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Chapter 1

Introduction

Expectation formation is a very important element of modern macroeconomics and finance where agents make intertemporal decisions. Stock traders need to make a forecast on the future market price of the stocks when they trade. Households need to make a forecast of the future interest and inflation rate when they decide whether or not to take a mortgage with a flexible mortgage rate. In the macroeconomics and finance literature, the rational expectation hypothesis (REH, Muth, 1961; Lucas, 1972) has been the standard way to model expectation formation for decades. Rational expectation models usually assume that individuals are able to make (on average) perfect forecasts of future economic variables, and make an optimal decision about their economic activity given their forecasts. Based on these assumptions, the models usually generate a Rational Expectation Equilibrium (REE) as their prediction of the market outcomes.

Rational expectation models however usually face two important criticisms:

(i) agents may not have enough information or depth of reasoning to predict the future perfectly;

(ii) agents may not have enough calculation capacity to make an optimal decision given

their forecast.

In response to these criticisms, some economists (Fourgeaud et al, 1986, Sargent, 1993) argue that if the rational expectation equilibrium is the limit of a learning process, it does not matter that much whether individuals know the model of the economy or not. Furthermore, it has been shown that some properly designed market institutions can generate a very high level of efficiency even if individual participants have zero-intelligence (Gode and Sunder, 1993).

The first goal of this thesis is to contribute to this discussion by using laboratory experiments to study the macro behavior of the *aggregate* market price and micro behavior of *individual* forecasts and quantity decisions. The experimental results will be helpful in answering (a) whether individual participants are able to form rational expectations; (b) whether individual agents are able to solve the optimal quantity decision given the price forecast, and (c) whether the aggregate market price converges to the rational expectation equilibrium. Depending on the focus of the research, there are two approaches in the experimental literature studying rational expectations. One is called *learning to forecast experiments* (LtFE, Marimon and Sunder, 1994) where subjects are asked to submit their forecasts, after which a computer program solves for the conditionally optimal quantity decisions which in turn determine the market price. Demand and supply are the optimal given the individual forecasts. The other approach is called *learning to optimize experiments* (LtOE, Duffy, 2008a, b) where subjects submit their quantity decisions on economic activities directly, while forecasts are not explicitly elicited. The first two chapters of the thesis will be devoted to study two specific questions:

1. Does the type of expectation feedback in the system have an impact on how the market price responds to large unanticipated shocks?

2. Does the elicitation method (LtFE vs. LtOE design) lead to a difference in the speed of convergence of the experimental market price to the REE?

Concerning question (1), we find that there is a big difference between the behavior of the market price in positive and negative expectation feedback systems. In a positive feedback system the market price is high when the average price forecast is high, while in a negative feedback system, the market price is low when the average price forecast is high. One can take the traditional "cobweb" economy as an example of negative feedback systems, and a speculative financial market as an example of positive feedback systems. Our experimental results show that negative expectation feedback systems convergence to the new RE equilibrium price very quickly after each large shock. In contrary, positive feedback systems fail to convergence, but show underreaction in the short run, and overshoot the equilibrium in the long run. The results in the positive feedback suggest that stylized facts such as under- and overreaction in financial markets may be caused by the positive feedback feature of the system. In the words of George Soros (2009):

"*That two-way connection-that you affect what you predict-is what I call 'reflexivity'. That is how financial markets really work..... In short, the boom-bust sequences, the bubbles, are endemic to the financial system.*"

This highlights the importance of governments to introduce more regulation, in particular during times when the market experiences a large systemic shock.

For question (2), we find that the elicitation method matters for the speed of convergence, because the LtFE design generates much quicker convergence compared to the LtOE design. In particular, we add a third treatment where one individual subject makes both a price forecast and a quantity decision, and find that this treatment generates the slowest convergence to the REE. Moreover, the quantity decision by the subjects are not

conditionally optimally given their price forecast. This finding strongly supports the hypothesis that individuals have limitations on the capacity to calculate the optimal decision.

The second goal of the thesis is to come up with a model that can explain the behavior of the aggregate market price as well as the individual forecasts and/or quantity decisions. The methodology we use mainly comes from the heterogenous expectations models by Brock and Hommes (1997, 1998) and its extension by Anufriev and Hommes (2102a, b). The key feature of this kind of models is that instead of assuming that agents are homogeneous and make rational expectations, they assume that agents are boundedly rational, and choose from a menu of simple behavioral heuristics when making their forecasts and decisions. Evolutionary selection based upon the relative performance will enforce selection among different types of heuristics. It turns out that this kind of models can explain both the aggregate market price and the individual decisions very well. The interaction of these individual learning mechanisms may enforce selection of different dominating heuristics in different market environments. In negative feedback markets it usually leads to the dominance of the adaptive expectation rule, which enforces nice convergence to the REE. In positive feedback markets however the trend extrapolation strategy dominates, which leads to persistent price oscillations and deviations from the rational expectation equilibrium.

One important feature of the heterogeneous expectation model by Brock and Hommes (1997, 1998) and Anufriev and Hommes (2102a, b) is that agents switch between the heuristics depending on their past performance. In order to better apply this kind of models, it is very important to make a good estimation of the intensity of choice parameter in the model, measuring how sensitive the agents are to the differences in fitness. In learning to forecast experiments, the agents do not see the menu of the forecasting heuristics directly, and therefore their switching behavior in the model is an implicit choice. On the

other hand, switching behavior is a common phenomenon in many aspects of life, ranging from a decision about a driving route to investment in financial markets. Therefore, it will be interesting to conduct an experiment where agents switch explicitly, and use the data from this experiment to estimate the intensity of choice parameter in the switching model.

The third goal of the thesis is therefore to conduct experiments on the switching behavior in mutual fund choice, a very common problem faced by many families in real life, and estimate the intensity of choice parameter of the switching model. The relation between this study and the heterogeneous expectations models is that some of the (exogenous) return time series are actually the performance measures of forecasting heuristics in the heterogeneous expectations models. We find that the magnitude of the intensity of choice parameter is affected by the structure in the past returns of the mutual funds. When there is a recognizable pattern in past returns, such as a strong autocorrelation or a periodic or quasi periodic structure, the intensity of choice tends to be larger. When there is little structure in past returns, for example when the return time series follows a white noise process or are chaotic, the intensity of choice tends to be smaller. We also consider how the mutual fund choice decision is affected by the fee structure of the funds. Former literature suggests that a front end load fee is generally more salient than operation expenses, and is therefore less used in the industry (Barber et al, 2005). We find when the fund that charges a fee generates a higher expected return, charging a front end load fee may lead to a higher frequency of investment in this fund due to a “lock in" effect.

1.1 Outline of the Thesis

This thesis studies heterogeneous expectations and individual switching behavior using market experiments. The results are reported in four chapters. These chapters are self-contained, with their own introductions, conclusions and appendix. Chapter 2 focuses on

the market response to large unanticipated shocks using a learning to forecast experiment, and explains the aggregate data as well as individual expectations with a heterogeneous agent model. Chapter 3 compares the speed of convergence to the REE under four different designs: a learning to forecast experiment, a learning to optimize experiment, one individual doing both forecasting and optimizing and a team of two participants specializing in forecasting and optimizing respectively. Chapter 4 estimates the intensity of choice parameter in a switching model when agents choose between investing in experimental funds with 3 different types of return time series. Chapter 5 studies how agents choose between two experimental funds of known different expected returns, and how the fee structure affects their frequency of choice of the fund with higher expected return. A (working) paper is extracted from each chapter: Bao, Hommes, Sonnemans and Tuinstra (2012) is based on Chapter 2; Bao, Duffy and Hommes (2011) is based on Chapter 3; Anufriev, Bao and Tuinstra (2012) is based on Chapter 4 and Anufriev, Bao, Sutan and Tuinstra (2012) is based on Chapter 5.

Chapter 2 studies how the type of different expectation feedback systems affect the response of the market price to large unexpected shocks using a learning to forecast experiment. In this chapter we find that markets with negative expectation feedback (strategic substitutes) quickly converge to the new fundamental, while markets with positive expectation feedback (strategic complements) do not converge, but show underreaction in the short run and overreaction in the long run. A simple evolutionary selection model of individual forecasting heuristics based on Brock and Hommes (1997) and Anufriev and Hommes (2012) provides good description of the differences in individual forecasting behavior as well as aggregate market price.

Chapter 3 extends the negative feedback treatment in Chapter 2 and investigates whether the speed of convergence to the REE in a negative feedback system depends on

whether we use a learning to forecast or a learning to optimize design. In this chapter we consider both forecasting and optimization decisions in an experimental cobweb economy. We report results from four experimental treatments: (1) subjects form forecasts only; (2) subjects determine quantity only (solve an optimization problem); (3) they do both forecasting and optimizing and 4) they are paired in teams and one member is assigned the forecasting role while the other is assigned the optimization task. All treatments converge to the REE, but at very different speeds. We observe that the performance is best in treatment 1 and worst in the treatment 3. We further find that most subjects use adaptive rules to forecast prices. Given a price forecast, subjects are less likely to make conditionally optimal production decisions in treatment 3 where the forecast is made by themselves, than in treatment 4 where the forecast is made by the other member of their team, which suggests that "two heads are better than one" in finding the REE.

In Chapter 4 we conduct an experiment where participants switch between different profitable alternatives explicitly. We report the results of experiments where subjects have to make choices between several (2, 3 or 4) experimental "funds" in multiple periods. The time series of funds' profits are exogenously generated prior to the experiment and participants are paid for that period according to the profit of the fund they choose. The data generating process of the profit time series is unrevealed to the subjects. The experimental results show that the subjects switch a lot between the funds. A discrete choice model with a few lags and a predisposition effect provides a good fit to the data. The intensity of choice parameter in the discrete choice model depends on the structure of the profit time series of the funds, and is not affected by experience.

In Chapter 5 we run an experiment similar to Chapter 4 where the return rate of the funds is independent of its past realization, and subjects are informed about this in the instruction. We find that the fund choice decision is still heavily driven by past

returns even when this information is irrelevant, and this bias cannot be mitigated with experience and learning. We also find that charging a fee in the form of front end load does not discourage investment more than charging it in the form of operation expense (management fee) per se. When the fund that charges a fee has higher expected return, front end load fee generates a “lock in" effect that helps to keep investors from switching to an alternative fund.