiments is the replicability, the possibility to reproduce the (economic) experiments under exactly the same circumstances and to verify the outcomes. Experimental economics is a relatively new research area. The first reported market experiment is an experiment of Chamberlin (1948). Since then the use of experimental methods to evaluate economic theories has increased and nowadays it has become an accepted method for research in economics.

The experimental literature can broadly be divided into three main research areas: (i) market experiments (ii) game experiments and (iii) individual choice experiments. The first kind of experiments, the market experiments, like the one of Chamberlin (1948) and later Smith (1962 and 1964) focus on the effects of institutions on market outcomes. In particular, under what conditions market equilibrium prices emerge. The second type of experiments are game experiments. For example, Sauerman and Selten (1959) and Siegel and Fouraker (1996) studied cooperation in oligopoly situations. The duopoly pricing problem can be seen as application of the well-known prisoners dilemma. In a duopoly, collusion of the firms is best for both firms but each firm has an incentive to deviate from the cartel solution. More recently researchers have become more interested in more complex applications of game theory but always in simple environments such that the implications of the theory can be derived explicitly. The third type of initial experiments, the individual-choice experiments, are experiments about the theory of choice under uncertainty. However not all individual decision making experiments involve expected-utility theory. For example, Williams (1987) designed an experiment to test whether subjects are rational in forecasting market prices.

There is a variety of objectives for running laboratory experiments. Three of the most common objectives are: (1) theory falsification, (2) sensitivity tests and (3) documentation of empirical regularities. Theory falsification is probably the most common goal for laboratory experiments. By constructing a laboratory environment such that it satisfies the theory's implications the experimenters can test whether the theoretic predictions hold in a laboratory setting. The second objective are sensitivity tests, this means that it is investigated whether the predictions of the theory hold under less restricted circumstances. The third aim is documentation of empirical regularities, that is observe "stylized facts" in experimental data. In this thesis all three objectives play a role. We compare some theoretic expectations hypotheses with the outcomes of our experiments (theory falsification). Furthermore we investigate how the (in)stability of the cobweb model or the
presence of fundamentalists in a financial market affects the prices and predictions (sensitivity test). Finally, we also investigate the main characteristics of the price dynamics and report some regularities.

**Related literature**

At this point we would like to briefly discuss some related experimental literature. As stated before, economic experiments are well suited for a detailed investigation of expectation formation in a controlled dynamic environment. Unfortunately, as for example pointed out in Sunder (1995), only little experimental work on expectation formation has been done. Williams (1987) considers expectation formation in an experimental double auction market which varies from period to period, by small shifts in the market clearing price. Participants predict the mean contract price for 4 or 5 consecutive periods. Adaptive expectations turn out to be a better description of the forecast strategies than rational expectations or extrapolative expectations. Also in Smith, Suchanek and Williams (1988) individual expectations have been investigated in this matter. There are some drawbacks to this approach to expectation formation. In particular, the data on expectation formation are obtained in market experiments where participants also have to trade and where the primary goal is to investigate behavior of market prices. For example, Hey (1994, p. 330) points out:

> In these studies the question of expectation formation has tended to be of rather peripheral concern, with the data on expectations elicited in a somewhat unsatisfactory and only partial motivated manner.

There have also been a number of experiments that focus on expectation formation exclusively. Probably the first of these is Schmalensee (1976). He presents subjects with historical data on wheat prices and asks them to predict the mean wheat price for the next 5 periods. Participants' behavior turns out to be better explained by adaptive expectations than by extrapolative expectations and the speed of adjustment seems to decrease in turning point periods. Two other noteworthy experiments on expectation formation are Dwyer et al. (1993) and Hey (1994). In Dwyer et al. (1993) participants have to sequentially predict a variable \( y_t \), where \( y_t \) follows a random walk. Participants are paid according to absolute forecast error. The variance of the forecast errors of the participant is larger than the rational forecast errors, but there is no evidence for a bias in participants' forecasts. Both findings supports the notion of "rational expectations with error". For half of the participants there is predictability in the forecast errors, which makes it inconsistent with "RE with error". Hey (1994) considers an experiment where
data are generated by a simple linear first order autoregressive process and participants have to, sequentially, predict the next realization. Participants do not seem to give rational forecasts, but base their forecasts on the latest observation. Hey claims that their prediction strategies are “rational in structure if not in detail”, because their predictions seems to be “broadly sensible”. The drawbacks of the last two papers is that no economic context is given to the participants and, most importantly, the expectations feedback is ignored. In Smith, Suchanek and Williams (1988) spot asset trading is studied and their main finding is that bubbles occur due to a lack of common expectations. Marimon and Sunder (1993) and Evans, Honkapahja and Marimon (2001) report experiments with an overlapping generations (OLG) model and show that agents behave adaptively. Furthermore, Marimon, Spear and Sunder (1993) show the existence of sunspot equilibria when agents use some adaptive learning rule. However, also in these experiments there is no expectations feedback. In our experiments there is expectation feedback, i.e. realizations depend upon expectations, and we obtain explicit information about expectations.

A disadvantage of laboratory experiments is that, because of the time constraint, subjects only make a couple of dozen decisions. Therefore, the learning possibilities are limited (especially in complicated situations) and it is also hard to detect exactly which expectation formation rules subjects use (because of the relatively few decisions made by the subjects). As a solution to this problem, Selten (1967) and Selten, Mitzkewitz and Uhlich (1997, p. 517) describe a method of experimentation which makes strategies observable.

This procedure, called the “strategy method”, first exposes a group of subjects to the repeated play of a game, and then asks them to design strategies on the basis of their experiences.

Where a strategy is a complete description of all the decisions in all possible states of the world. Only recently the strategy method has become a popular tool in experimental economics. In Selten, Mitzkewitz and Uhlich (1997) the participants have to make strategies in a non-symmetric Cournot duopoly with linear cost functions. Typically, participants in the final round make no attempt to predict the opponent’s reactions and nothing is optimized. Instead a cooperative goal is chosen by fairness considerations. Other studies that make use of the strategy method are Offerman et al. (2001), Sonnemans (1998), Brandts and Schram (2001) and Keser (1992); see also the classic work of Axelrod (1984). This “strategy method” approach seems to be well suited for our purposes to study expectation formation and learning. In this thesis we report the results of a strategy method experiment about expectation formation with a cobweb model as well as an asset pricing model.
Chapter 1: Introduction

1.3 Outline of this thesis

This thesis may be viewed as an experimental testing of the expectations hypothesis in dynamic economic systems, where market equilibrium equations are unknown. All experiments are conducted in the experimental laboratory of CREED\textsuperscript{1} at the Universiteit van Amsterdam. The thesis is divided into two parts. In Part I (Chapters 2-5) we study expectation formation in the cobweb or 'hog cycle' model while in Part II (Chapters 6-8) we study expectation formation in a standard asset pricing model. In this section we give a brief outline of the different chapters of this thesis.

In Chapter 2 we give an overview of the theoretical work on price dynamics in the well-known cobweb model with a production lag under various expectations hypotheses. In his classical paper Ezekiel (1938) developed the price dynamics under naive expectations and linear demand and supply. In chapter 2 we focus on a different specification of the cobweb model, i.e. we use a linear decreasing demand and a nonlinear monotonically increasing supply curve. The dynamics of the cobweb model depends on the expectations used. We discuss important benchmarks of expectation formation, including rational expectations, naive expectations and adaptive expectations. We also discuss bounded rationality and heterogeneous expectations. Price fluctuations under each of these expectation schemes are examined. In the cobweb model with these specification of demand and supply, periodic and even erratic, chaotic price behavior can occur.

In Chapters 3 and 4 we report the results of the cobweb laboratory experiments\textsuperscript{2}. Market equilibrium equations are controlled and fixed during the experiment (although they are subject to unexpected exogenous shocks and/or noise). Subjects are asked to predict prices and their earnings are inversely related to their quadratic forecasting errors. Price realizations depend upon subjects' price expectations. In the experiments we distinguish between a single-agent treatment (Chapter 3), where the market equilibrium price depends only upon the price expectation of a single subject, and a multi-agent treatment (Chapter 4), where the market equilibrium price is based upon the expectations of a group of individuals. Another distinction in the experimental setups is between a noise treatment, where the demand and supply curves are fixed but the model is buffeted with (small) random noise in each time period, and a permanent shock treatment, where the demand curve

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is shifted three times due to three unexpected, permanent shocks. As a consequence, in the noise treatment, the experimental environment is stationary and the RE steady state is fixed and constant over time. In contrast, in the permanent shock treatment, the experimental environment is non-stationary and the RE steady state changes three times (but is fixed during the corresponding four subsamples). In the single-agent treatment, only about 35% of the subjects is able to learn the unique RE equilibrium steady state; for the remaining 65% of the subjects the prices keep fluctuating around the (unstable) RE steady state. In the multi-agent treatments forecasting errors are lower and consequently average earnings higher than in the single-agent treatments. However, although the amplitude of the price fluctuations is significantly smaller than in the single-agent treatments, in general prices do not converge to the RE steady state. Our experiments suggest that dynamic economic expectation feedback systems can exhibit excess price volatility caused by the interaction of individual forecasts.

In Chapter 5 we present a strategy experiment to investigate expectations and learning in the cobweb model\textsuperscript{3}. Participants in this experiment are asked to formulate a complete strategy, that is, a description of all their forecasts in all possible states of the world (e.g. history of prices). In each period all strategies that participate in the market forecast the next price. There are six strategies in each market. The realized market equilibrium price is then determined by a fixed, but unknown, (linear) demand curve, and (nonlinear) supply, depending upon individual expected market prices, aggregated over all six producers. Subjects gain experience in forecasting next period’s price in an introductory experiment. Immediately after this introductory experiment the subjects submit their first strategy. These strategies are then programmed and markets are simulated. In each of the four rounds of the strategy experiment (as well as in the introductory experiment) financial incentives, based upon prediction performance, are used to motivate the subjects. The strategy approach provides us with information about the kind of rules individuals use in forecasting prices. Furthermore, it enables us to do an analysis of the stability and instability of the dynamic economic system. Over the rounds the strategies tend to get more complicated. Only in 10% of all simulations the market converges to either a steady state or a low periodic cycle. Moreover, the complexity of the price fluctuations increases over the rounds. In round 4 in more than 60% of the cases chaotic price fluctuations around an unstable RE steady state price arises.

In Chapter 6 we discuss the theoretical background of the standard asset pricing model

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\textsuperscript{3}This chapter is based upon the working paper 'The instability of a heterogeneous cobweb economy: a strategy experiment on expectation formation' by Sonnemans, J., Hommes, C.H., Tuinstra, J. and van de Velden, H. (1999).
Chapter 1: Introduction

which is used throughout Part II of the thesis. The agents in this model have to choose between investing in a risky and a risk free asset. The price of the risky asset is determined by equilibrium between demand and supply of the risky asset given that the agents are mean variance optimizers. An important difference between the cobweb model and the asset pricing model is that the cobweb model has an unique RE steady state while the asset pricing model has multiple RE solutions, namely a constant fundamental price and infinitely many RE bubble solutions. Another difference between the cobweb model and the asset pricing model is that (for the specifications we choose) the cobweb model is unstable under naive expectations while the asset pricing model is stable under naive expectations.

The purpose of Chapter 7 is to investigate expectation formation in a controlled experimental asset pricing model. Subject are asked to predict the price of a risky asset. They do not have knowledge of the underlying market equilibrium equations, but they know all past realized prices and, of course, their own past predictions. Furthermore, they are also given enough information about the economic fundamentals to predict the RE fundamental price. Their earnings are inversely related to the average prediction errors they make. The realized market equilibrium price is some function of the forecasts of the participants. Two different treatments are considered. 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. The robot trader expects that the market price will be equal to the fundamental price. This robot trader may be seen as a 'stabilizing force', since its influence on the market price increases as the difference between the market price and the fundamental price increases. In both treatments we find that the asset markets are (close to) informationally efficient but prices may deviate from the RE fundamental price. Participants seem to coordinate on a common prediction strategy. In the NoRobot treatment speculative bubbles occur for a most groups while in the Robot treatment we find oscillating asset prices in some groups and convergence to the fundamental price in other groups.

In Chapter 8 we use the strategy method to study expectation formation in the asset pricing model. The experiment lasts 8 weeks and consists of four rounds. Every round the subjects have to submit a strategy. The subjects gain experience in their forecasting task in a introductory experiment similar to the NoRobot treatment of Chapter 7. One of the most striking results is that we do not find convergence to a steady state price in the short run (first 50 periods). In contrast, in the long run in round 4 almost 80% of the simulations converge to a steady state. However, only 40% of all simulations in round 4 converge to the fundamental price. The strategies thus have difficulty with learning the
correct (fundamental) price level.

Finally, Chapter 9 summarizes the main results of both types of experiments and compare the results. We end this thesis with some general conclusions we found in both kinds of experiments.