When Speculators Meet Constructors: Positive and Negative Feedback in Experimental Housing Markets*

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Abstract. Asset markets are characterized by positive feedback through speculative demand. But housing markets distinguish themselves from other asset markets in that the supply of housing is endogenous, and adds negative feedback to the market. We design an experimental housing market and study how the strength of the negative feedback, i.e., the supply elasticity, affects market stability. In the absence of endogenous housing supply, the experimental markets exhibit large bubbles and crashes because speculators coordinate on trend-following expectations. When the positive feedback through speculative demand is offset by the negative feedback of elastic housing supply the market stabilizes and prices converge to fundamental value. Individual expectations and aggregate market outcome is well described by a behavioral forecasting heuristics model. Our results suggest that negative feedback policies may stabilize speculative asset bubbles.

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1 Introduction

Are housing price bubbles and crashes cycle less likely to emerge when the market supply is more elastic? This question deserves careful investigation because the boom and bust in the US housing market in early 2000s is considered a main contributor to the recent financial crisis. Many previous studies focused on speculative asset pricing models on the demand side of the market, but real estate assets also distinguishes themselves from other assets in that the supply of housing is endogenous and responds to price changes. As Glaser et al (2008) observed "models of housing price volatility that ignore supply miss a fundamental part of the housing market".

The answer to the question seems straightforward at first glance. An intuitive argument would be that if housing supply is very elastic, it increases immediately in response to positive demand shocks, and hence makes bubbles less likely, or last shorter. Wheaton (1999) shows in a theoretical model that housing cycles are less likely when the elasticity of supply is larger than the elasticity of demand. Glaser et al. (2008) search for empirical evidence to address this question. They categorize US cities to areas with high versus low supply elasticities according to Saiz (2008), but find that price boom and bust also happened in high elasticity cities, although in these cases, the duration of cycles is indeed shorter than in low elasticity cities. Figure 1 plots the Case-Shiller index in some major cities in the US. Among these cities, New York, Seattle and Chicago are considered as low elasticity cities, and Denver, Atlanta and Las-Vegas are considered as high elasticity cities. Both types of cities may experience large boom-bust cycles (e.g., New York and Las Vegas). Seattle and Chicago have mild fluctuations. Atlanta does not experience very rapid appreciation of house prices in the boom periods, but shows a severe price decline in the bust. Denver is the only one among these cities that does not experience large fluctuation during the first decade of the 21st century.

Thus, an empirical answer to the question may not be as straightforward as it appears at first sight. One reason may be that when the supply elasticity is higher, the market is also more likely to "overbuild" once the housing price increases. The larger "overbuilding" drives the housing price down more severely in a bust, and contributes to the fluctuation of the housing price.

In this paper, we run a laboratory experiment on how the elasticity of housing

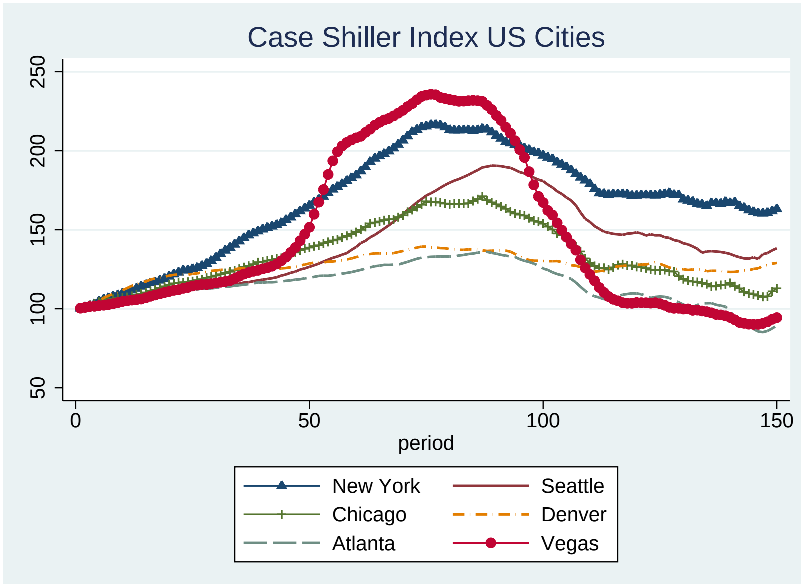

Figure 1: Case-Shiller index in 6 US major cities. New York, Seattle and Chicago are considered as low elasticity cities, and Denver, Atlanta and Las-Vegas are considered as high elasticity cities according to Saiz (2008). The time series are monthly data from January 2000 to June 2012.

supply affect the likelihood of boom-bust cycles in housing markets. Ideally, one would like to address this question with field data. But as is seen from the discussion of the literature, there are many factors that influence housing prices, which makes it difficult to disentangle the effect of the supply elasticity *alone*. For example, Glaser et al. (2008) argue that due to this difficulty, it is hard to conclude how the supply elasticity influences the stability of the housing market. One advantage of laboratory experiment is that it takes full control over other variables, and therefore single out the effect of a change in one variable or parameter (housing supply elasticity in this paper). The main result of this paper is that *ceteris paribus*, there are indeed fewer boom-bust cycles in experimental housing markets with higher supply elasticity. The contributions of our paper include:

First, we design an experiment where we take full control over the fundamental price of housing so that the only difference between markets in different treatments is the supply elasticity. This effectively rules out the confounding variables with field data, and helps to draw clean causal inference. We compare three treatments where the housing supply is (1) completely inelastic, (2) of low elasticity and (3) of high elasticity. We find strong evidence that, *ceteris paribus*, the market price is less volatile and deviates less from the REE in markets with high supply elasticity.

Secondly, this may be the first laboratory experiments on housing market. Stephens and Tyran (2012) studied nominal loss aversion on housing market using survey experiment, and find that people may have difficulty in finding that a housing transaction is disadvantageous when it generates a real loss but nominal gain. Hirota et al. (2015) study how endowment effect influences price setting by home sellers in the market. But to our knowledge, there is not yet a laboratory experiment on housing markets that studies the individual decisions and its influence on the market (in)stability.

Thirdly, in terms of the relation between individual expectation and aggregate market outcomes, the housing market is a positive expectation feedback system to the investors, but a negative feedback system to the housing developers/constructors. When investors predict that the price will go up, the demand increases, which has a tendency to drive the price up. In contrast, when the constructors predict that the price will increase, they will tend to build more, which makes the supply increase, and has a tendency to drive the price down. There have been several experimental studies of purely negative feedback markets (Hommes et al, 2007), as well as purely positive feedback markets (Hommes et al, 2005, 2008; Bao et al., 2015). There have also been experimental studies comparing the two different types of markets (Heemeijer et al, 2009, Sonnemans and Tuinstra, 2010, Bao et al, 2012)[1]. The current paper designs the first experimental market combining both features. The main result of former studies is that markets with negative feedbacks have a natural tendency to stabilize, i.e. the price converges to the rational expectation equilibrium (REE) within a few periods, while it is generally very difficult for the markets with positive feedback to converge to the REE, and it is very likely to observe price bubbles and crashes in positive feedback markets. A natural question to ask is then: is it possible stabilize a market with positive feedbacks by adding negative feedback to it? In the specific environment like experimental housing market, this would be to increase the supply elasticity. Our finding suggests the answer is "yes". This result has important policy implications: speculative bubbles and crashes may be mitigated by negative feedback

[1]Fehr and Tyran (2008) also find the market price converges faster to the REE under strategic substitutes (similar to negative feedback) than strategic complements (positive feedback). Positive expectation feedback is also similar to the concept of "reflexivity" proposed by George Soros (2003). Hommes (2013) provides a detailed discussion about the relation between the concepts.

policies that weaken the overall positive feedback in markets.

This paper employs a “learning to forecast” experimental design (for the discussion on the difference between “learning to forecast” versus “learning to optimize” design, see Duffy, 2008 and Assenza et al. 2014), where participants submit a price expectation and their optimal quantity decision is determined by computer trading. Expectations are known to play an important role in asset markets, and the housing market is certainly no exception. There is a literature in real estate economics that finds that rational expectation hypothesis may not provide good prediction for the price dynamics on the housing market. Mankiw and Weil (1989) notice that it is difficult to explain the sharp increase of housing prices in the 1970s with traditional models assuming rational expectation and efficient markets. Clayton (1997) finds that housing price may move in a direction opposite to the rational expectation fundamental. One possible explanation is that the sharp increase of housing prices in the short run may be driven by “irrational” expectations. Another contribution of our paper is that we use a behavioral heuristics switching model (Brock and Hommes, 1997; Anufriev and Hommes, 2012) to explain individual as well as aggregate behavior. The results of former learning to forecast experiments suggest that agents tend to use different expectation rules in the positive and negative feedback markets. In positive feedback markets, they are more likely to coordinate on a common expectation and become users of trend extrapolation rules, while in negative feedback markets, there is low level of coordination of expectations across agents, and they are more likely to become users of adaptive or contrarian expectations (Anufriev and Hommes, 2012b; Bao et al., 2012). For a market that is a negative feedback system to some participants (constructors) and a positive feedback system to others (speculators), a natural research question will be whether there will be coordination of expectations between all agents. When positive feedback from speculative demand dominates negative feedback from housing supply, housing bubbles arise through agents’ coordination on a trend-following strategy. If on the other hand positive feedback is weakened enough by housing supply the market is rather stable and individuals coordinate on stabilizing adaptive expectations.

The organization of the paper is as follows. Section 2 describes the experimental design, while Section 3 reports the experimental results. Section 4 calibrates a heuristics switching model explaining individual as well as aggregate behavior. Finally, Section 5 concludes.

2 Experimental Design

2.1 The Economy

We consider an economy where $z^s_{i,t}$ is the housing supply by the constructor i in period t, and $z^d_{h,t}$ is the housing demand from the speculative investor h at period t. The individual supply and demand depends on $p^e_{i,t+1}, p^e_{h,t+1}$, which are the prediction on the housing price for made by constructor i or investor h for period $t+1$.

$$
\begin{aligned}
z^s_{i,t} &= \frac{cp^e_{i,t+1}}{I} \\
z^d_{h,t} &= \frac{p^e_{h,t+1} + E_t y_{t+1} - Rp_t}{a\sigma^2}
\end{aligned}
$$

These supply and demand functions can be derived from maximization problem of the constructors and investors as in Appendix A, where R is the gross interest rate for a risk free investment (i.e. a bond), and c is a parameter taking care of the marginal cost in a quadratic cost function for the constructors. Let H, I be the number of investors and constructors in the market. For simplicity, we let $a\sigma^2 = H$. By imposing market clearing condition we have:

$$
\begin{aligned}
\sum_i z^s_{i,t} &= \sum_h z^d_{h,t} \\
\sum_i z^s_{i,t} &= c\frac{\sum_i p^e_{i,t+1}}{I} = c\overline{p}^e_{i,t+1} \\
\sum_h z^d_{h,t} &= \frac{\sum_h (p^e_{h,t+1} + E_t y_{t+1} - Rp_t)}{a\sigma^2} = \overline{p}^e_{h,t+1} + E_t y_{t+1} - Rp_t
\end{aligned}
$$

where $\overline{p}^e_{i,t+1}, \overline{p}^e_{h,t+1}$ are the average expected housing price by constructors and investors. The supply and demand function by individual speculator and constructor can be derived from maximization problem of mean-variance utility by the speculators, or the expected profit for the constructors. This model setting can be developed from the pure asset pricing model used in Hommes et al (2005) (based on the asset pricing model in Cuthbertson and Nitzsche (2005) or Campbell, Lo and MacKinlay

(1997)), which is later used in the empirical work by Bolt et al (2015). The theoretical work by Dieci and Westerhoff (2012) also adopt a similar model setup. For simplicity, y_{t+1} is the dividend paid by the asset, typically in terms of housing rent in this case. We assume $E_t y_{t+1}$ is constant over time, and $E_t y_{t+1} = \overline{y}$.

By substituting in these conditions, the reduced form equation for prices is given by:

$$p_t = \frac{1}{R}(\overline{p}^e_{h,t+1} + \overline{y} - c\overline{p}^e_{i,t+1}) + \nu_t \tag{1}$$

where we add a small noise term $\nu_t \sim N(0,1)$, which represents other random shocks that may influence the housing price. As can be seen from the equation, the housing price will increase when the average price prediction by the investors goes up, and decrease when the average price prediction by the constructors goes up. Therefore this market is a positive expectation feedback system for the investors, and negative expectation feedback system for the constructors.

By substituting in $\overline{p}^e_{h,t+1} = \overline{p}^e_{i,t+1} = p_t$, a rational expectation equilibrium, as well as steady state of the system is:

$$p^* = \frac{\overline{y}}{R - 1 + c} \tag{2}$$

The rational expectation equilibrium of housing price is an increasing function of the dividend (rent) payment $\overline{y}$, and a decreasing function in the gross interest rate R, and the elasticity of housing supply c.

2.2 Parameterizations

We use $R = 1.05$, which is an interest rate commonly used in the literature. This means holding the supply by the constructors equal, one unit increase in the expected price in period $t + 1$ by the investors will lead to $1/1.05 \approx 0.95$ unit increase in the market price in period t. For a given parameter c, one unit increase in the expected price for period $t+1$ by the constructors will lead to c/R decrease in the housing price in period t. In other words, if the constructors and speculators have homogeneous expectations, equation (1) will become equation (3):

$$p_t = \frac{1 - c}{R}(\overline{p}^e_{t+1} + \overline{y}) + \nu_t, \tag{3}$$

where $\overline{p}^e$ is the average price expectation of all the speculators and constructors. We can call the new slope of the equation $\frac{1-c}{R}$ the "overall strength of expectation feedback". In this experiment, we take three values of c, which are $c = 0, 0.1$ and 0.25. Therefore, the slope $\frac{1-c}{R}$ is always positive. $\frac{1-c}{R}$ measures when the average expected price in the whole market goes up by 1 unit, how much the realized price change. $c = 0$ is the benchmark case where there is no constructors, and the market is purely positive feedback system. When $c = 0.1$, $\frac{1-c}{R} = 0.86$, the price goes up by about 0.86 when the average expected price goes up by 1 unit, and $c = 0.25$, $\frac{1-c}{R} = 0.71$, the price goes up by about 0.71 when the average expected price goes up by 1 unit. The research question is when we increase the slope of the supply function c, and therefore makes the slope of the overall expectation feedback system smaller, whether it makes the market price more stable[2].

The REE is the same ($p^* = 60$) in all three treatments. According to equation (2), this means different levels of $\overline{y}$ need to be chosen for each treatment. Therefore we have $\overline{y} = 3$ when $c = 0$, $\overline{y} = 9$ when $c = 0.1$, and $\overline{y} = 18$ when $c = 0.25$.

2.3 Treatments

Based on the supply elasticity of the market, three treatments are set up:

> Treatment with no supply (**treatment N**): there is no constructor on the market. Therefore c can be considered as 0. We let 6 investors participate in each market, and the market price only depends on the average price expectation by the investors.

[2] Sonnemans and Tuinstra (2010) study the price behavior in positive feedback markets with two different "strengths of feedback" (i.e., slope of the price feedback map) 0.67 and 0.95. They find that the market price deviates persistently from the REE benchmark in the strong positive feedback markets where the slope is 0.95, while the price mostly converges in the markets with weak positive feedback with slope 0.67. Our experiment sheds some light on the price behavior when the slope is between 0.67 and 0.95. We find that the market price converges to the REE when the overall slope is 0.71 (i.e., when the supply coefficient $c = 0.25$). Given that there is no systematic difference between the price expectations by the constructors and speculators, this suggests that the necessary condition for the price in a positive feedback markets to converge is that the slope of the price feedback map is less than or equal to 0.7.

Treatment with low supply elasticity (**treatment L**): There 5 investors and 5 constructors in each market. The slope of the supply function is $c = 0.1$. The market price depends on both expectations by the investors and constructors, but the influence from the constructors is very small.

Treatment with high supply elasticity (**treatment H**): There 5 investors and 5 constructors in each market. The slope of the supply function is $c = 0.25$. The market price depends on both expectations by the investors and constructors, and the influence from the constructors is larger than in treatment L.

2.4 Payoff Scheme

The subjects are paid in terms of points, which are converted into Euros after the experiment. The payoff function is show in equation (4). It is a decreasing function of their prediction error. The subjects earn 0 points if their prediction error is larger than 7.

$$\text{Payoff}_{h,t} = \max\{1300 - \frac{1300}{49}(p_t - p^e_{h,t})^2, 0\} \tag{4}$$

This is a quadratic loss function, and the subjects earn 0 points if his prediction error is larger than 7. At the end of the experiment, subjects are paid 1 Euro for each 3000 points they earned in the experiment, plus a 7 Euro show up fee.

3 Experimental Result

The experiment was run on June 6, August 26, August 29 and October 23, 2013 at the CREED lab, University of Amsterdam. 134 subjects were recruited. 4 markets were established for treatment N, 5 for treatment L and 6 for treatment H. The fluctuation in the number of observations is due to show up rate of subjects. We use slightly fewer observation for treatment N because the design in this treatment is the same as the asset market experiment by Hommes et al. (2008), except that we use the framing of housing market instead of stock market. Therefore, it is conducted to make sure that the bubbles/crashes patter in the data of Hommes et al. (2008)

is not affected by the change of framing. Given we confirmed that this is true, 4 observations can be considered a representative sample to make comparison with the markets in other treatments. The duration of a typical session is 1 hour and 5 minutes, including instructions reading and payment. The experiment uses purely between subjects design. No subject participates in more than one session.

3.1 Market Price Dynamics

Figure 2 to 4 report the market price in different treatments. Generally, the prices are more stable in treatment with higher supply slopes/elasticities. If we claim that the market price converges to the REE when the difference between the price and the REE is smaller than 3, and forever afterwards, none of the markets in treatment N and L converges, while all markets in treatment H converge. It takes between 27 periods and 42 periods before the prices in treatment H converge to the REE. There is one market in treatment N that experiences a huge bubble, peaking at about 800, which is about 13 times the fundamental price (REE).

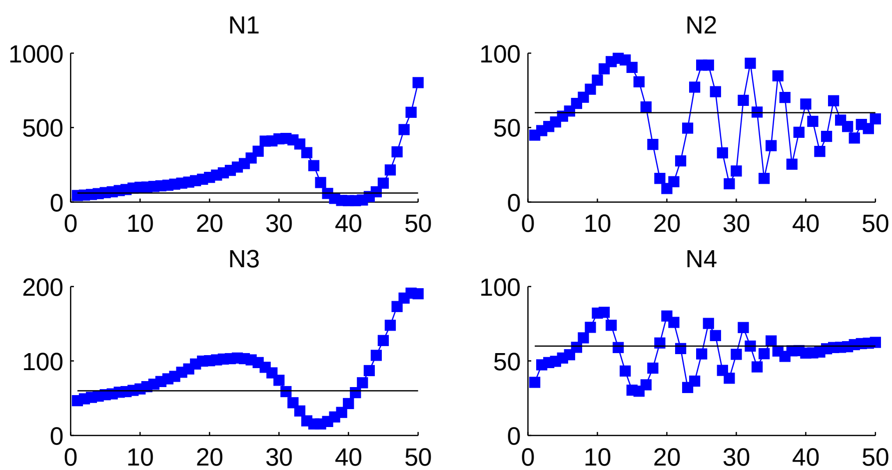

Figure 2: The market prices against the REE price in treatment N.

To quantify the deviation of the market price from the REE, we calculate the Relative Absolute Deviation (RAD) and Relative Deviation (RD) in each market following the definition by Stökl et al. (2010). These two definitions are used to show the average deviation of the market price over the periods as a fraction of the

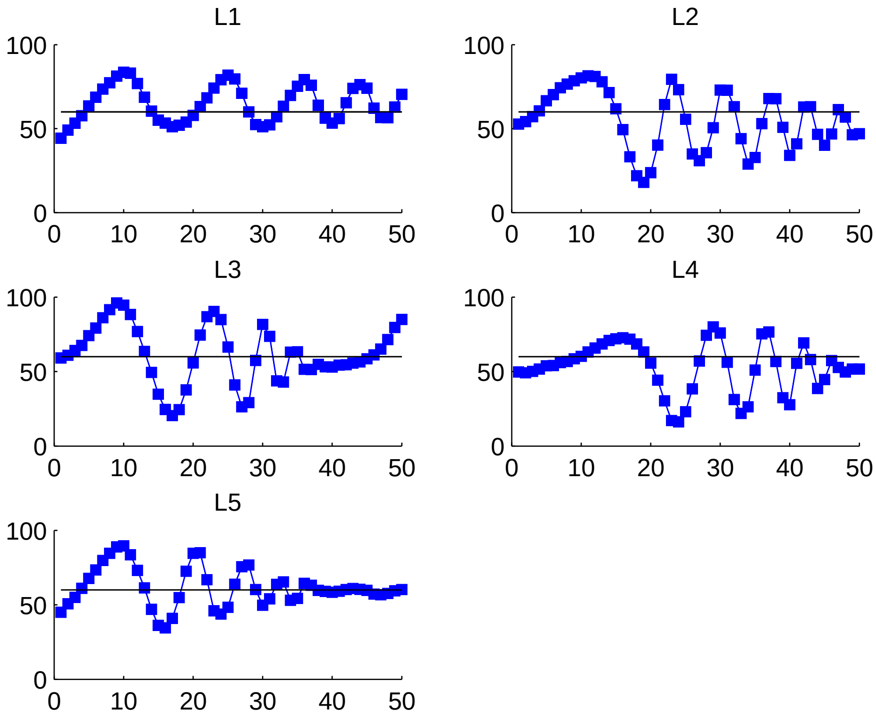

Figure 3: The market prices against the REE price in treatment L.

REE. It is typically written in percentage. The equations of the definitions are as the following:

$$RAD_i \equiv \frac{1}{50} \sum_{t=1}^{50} \frac{|p_{i,t} - 60|}{60} \times 100\%, \tag{5}$$

$$RD_i \equiv \frac{1}{50} \sum_{t=1}^{50} \frac{p_{i,t} - 60}{60} \times 100\%, \tag{6}$$

where i is the notation for each market, and $p_{i,t}$ is the price in market i at period t. The results are presented in Table 1. Clearly, the average RAD is largest in treatment N, followed by treatment L, and smallest in treatment H. The average RD is the largest in treatment N, however, very similar in treatment L and H. A Wilcoxon-Mann-Whitney test suggests that the difference between the RAD in treatment H and each of treatment L and N is significant at 5% level, while the difference between other pairs of treatments is not significant. The difference between the RD in treatment H

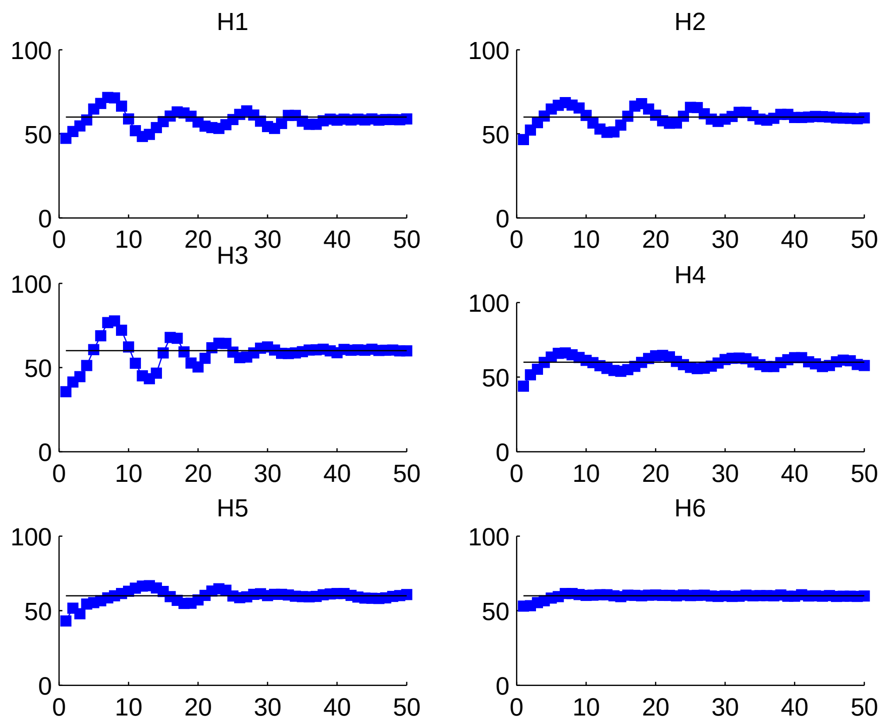

Figure 4: The market prices against the REE price in treatment H.

and N is significant at 5% level, but not between other pairs of treatments.

Table 2 shows the variance of market prices in each market. The variance is very larger for markets in treatment N, and much smaller for markets in treatment L and H.

3.2 Individual Prediction

Figure 5 shows the individual predictions in a typical market (market 1) in each of treatment N, L and H (namely, N1, L1 and H1). Previous studies (Heemeijer et al. 2009, Bao et al. 2012) show that agents have high level of coordination of expectations (expectations are highly homogeneous) in the positive feedback markets, and low level of coordination in the negative feedback markets. The housing markets in our experiment is a negative feedback system to the constructors, and a positive feedback system to the speculators. Therefore, there are three possibilities ex ante: (1) all agents coordinate their expectations at a high level, (2) there is little coordination

Treatment	Treatment N		Treatment L		Treatment H	
Market	RAD	RD	RAD	RD	RAD	RD
Market 1	241.78%	221.64%	16.23%	8.15%	6.79%	-3.01%
Market 2	33.71%	-5.01%	22.74%	-11.55%	5.33%	-0.10%
Market 3	56.29%	32.74%	25.97%	2.66%	8.43%	-2.27%
Market 4	16.91%	-6.27%	24.76%	-8.18%	5.03%	-1.04%
Market 5			16.20%	2.89%	4.47%	-0.92%
Market 6					1.33%	-0.60%
Mean	87.17%	60.77%	21.18%	-1.21%	5.23%	-1.32%
Median	45.00%	13.86%	22.74%	2.66%	5.18%	-0.98%

Table 1: The RAD and RD in each market.

Treatment	Market	Variance
Treatment N	N1	29202.84
	N2	604.55
	N3	1846.77
	N4	170.73
	Average	7956.22
Treatment L	L1	115.07
	L2	303.11
	L3	384.73
	L4	273.21
	L5	173.80
	Average	249.99
Treatment H	H1	24.79
	H2	20.27
	H3	63.28
	H4	16.01
	H5	17.35
	H6	2.70
	Average	24.07

Table 2: The variance of market price in each market.

between the expectations of the agents and (3) the speculators have a high level of coordination of expectations between each other, while the constructors have low level of coordinations between themselves, and with the speculators. The results generally confirm with the first conjecture. There is high level of coordination between the price expectations of both speculators and constructors. After a few initial periods, all the prediction time series tend to follow the same direction, which is generally the direction of the price movement. Meanwhile, there is heterogeneity in individual expectations, in the sense that the expectations of some subjects are persistently further away from the market price.

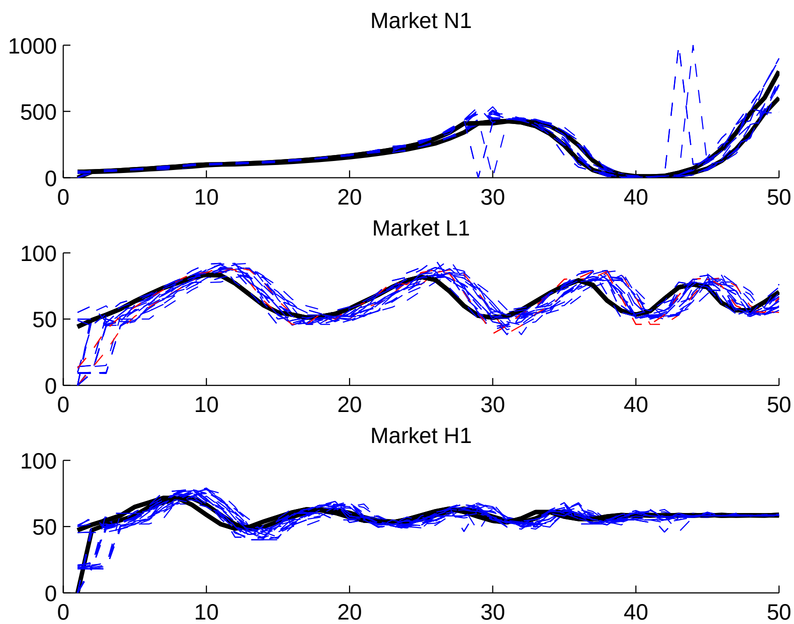

Figure 5: The individual predictions (dashed lines) plotted against the market price (thick line) in a typical market in each of treatment N (market N1, upper panel), L (market L1, middle panel) and H (market H1, lower panel).

To better examine whether there is a systematic difference between the predictions made by the speculators and constructors in the same market, Figure 6 and 7 shows the average price forecast by the investors (circles) and constructors (triangles) plotted against the market price (thick line). The graphs suggest that there is no systematic difference between the average predictions by the two types of agents in the same market. We conducted a t-test on the two samples (expectations by investors and constructors), and the means are also not significant at 5% level in any of the markets in treatment L and H.

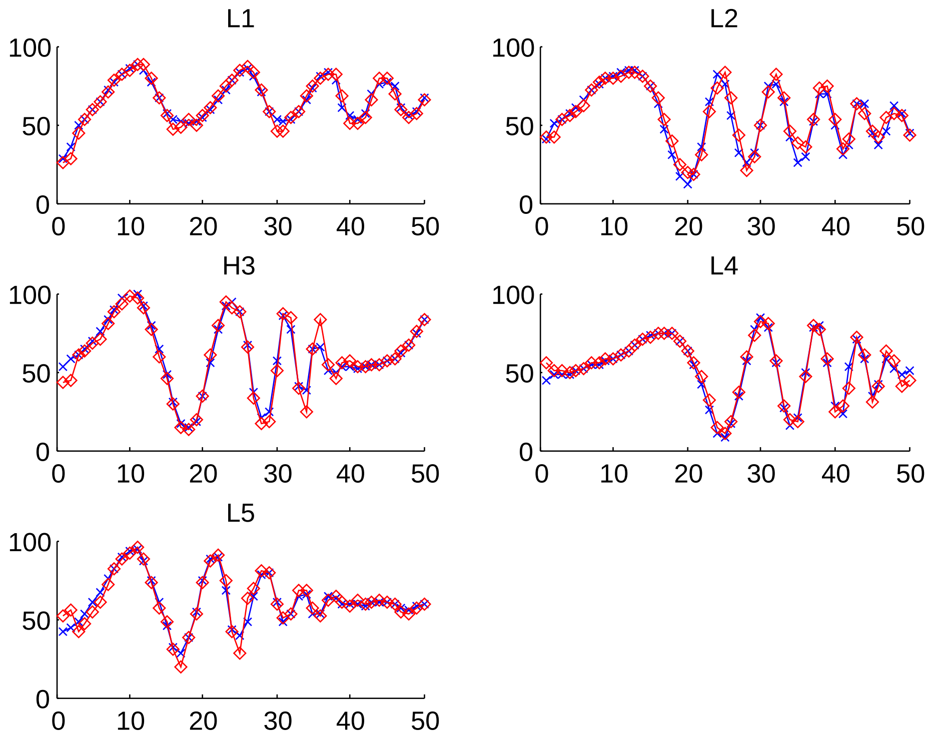

Figure 6: The average predictions by the speculators (Xs) and constructors (diamonds) in each market in treatment L.

3.3 Estimation of Individual Forecasting Strategies

We consider two types of simple heuristics. The first type is a trend rule, where the participants extrapolate a price change from the last observed price.

$$p^e_{h,t+1} = p_{t-1} + \gamma_h (p_{t-1} - p_{t-2}). \tag{7}$$

A positive coefficient γ means a trend following rule; while a negative coefficient γ means a contrarian rule. Table 6 to 8 show the estimation results of equation 7 with a coefficient that is significant at 5% level. It turns out the coefficient is significant for 15 out of 24 subjects in treatment N, 26 out of 50 subjects in treatment L and 60 out of 60 subjects in treatment H. The range of γ is $[0.49, 2.63]$ in treatment N,

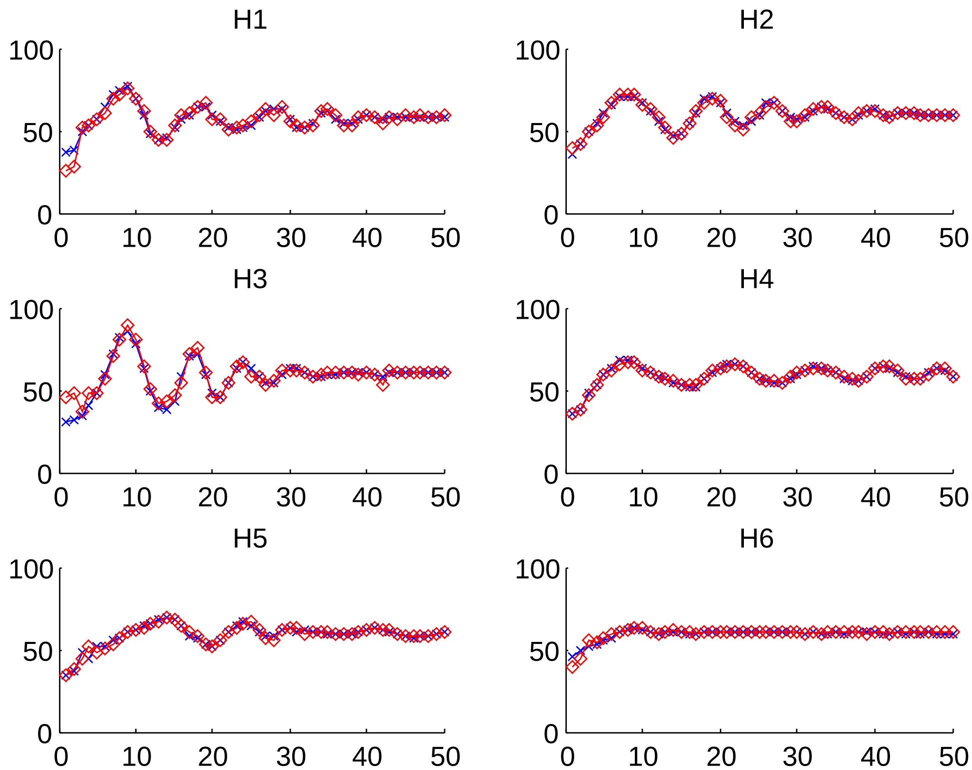

Figure 7: The average predictions by the speculators (Xs) and constructors (diamonds) in each market in treatment H.

$[-1.51, 1.16]$ in treatment L and $[-1.65, 1.68]$ in treatment H. The median of γ is 1.28 in treatment N, 0.52 in treatment L and 1.38 in treatment H.

The second simple rule is the adaptive expectations rule:

$$p^e_{h,t+1} = p^e_{t-1} + w_h(p_{t-1} - p^e_{t-1}), \tag{8}$$

where the prediction is a weighted average of the previous prediction and the last observed price. Tables 9 to 11 show the estimation result of equation 8 with a coefficient that is significant at 5% level. It turns out the coefficient is significant for 20 out of 24 subjects in treatment N, 50 out of 50 subjects in treatment L and 60 out of 60 subjects in treatment H. The range of w is $[-1.95, 2.39]$ in treatment N, $[0.30, 1.98]$ in treatment L and $[0.68, 2.01]$ in treatment H. The median of w is 0.87 in treatment N, 0.55 in treatment L and 1.54 in treatment H.

4 Estimation of Heuristic Switching Model

The heuristic switching model (HSM) is a heterogeneous expectations model based on evolutionary selection of forecasting heuristics proposed by Anufriev and Hommes (2012). It is an extension of Brock and Hommes (1997, 1998). HSM is able to explain the *different* price dynamics: monotonic convergence, persistent oscillations and dampened oscillations in different experimental markets in the asset pricing experiment of Hommes et al (2005) and Hommes et al (2008). In our experiment, we also see all these types of price dynamics. In general, most markets exhibit monotonic convergence in treatment H, persistent oscillations in treatment N and dampened oscillations in treatment L. It assumes that the subjects chose between a finite menu of four simple heuristics depending upon their relative performance (measured by mean squared error). Hommes et al (2005, 2008) are two 2-period ahead LtFE asset pricing experiments. The four rules in the model are therefore as follows:

An adaptive expectation (ADA) rule:

$$p^e_{t+1,1} = p^e_t + 0.75(p_t - p^e_{t,1}). \tag{9}$$

The weak trend rules (WTR) given by:

$$p^e_{t+1,2} = p_t + 0.4(p_t - p_{t-1}). \tag{10}$$

The strong trend extrapolating rule (TRE) given by:

$$p^e_{t+1,2} = p_t + 1.3(p_t - p_{t-1}). \tag{11}$$

The fourth rule is called an anchoring and adjustment heuristic (A&A), as in Tversky and Kahneman (1974):

$$p^e_{t+1,4} = 0.5(p^{av}_t + p_t) + (p_t - p_{t-1}). \tag{12}$$

We use $w = 0.75$ for the adaptive rule because it is about the median of the estimated coefficient using equation (8). We use 0.4 and 1.3 as the coefficient for weak and strong trend rule because they are about the minimum and maximum of the estimated coefficient for equation (7), and also the same as those parameters used in Anufriev and Hommes (2012). The learning, anchoring and adjustment (LAA) rule uses a time varying anchor, $0.5(p^{av}_t + p_t)$, which is the average of the price in the last period and the sample mean of all past prices, and extrapolates the last price trend $p_t - p_{t-1}$. Because it includes a flexible time-varying anchor, the LAA rule was successful in explaining persistent oscillations in Hommes et al (2005, 2008).

Subjects switch between these forecasting heuristics based on their relative performance in terms of mean squared error. The performance of heuristic h, $h \in \{1, 2, 3, 4\}$ is written as:

$$U_{t,h} = -(p_t - p^e_{t,h})^2 + \eta U_{t-1,h}, \tag{13}$$

where $n_{h,t}$ is the fraction of the agents using heuristic h in the whole population. The parameter $\eta \in [0, 1]$ shows the relative weight the agents give to errors in all past periods compared to the most recent one. When $\eta = 0$, only the most recent performance is taken into account, and when $\eta > 0$, all past errors matter for the performance. The specific weight updating rule is given by a *discrete choice model with asynchronous updating* rule from Hommes, Huang and Wang (2005) and Diks and van der Weide (2005):

$$n_{t,h} = \delta n_{t-1,h} + (1-\delta)\frac{\exp(\beta U_{t-1,h})}{\sum_{i=1}^{4}\exp(\beta U_{t-1,i})}. \tag{14}$$

The parameter $\delta \in [0, 1]$ represents the inertia with which participants stick to their past forecasting heuristic. When $\delta = 1$, the agents do not update at all. When $\delta > 0$, each period a fraction of $1 - \delta$ participants updates their weights. The parameter $\beta \geq 0$ represents the "sensitivity" to switch to another strategy. The higher the β, the faster the participants switch to more successful rules in the most recent past. When $\beta = 0$, the agents allocate equal weight on each of the heuristics. When $\beta = +\infty$, all agents who switch to the most successful heuristic in the last period immediately.

Figure 4 shows the simulated market price by the HSM model with the benchmark parameterization $\beta = 0.4, \eta = 0.7, \delta = 0.9$, against the experimental market price in a typical market (market 1) in each treatment. The benchmark parameters were used in Anufriev and Hommes (2012a,b) to describe different experimental asset markets in Hommes et al (2005, 2008). Since we have similar patterns of price dynamics, we can check whether the model can be applied to a completely different experiment

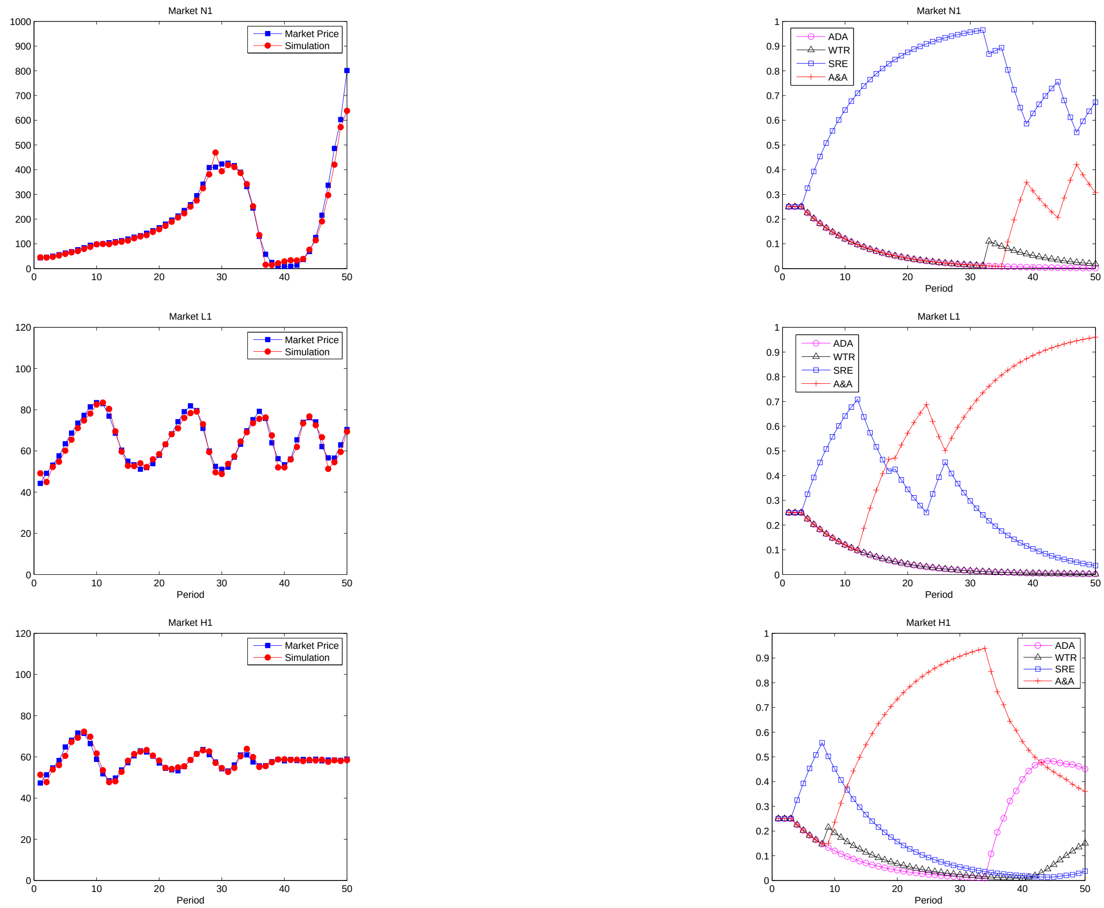

Figure 8: The simulated and experimental market price (left panel) and the simulated fractions of users of different heuristics (right panel) in a typical market in treatment N (upper panel), L (middle panel) and H (lower panel).

with the original setting. The result turns out to be very good. The simulated prices fit the experimental data very well. When we check the weights of different forecasting heuristics: the typical market in treatment N is mostly dominated by the strong trend rule, which leads to sharp price fluctuations; the typical market in treatment L is firstly dominated by strong trend rule, but then the anchoring and adjustment rule in later periods, which leads to dampened oscillations; the typical market in treatment H is firstly dominated by the anchoring and adjustment rule and then the adaptive rule near the end of the experiment, which leads to convergence via dampened oscillation at the beginning periods of the price dynamics.

Table 4 reports the mean squared error of several forecasting heuristics and the HSM. We highlight the model that provides the best fit in terms of mean squared error for each market. Out of 15 markets in this experiment, the HSM Benchmark provides the best fit for 14 markets.

Besides HSM Benchmark, we also conducted a grid search of optimal values of β, η, δ that minizes the mean squared error of the model. We do it on the domain $[0, 10], [0, 1], [0, 1]$ with step length of 0.1. It turns out for most markets, β is typicall about 0.1, η is zero, and δ is either around 0.5 or 0.9. The result suggests that the agents switch between the heuristics at a very low intensity in this experiment, and the inertia of choice is very high. The HSM optimal model provides smaller MSE than all other models, including HSM Benchmark in all markets.

Based on the results of the HSM optimal model, we calculated the average weight of each heurisitic over the markets in each treatment at each time period, and over all the periods. Table 4 reports the average weight of each heurisitic over all the markets and periods in each treatment. When the supply elasticity increases from treatment N to L and hence H, the average weight of the strong trend (STR) heurisitic declines substantially, and the weight of the adaptive (ADA) rule increases. The weight of LAA heurisitic is very high in treatment L, which imposes dampened oscillation. Figure 4 shows the evolvement of the average weight of each heurisitic over the periods in each treatment. In general, the figure confirms that there are more users of the strong trend rule in treatment N, more for LAA heuristic in treatment L and for the adaptive heurisitic in treatment H.

	Treatment N					
Specification	Market 1	Market 2	Market 3	Market 4		
Fundamental	46297.37	596.94	2192.08	169.55		
Naive	2899.56	385.22	82.24	108.40		
ADA heuristic	13576.30	851.81	506.54	271.25		
WTR heuristic	6862.86	1117.51	214.25	321.66		
STR heuristic	2881.01	1486.85	**78.65**	472.72		
LAA heuristic	8145.86	1020.85	427.07	251.19		
HSM Benchmark	**1897.91**	**204.77**	93.21	**49.15**		
HSM Optimal	1014.93	97.41	32.36	37.96		
β	0.1	0.1	0.1	0.3		
η	0.1	0	0	0		
δ	0.9	0.5	0.9	0.4		
	Treatment L					
Specification	Market 1	Market 2	Market 3	Market 4	Market 5	
Fundamental	131.70	320.03	379.56	313.65	168.85	
Naive	32.14	131.53	128.32	132.73	69.87	
ADA heuristic	127.65	379.22	417.70	381.17	226.63	
WTR heuristic	90.41	392.73	375.29	396.44	203.89	
STR heuristic	80.04	507.04	457.50	518.97	240.71	
LAA heuristic	48.29	267.91	261.55	259.78	129.23	
HSM Benchmark	**27.64**	**102.19**	**94.19**	**104.01**	**53.19**	
HSM Optimal	18.73	60.23	64.93	41.37	32.99	
β	0.1	0.1	0.1	0.1	0.1	
η	0	0.1	0	0	0	
δ	0.6	0.6	0.5	0.5	0.5	
	Treatment H					
Specification	Market 1	Market 2	Market 3	Market 4	Market 5	Market 6
Fundamental	24.33	16.27	51.97	10.91	11.59	1.80
Naive	8.66	7.45	21.68	4.75	4.71	0.45
ADA heuristic	33.20	28.17	80.08	19.87	12.71	1.50
WTR heuristic	24.49	21.17	62.51	12.66	9.34	1.04
STR heuristic	23.25	20.74	62.64	10.67	12.69	1.29
LAA heuristic	13.94	13.10	40.29	9.48	11.21	1.65
HSM Benchmark	**5.29**	**4.90**	**14.02**	**2.90**	**1.67**	**0.13**
HSM Optimal	3.92	2.92	10.66	1.63	1.56	0.11
β	0.1	0.1	0.1	0.1	0.1	10
η	0	0	0	0	0	0.5
δ	0.9	0.5	0.9	0.9	0.9	0.9

Table 3: The fitness of different models to the experimental data. HSM benchmark means the heuristic switching model where $\beta = 0.4, \eta = 0.7, \delta = 0.9$.

Heuristic	Treatment N	Treatment L	Treatment H
ADA	19.85%	21.20%	27.07%
WTR	16.55%	12.31%	19.81%
STR	40.12%	30.57%	25.42%
LAA	23.48%	35.92%	27.69%

Table 4: The average weight of each heuristic over the markets in each treatment according to the HSM optimal model.

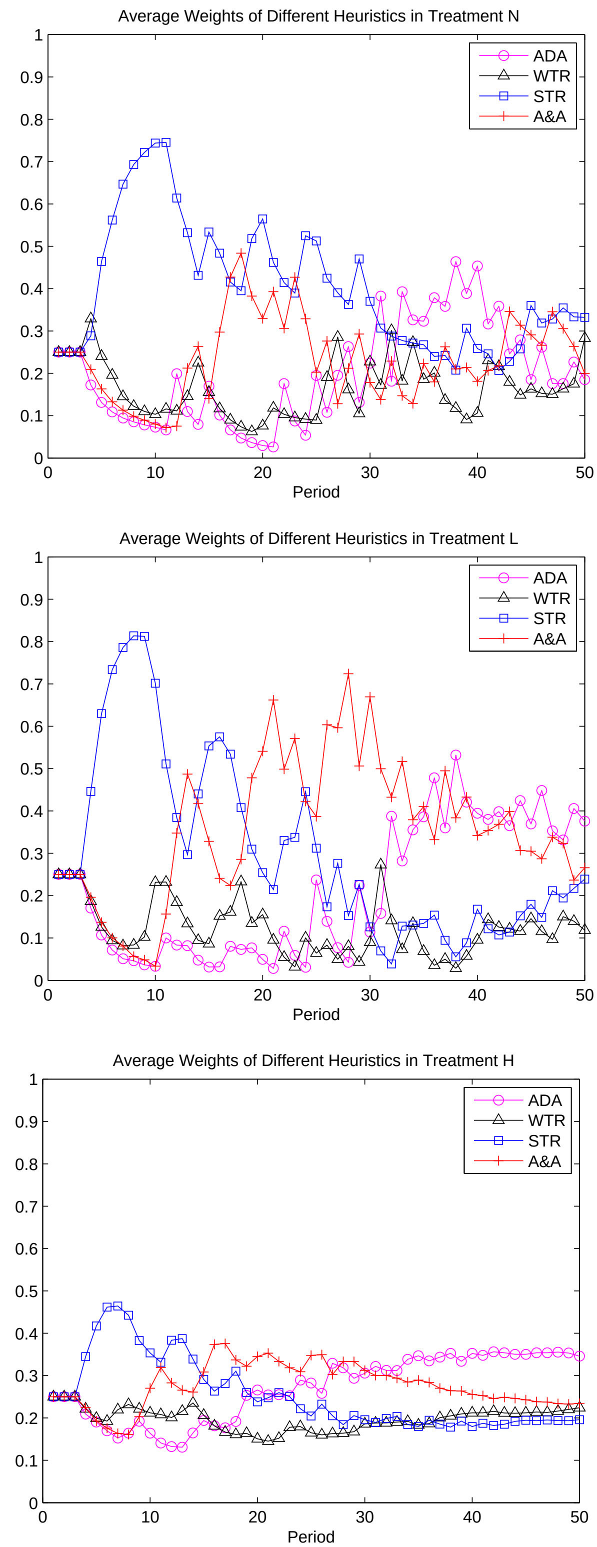

Figure 9: The average simulated fractions of users of different heuristics in treatment N (upper panel), L (middle panel) and H (lower panel).

5 Conclusion

We study the relationship between supply elasticity and price dynamics in experimental housing markets using a "learning to forecast" design. The main result is that when the supply elasticity increases, the market price becomes more stable.

The housing market exhibits both positive feedback through speculative demand and negative feedback from endogenous housing supply. While the market is a positive feedback system to the investors and a negative feedback system to the constructors, there is generally no systematic difference in price predictions made by the two types of agents. We find that when positive feedback dominates negative feedback, i.e., the demand elasticity is larger than the supply elasticity, housing bubbles arise because most agents, regardless of their types, will tend to use a trend extrapolation strategy when making price forecasts.

In order to capture the heterogeneity in individual expectations and their impact on aggregate market outcome, we calibrate a heuristic switching model to the experiment. The model provides a very good fit to individual decisions as well as aggregate market data in all treatments. Depending on the relative strength of positive versus negative feedback, i.e. demand versus supply elasticity, the evolutionary selection among the forecasting heuristics selects a different dominating strategy. For a low supply elasticity (strong positive feedback) trend-following rules dominate leading to housing bubbles and crashes; for intermediate supply elasticity (medium positive feedback) an anchoring and adjustment rule dominates leading to (non-exploding) price oscillations; for high elasticity (weak positive feedback) housing prices converge to REE fundamental through coordination on adaptive expectations. This confirms the obervation by Glaeser and Nathanson (2014) on housing bubbles:

"Many non-rational explanations for real estate bubbles exist, but the most promising theories emphasize some form of trend-chasing, which in turn reflects boundedly rational learning."

Our results have important policy implications: negative feedback policies that reduce the overall positive feedback in speculative markets can mitigate bubbles and market crashes.

Finally, for simplicity we studied only a spot market for housing in this experiment.

In order to address the role of supply elasticity in real housing markets, it would be interesting to take into account the stock-flow feature of the market (Wheaton, 1999), namely that the houses built in the previous period may enter the market again in later periods. We leave this question to future extension of this work.

References

1. Anufriev, M., and Hommes, C. (2012a). Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments. American Economic Journal: Microeconomics, 4(4), 35-64.

2. Anufriev, M., and Hommes, C. (2012b). Evolution of market heuristics. Knowledge Engineering Review, 27(2), 255-271.

3. Assenza, T., Bao, T., Hommes, C., and Massaro, D. (2014). Experiments on expectations in macroeconomics and finance. Experiments in Macroeconomics: Research in Experimental Economics, 17, 11-70.

4. Bao, T., Hommes, C.H. and Makarewicz, T. (2015). Bubble formation and (in)efficient markets in learning-to-forecast and -optimise experiments, *The Economic Journal*, forthcoming.

5. Bao, T., Hommes, C., Sonnemans, J., and Tuinstra, J. (2012). Individual expectations, limited rationality and aggregate outcomes. Journal of Economic Dynamics and Control, 36(8), 1101-1120.

6. Bolt, W., M. Demertzis, C. Diks, van der Leij, M., (2015), Identifying booms and busts in house prices under heterogeneous expectations, CeNDEF working paper, University of Amsterdam.

7. Campbell, J. Y., Lo, A. W., and A.C. Mickinlay (1997). The Econometrics of Financial Markets. Princeton University Press.

8. Campbell, S. D., Davis, M. A., Gallin, J., and Martin, R. F. (2009)., What moves housing markets: A variance decomposition of the rent-price ratio. Journal of Urban Economics 66: 90-102.

9. Clayton, J., (1997), Are housing price cycles driven by irrational expectations? Journal of Real Estate Finance and Economics, 14(3), 341-363.

10. Cuthbertson, K., and Nitzsche, D. (2005). Quantitative financial economics: stocks, bonds and foreign exchange. John Wiley and Sons.

11. deLeeuw, F., and N. F. Ekanem. (1971). The supply of rental housing,' American Economic Review 61, 806-817.

12. De Long, B., A. Shleifer, L. Summers, and R. Waldman, (1990), Positive feedback investment strategy and destabilizing rational speculation, Journal of Finance, 45 (2), 379-395

13. Dieci, R. and Westerhoff, F. (2012), A simple model of the speculative housing market. Journal of Evolutionary Economics, 22, 303-329.

14. Diks, C., and Van Der Weide, R. (2005). Herding, a-synchronous updating and heterogeneity in memory in a CBS. Journal of Economic Dynamics and Control, 29(4), 741-763.

15. DiPasquale, Denise, and William C. Wheaton. (1994). Housing market dynamics and the future of housing prices, Journal of Urban Economics 35(1), 1-27.

16. Duffy, J. (2008). Macroeconomics: a survey of laboratory research. Handbook of Experimental Economics, Volume 2.

17. Fehr, E., and Tyran, J. R. (2008). Limited rationality and strategic interaction: the impact of the strategic environment on nominal inertia. Econometrica, 76(2), 353-394.

18. Glaeser, Edward L. (2013), A nation of gamblers: real estate speculation and American history.", mimeo.

19. Glaeser, E.L., J. Gyouko, A. Saiz, (2008), Housing supply and housing bubbles, Journal of Urban Economics, 64, 198-217.

20. Glaeser, E. L., and Nathanson, C. G. (2014). Housing Bubbles (No. w20426). National Bureau of Economic Research.

21. Haughwout, A., R.W. Peach, J. Sporn and J. Tracy, (2012), The supply side of the housing boom and bust of the 2000s, Federal Reserve Bank of New York Staff Reports.

22. Heemeijer, P., Hommes, C., Sonnemans, J., and Tuinstra, J. (2009). Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. Journal of Economic Dynamics and Control, 33(5):1052-1072.

23. Hirota, S., Suzuki-Loffelholz, K., and Udagawa, D. (2015). When owners buy higher, they offer higher rents: experimental evidence, Waseda University Working Paper.

24. Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2005). Coordination of expectations in asset pricing experiments. Review of Financial Studies, 18(3):955-980.

25. Hommes, C., Sonnemans, J., Tuinstra, J., and Van De Velden, H. (2007). Learning in cobweb experiments. Macroeconomic Dynamics, 11(S1), 8-33.

26. Hommes, C. (2013). Reflexivity, expectations feedback and almost self-fulfilling equilibria: economic theory, empirical evidence and laboratory experiments. Journal of Economic Methodology, 20(4), 406-419.

27. Knight, J.R., and C.F. Sirmans. Depreciation, maintenance, and housing prices. Journal of Housing Economics 5.4 (1996): 369-389.

28. Mankiw, N. Gregory, and David N. Weil. (1989) The baby boom, the baby bust, and the housing market. Regional Science and Urban Economics 19(2): 235-258.

29. Mayer, C.J., and C.T. Somerville. (2000) Land and use regulation and new construction. Regional Science and Urban Economics 30: 639-662.

30. Poterba, J.M. (1984). Tax subsidies to owner occupied housing: an asset market approach, Quarterly Journal of Economics 99(4), 729-52.

31. Saiz, A., (2008), On Local Housing Supply Elasticity, Working Paper. University of Pennsylvania, The Wharton School.

32. Shilling, J. D., C. F. Sirmans, and J. F. Dombrow. (1991), Measuring depreciation in single-family rental and owner-occupied housing. Journal of Housing Economics 1(4): 368-383.

33. Sonnemans, J., and Tuinstra, J. (2010). Positive expectations feedback experiments and number guessing games as models of financial markets. Journal of Economic Psychology, 31(6), 964-984.

34. Soros, G. (2003). The Alchemy of Finance. John Wiley and Sons.

35. Stephen, M., (1981), Theory and estimation in the economics of housing demand. Journal of Urban Economics 10: 95-116.

36. Stephens, T., and Tyran, J. R. (2012). "At least I didn't lose money"-nominal loss aversion shapes evaluations of housing transactions. University of Copenhagen Department of Economics Discussion Paper (12-14).

37. Stöckl, T., Huber, J., and Kirchler, M. (2010). Bubble measures in experimental asset markets. Experimental Economics, 13(3), 284-298.

38. Wheaton, W., (1999). Real estate "cycles": some fundamentals, Real Estate Economics, 27 (2), 209-230.

A Derivation of Individual Supply and Demand Functions of the Market Participants

This section shows the derivation of the individual supplies and demands as a function of the price expectations in section 2.1.

For the individual supply function of the constructors, we assume there are I constructors, and each of them has a cost function $c(q) = \frac{Iq^2}{2}$. The expected profit of firm i, $\pi^e_{h,t+1}$, is then given by:

$$\pi^e_{i,t+1} = p^e_{i,t+1} q_{i,t} - c(q_{i,t}), \tag{15}$$

where $p^e_{i,t+1}$ is the expected housing price by constructor i for period $t+1$. It takes one period to finish the constructor. Therefore the price expectation for period $t+1$ determined housing constructor in period t. To maximize this expected profit function, one has to take the first order derivative with respect to $q_{i,t}$, and let it equal to 0. This will lead to $Iq_{i,t} = p^e_{t+1,i}$, $q_{i,t} = \frac{p^e_{i,t+1}}{I}$, or $z^s_{i,t} = \frac{p^e_{i,t+1}}{I}$.

For the individual demand function of the speculators, we can assume that they have a myopic mean-variance utility function as the following:

$$U_{h,t}(z^d_{h,t}) = E_{h,t} W_{h,t+1} - \frac{a}{2} V_{i,t}(W_{h,t+1}), \tag{16}$$

where $W_{h,t+1}$ is their wealth, given by

$$W_{h,t+1} = RW_{h,t} + z^d_{h,t}(p_{t+1} + y_{t+1} - Rp_t), \tag{17}$$

where R is the gross interest rate of a risk-free asset. $z^d_{h,t}$ is the individual demand of the asset by each speculator. y_{t+1} is the assets dividend paid at the beginning of period $t+1$ and a is the risk aversion factor. For simplicity, we assume that the variance of the return to one unit of the asset is a constant, which equals to σ^2 over time, and the variance of the portfolio is just a quadratic function of the demand, *i.e.* $V_{h,t}(p_{t+1} + y_{t+1} - Rp_t) = \sigma^2 {z^d_{h,t}}^2$.

Standing at the beginning of each period, the current wealth $W_{h,t}$ is a given number. The speculator just need to take first order condition with respect to $z^d_{h,t}$, which leads to $asigma^2 z^d_{h,t} = E_{h,t}(p_{t+1} + y_{t+1} - Rp_t)$. Moreover, we assume the expected value of y_{t+1} is also a constant over time, which equals to $\overline{y}$. This will lead to $a\sigma^2 z^d_{h,t} = E_{h,t}(p_{t+1} + y_{t+1} - Rp_t) = p^e_{h,t+1} + \overline{y} - Rp_t$, namely,

$$z^d_{h,t} = \frac{p^e_{h,t+1} + \overline{y} - Rp_t}{a\sigma^2} \tag{18}$$

B Experimental Instructions

This section shows the experimental instructions for constructors and speculators in the experiment in Treatment L. There is no instructions for developers in treatment N, because there is no developers in the market in this treatment. The instructions for speculators in treatment N and constructors and speculators in H are the same as in treatment L, except that the dividend (rent) is 3 in treatment N, and 18 in treatment H, and the instructions for the speculators in treatment N does not contain a section about the developers.

B.1 Experimental Instructions for Construction Advisors

General information.

You are a construction advisor to real estate developer that wants to optimally supply new houses to the market. In order to make an optimal decision the developer needs an accurate prediction of the housing prices. As their construction advisor, you have to predict the housing price during 50 subsequent time periods. Your earnings during the experiment depend upon your forecasting accuracy. The smaller your forecasting errors in each period, the higher your total earnings.

Information about the price determination in the housing market.

The housing price is determined by market clearing, namely supply equals demand. The supply of housing is determined by the main real estate developers in the market. The demand for houses is determined by the sum of aggregate demand of a number of large investment funds and demand from housing consumers. There are also some small random shocks to housing prices due to fluctuation in the cost of construction materials etc.

Information about the construction strategies of real estate developers.

Each of the real estate developer is advised by a construction advisor played by a participant in the experiment, and there is no difference between these developers except that they may receive different price forecast from their own advisors. The precise strategy of the real estate developers you are advising is unknown. The target of the developer is to maximize expected profit. The profit is the price times supply minus cost. The cost is a typical concave function of the supply quantity. So the supply by your firm is increasing in your price forecast. The higher your price forecast, the larger amount you developer will construct. If all construction advisors predict high/low housing price, the total supply will be high/low.

Information about the strategies of the investment funds.

Each of the investment funds is advised by a financial advisor played by one participant in the experiment. The precise investment strategy of the investment fund is unknown. The decision of the investment fund is to allocate money between a riskless option (saving at a bank), and a risky option (buying houses). The bank account of the risk free investment pays a fixed interest rate of 5% per period. The holder of the houses receives a rental payment in each time period. These dividend payments are uncertain however and vary over time. Economic experts of the investment funds have computed that the average dividend (rent) payments are 9 (the same unit as housing price) per time period. The return of investing in the housing market per period is uncertain and depends upon (unknown) rental payments and the price changes of the houses. The financial advisor of an investment fund is not asked to forecast housing price in each period. Based upon his/her price forecast, his/her investment fund will make an optimal investment decision. The higher the price forecast the larger will be the fraction of money invested by the investment fund in the housing market, so the larger will be their demand for houses.

The financial advisors also know there are construction advisors for real estate developers. The information the financial advisors have about you is the same as the information you have about them.

In sum, the most important information about the price determination in the housing market includes:

1. The price is determined by supply and demand. Higher supply/demand will generally lead to lower/higher price.
2. The demand by an investment fund goes up/down when the forecast by its financial advisor goes up/down.
3. The supply by a real estate developer goes up/down when the forecast by its construction advisor goes up/down.

Forecasting task of the construction advisor.

The only task of the financial advisors in this experiment is to forecast the housing price in each time period as accurate as possible. The forecast has to be made two periods ahead. In the first period you have to make price forecasts for the both period 1 and period 2. The prices in period 1 and 2 are between 0 and 100 per unit (this restriction is only for the first 2 periods, and the price in later periods is not necessarily always below 100). After all participants have given their predictions for the first two periods, the housing price in period 1 will be revealed and based upon your forecasting error your earnings for period 1 will be given. After that you have to give your prediction for period 3. After all participants have given their predictions for period 3, the housing market price in period 2 will be revealed and, based upon your forecasting error your earnings for period 2 will be given. This process continues for 51 periods.

To forecast the housing price p_{t+1} in period t, the available information thus consists of

- past prices up to period $t-1$,
- your past predictions up to period $t-1$,
- past earnings up to period $t-1$.

Earnings.

Earnings will depend upon forecasting accuracy only. The better you predict the housing price in each period, the higher your aggregate earnings. Earnings will be according to the following earnings table.

B.2 Instruction for Financial Advisors

General information.

You are a financial advisor to an investment fund that wants to optimally invest a large amount of money. The investment fund has two investment options: a risk free investment and a risky investment. The risk free investment is putting money on a bank account paying a fixed interest rate. The alternative risky investment is an investment in the housing market. In each time period the investment fund has to decide which fraction of their money to put on the bank account and which fraction of the money to spend on buying houses. In order to make an optimal investment decision the investment fund needs an accurate prediction of the housing price. As their financial advisor, you have to predict the housing price during 50 subsequent time periods. The forecast has to be made two periods ahead. Your earnings during the experiment depend upon your forecasting accuracy. The smaller your forecasting errors in each period, the higher your total earnings.

Information about the price determination in the housing market.

The housing price is determined by market clearing, namely supply equals demand. The supply of housing is determined by the main real estate developers in the market. The demand for houses is determined by the sum of aggregate demand of a number of large investment funds and demand from housing consumers. There are also some small random shocks to housing prices due to fluctuation in the cost of construction materials etc.

Information about the investment strategies of the investment funds.

Each of the investment funds is advised by a financial advisor played by a participant in the experiment, and there is no difference between these funds except that they may receive different price forecast from their own advisors. The precise investment strategy of the investment fund that you are advising and the investment strategies of the other investment funds are unknown. The bank account of the risk free investment pays a fixed interest rate of 5% per period. In each period, the holder of the houses receives a rental payment. These rental payments are uncertain however and vary over time. Economic experts of the investment funds have computed that the average rental payments are 9 (the same unit as housing price) per time period. The return of investing in the housing market per period is uncertain and depends upon (unknown) rental payments and price changes of the houses. As the financial advisor of an investment fund you are not asked to forecast rental payment, but you are only asked to forecast the housing price in each period. Based upon your price forecast, your investment fund will make an optimal investment decision. The higher your price forecast the larger will be the fraction of money invested by your investment fund in the housing market, so the larger will be their demand for houses.

Information about the strategies of the real estate developers.

Each of the real estate developers is advised by a construction advisor (also forecasting housing price) played by one participant in the experiment. The precise strategy of the real estate developers is unknown. The higher the price forecast by the construction advisor, the larger the number of houses the developer he/she is advising will construct, so the larger will be their supply for houses. These construction advisors also know there are financial advisors for investment funds. The information the construction advisors have about you is the same as the information you have about them.

In sum, the most important information about the price determination in the housing market includes:

1. The price is determined by supply and demand. Higher supply/demand will generally lead to lower/higher price.
2. The demand by an investment fund goes up/down when the forecast by its financial advisor goes up/down.
3. The supply by a real estate developer goes up/down when the forecast by its construction advisor goes up/down.

Forecasting task of the financial advisor.

The only task of the financial advisors in this experiment is to forecast the housing price in each time period as accurate as possible. The forecast has to be made two periods ahead. In the first period you have to make price forecasts for the both period 1 and period 2. The prices in period 1 and 2 are between 0 and 100 per unit (this restriction is only for the first 2 periods, and the price in later periods is not necessarily always below 100). After all participants have given their predictions for the first two periods, the housing price in period 1 will be revealed and based upon your forecasting error your earnings for period 1 will be given. After that you have to give your prediction for period 3. After all participants have given their predictions for period 3, the housing market price in period 2 will be revealed and, based upon your forecasting error your earnings for period 2 will be given. This process continues for 51 periods.

To forecast the housing price in period , the available information thus consists of

- past prices up to period $t-1$,
- your past predictions up to period $t-1$,
- past earnings up to period $t-1$.

Earnings. Earnings will depend upon forecasting accuracy only. The better you predict the housing price in each period, the higher your aggregate earnings. Earnings will be according to the following earnings table.

C Payoff Table

Table 5 is the payoff table used in this experiment.

Payoff Table for Forecasting Task							
Your Payoff=max$[1300 - \frac{1300}{49}(\text{Your Prediction Error})^2, 0]$							
2600 points equal 1 euro							
error	points	error	points	error	points	error	points
0	1300	1.85	1209	3.7	937	5.55	483
0.05	1300	1.9	1204	3.75	927	5.6	468
0.1	1300	1.95	1199	3.8	917	5.65	453
0.15	1299	2	1194	3.85	907	5.7	438
0.2	1299	2.05	1189	3.9	896	5.75	423
0.25	1298	2.1	1183	3.95	886	5.8	408
0.3	1298	2.15	1177	4	876	5.85	392
0.35	1297	2.2	1172	4.05	865	5.9	376
0.4	1296	2.25	1166	4.1	854	5.95	361
0.45	1295	2.3	1160	4.15	843	6	345
0.5	1293	2.35	1153	4.2	832	6.05	329
0.55	1292	2.4	1147	4.25	821	6.1	313
0.6	1290	2.45	1141	4.3	809	6.15	297
0.65	1289	2.5	1134	4.35	798	6.2	280
0.7	1287	2.55	1127	4.4	786	6.25	264
0.75	1285	2.6	1121	4.45	775	6.3	247
0.8	1283	2.65	1114	4.5	763	6.35	230
0.85	1281	2.7	1107	4.55	751	6.4	213
0.9	1279	2.75	1099	4.6	739	6.45	196
0.95	1276	2.8	1092	4.65	726	6.5	179
1	1273	2.85	1085	4.7	714	6.55	162
1.05	1271	2.9	1077	4.75	701	6.6	144
1.1	1268	2.95	1069	4.8	689	6.65	127
1.15	1265	3	1061	4.85	676	6.7	109
1.2	1262	3.05	1053	4.9	663	6.75	91
1.25	1259	3.1	1045	4.95	650	6.8	73
1.3	1255	3.15	1037	5	637	6.85	55
1.35	1252	3.2	1028	5.05	623	6.9	37
1.4	1248	3.25	1020	5.1	610	6.95	19
1.45	1244	3.3	1011	5.15	596	$error \geq 0$	
1.5	1240	3.35	1002	5.2	583		
1.55	1236	3.4	993	5.25	569		
1.6	1232	3.45	984	5.3	555		
1.65	1228	3.5	975	5.35	541		
1.7	1223	3.55	966	5.4	526		
1.75	1219	3.6	956	5.45	512		
1.8	1214	3.65	947	5.5	497		

Table 5: Payoff Table for Forecasters

D Estimated Forecasting Rules

D.1 Trend Extrapolation Rules

sub no.	coefficient	p-value	R-squared	MSE
n11	2.4337	0.0000	0.9414	2034.27
n12	2.1157	0.0000	0.8066	6453.40
n13	1.7794	0.0000	0.9112	2364.41
n14	1.8408	0.0000	0.9344	1813.48
n15	2.4010	0.0000	0.4922	22966.66
n16	2.6337	0.0000	0.9010	3552.42
n31	1.1605	0.0000	0.9803	38.04
n33	1.7259	0.0000	0.9862	28.83
n34	0.9861	0.0000	0.9647	59.05
n35	1.3398	0.0000	0.9805	35.25
n36	1.5440	0.0000	0.9754	51.99
n41	0.7395	0.0000	0.6426	90.51
n42	0.4897	0.0003	0.5547	95.23
n43	0.8246	0.0000	0.8049	60.35
n44	0.5080	0.0018	0.4978	134.35

Table 6: Above is the result of estimating $p^e_{h,t+1} = p_{t-1} + \gamma(p_{t-1} - p_{t-2})$ (trend rule) for the treatment N. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.

sub no.	coefficient	p-value	R-squared	MSE
l11	0.6049	0.0067	0.0356	154.32
l12	0.5037	0.0347	-0.1278	176.54
l13	0.6001	0.0183	-0.1617	200.85
l16	0.7205	0.0114	-0.3128	251.84
l17	0.3462	0.0404	0.1947	88.56
l18	0.5514	0.0311	-0.2837	203.20
l110	0.6018	0.0350	-0.4744	252.79
l41	-1.3363	0.0032	-0.9016	588.95
l42	-1.3089	0.0036	-0.6096	580.49
l43	-1.3359	0.0022	-0.3587	544.47
l44	-1.3208	0.0045	-0.3413	619.55
l45	-1.4331	0.0014	-0.4316	575.22
l46	-1.5156	0.0007	-0.4679	567.84
l47	-1.4167	0.0020	-0.5371	601.21
l48	-1.3288	0.0036	-0.6544	598.22
l49	-1.4837	0.0015	-0.2907	626.42
l410	-1.2902	0.0027	-0.3440	530.24
l51	0.9958	0.0000	0.8782	40.10
l52	0.8816	0.0000	0.5864	106.77
l53	0.3761	0.0418	0.4392	111.79
l54	0.8051	0.0000	0.8480	44.16
l55	0.9309	0.0000	0.6778	88.33
l56	1.1615	0.0000	0.6191	111.43
l57	0.8573	0.0000	0.7004	79.51
l58	0.6806	0.0015	0.6202	150.66
l59	0.7655	0.0000	0.8042	43.67
l510	0.8300	0.0000	0.6855	90.46

Table 7: Above is the result of estimating $p^e_{h,t+1} = p_{t-1} + \gamma(p_{t-1} - p_{t-2})$ (trend rule) for the treatment L. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.

sub no.	coefficient	p-value	R-squared	MSE
h11	1.6800	0.0000	0.8999	5.93
h12	1.2638	0.0000	0.6702	16.08
h13	1.3632	0.0000	0.8633	6.87
h14	0.8668	0.0000	0.7905	10.89
h15	0.7801	0.0000	0.6656	10.50
h16	0.9782	0.0000	0.9083	3.72
h17	0.8128	0.0000	0.9084	3.28
h18	1.0079	0.0000	0.7970	6.01
h19	0.8899	0.0000	0.8507	6.53
h110	1.0551	0.0000	0.8942	4.05
h21	0.8434	0.0000	0.8304	5.69
h22	0.3924	0.0094	0.6342	7.98
h23	1.3063	0.0000	0.8170	7.20
h24	1.1792	0.0000	0.7111	11.02
h25	1.0043	0.0000	0.5941	9.86
h26	1.4359	0.0000	0.8201	8.90
h27	1.3309	0.0000	0.8471	6.86
h28	1.0385	0.0000	0.8722	4.69
h29	0.8299	0.0000	0.7157	7.58
h210	1.3020	0.0000	0.7530	7.63
h31	0.9991	0.0000	0.8340	14.47
h32	0.8308	0.0000	0.7137	22.66
h33	1.0217	0.0000	0.7923	16.51
h34	1.5963	0.0000	0.8581	16.51
h35	1.0453	0.0000	0.7876	22.65
h36	0.8595	0.0000	0.7749	15.90
h37	1.2799	0.0000	0.6984	24.20
h38	1.0833	0.0000	0.8684	11.72
h39	1.0178	0.0000	0.9056	12.00
h310	0.9741	0.0000	0.7210	28.72
h41	1.2125	0.0000	0.8900	2.18
h42	0.6838	0.0000	0.6961	5.48
h43	0.5317	0.0000	0.8832	1.82
h44	0.4743	0.0000	0.8977	1.38
h45	0.9873	0.0000	0.7496	6.30
h46	1.5941	0.0000	0.8939	2.19
h47	1.0111	0.0000	0.7412	6.18
h48	0.8454	0.0000	0.9236	1.31
h49	0.9166	0.0000	0.8122	2.89
h410	0.7724	0.0000	0.7266	4.15
h51	0.2647	0.0103	0.8732	2.35
h52	0.4867	0.0002	0.8361	3.74
h53	0.7634	0.0004	0.5233	10.24
h54	0.5793	0.0001	0.7596	4.81
h55	0.8311	0.0000	0.6578	5.71
h56	0.4544	0.0002	0.8191	3.17
h59	-1.6471	0.0001	0.5233	37.46
h510	0.3162	0.0035	0.8614	2.59
h61	0.9492	0.0000	0.6132	0.64
h62	0.8532	0.0000	0.7835	0.56
h63	0.6564	0.0000	0.7945	0.33
h64	0.7508	0.0002	0.2124	0.88
h65	0.6911	0.0000	0.8702	0.20
h66	0.5181	0.0020	0.7437	0.59
h67	0.4139	0.0005	0.8560	0.30
h68	1.1561	0.0000	-0.0035	1.04
h69	-0.5571	0.0000	0.9427	0.17
h610	0.8633	0.0000	0.6939	0.62

Table 8: Above is the result of estimating $p^e_{h,t+1} = p_{t-1} + \gamma(p_{t-1} - p_{t-2})$ (trend rule) for the treatment H. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.

D.2 Adaptive Expectations

sub no.	coefficient	p-value	R-squared	MSE
n12	1.1441	0.0001	0.5632	14784.77
n14	2.3901	0.0001	0.7382	7373.22
n15	0.8991	0.0000	0.2681	33594.84
n16	-1.9474	0.0002	0.7294	9864.02
n23	1.6129	0.0014	-0.4811	1139.47
n24	0.7178	0.0111	-0.3866	1602.55
n25	2.3567	0.0000	-0.2735	1073.32
n26	1.6181	0.0010	-0.4054	1226.46
n31	1.8283	0.0000	0.9700	58.58
n32	0.9630	0.0000	0.8961	123.36
n33	2.1549	0.0000	0.8971	215.87
n34	1.9045	0.0000	0.9778	37.61
n35	1.8097	0.0000	0.9355	117.92
n36	1.9969	0.0000	0.9308	147.49
n41	1.4924	0.0000	0.6379	94.74
n42	1.0620	0.0000	0.1855	205.61
n43	1.4220	0.0000	0.7582	76.81
n44	1.4690	0.0000	0.5397	127.19
n45	0.8764	0.0006	-0.7967	356.84
n46	1.1083	0.0000	0.4056	104.89

Table 9: Above is the result of estimating $p^e_{h,t+1} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$ (adaptive rule) for the treatment N. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.

sub no.	coefficient	p-value	R-squared	MSE
l11	0.4619	0.0000	0.0479	150.67
l12	0.4849	0.0000	0.2471	125.01
l13	0.4840	0.0000	0.2772	128.48
l14	0.4430	0.0000	0.2834	127.34
l15	0.3891	0.0000	0.2928	106.76
l16	0.4757	0.0000	0.2459	153.92
l17	0.3937	0.0000	0.2302	91.35
l18	0.4738	0.0000	0.1891	135.73
l19	0.4068	0.0000	0.2375	124.50
l110	0.4179	0.0000	0.2669	132.49
l21	0.5967	0.0000	0.0164	430.89
l22	0.5143	0.0000	-0.0013	344.09
l23	0.6303	0.0000	0.0812	469.06
l24	0.5391	0.0000	0.0232	395.85
l25	0.6113	0.0000	0.0811	462.14
l26	0.7099	0.0000	0.0019	458.48
l27	0.3914	0.0001	0.1809	310.61
l28	0.5274	0.0000	0.0155	442.46
l29	0.5268	0.0000	0.0635	405.38
l210	0.2982	0.0024	0.0430	278.46
l31	0.7413	0.0000	0.1891	475.53
l32	0.8465	0.0000	-0.0452	681.46
l33	0.6175	0.0001	0.0431	488.52
l34	0.5717	0.0005	0.1015	469.95
l35	0.7429	0.0000	-0.0078	572.82
l36	0.7956	0.0000	-0.0180	488.15
l37	0.5062	0.0019	0.1377	482.55
l38	0.7632	0.0000	-0.0195	602.55
l39	0.7369	0.0000	-0.0381	632.69
l310	0.8273	0.0000	-0.0406	684.74
l41	0.2791	0.0333	-0.3353	414.09
l43	0.3348	0.0199	-0.4383	578.56
l44	0.4633	0.0043	-0.5846	731.95
l45	0.3193	0.0264	-0.3835	555.97
l46	0.4213	0.0068	-0.5106	584.35
l47	0.3222	0.0341	-0.5338	600.14
l48	0.4053	0.0083	-0.5638	566.77
l49	0.4615	0.0029	-0.4541	707.45
l410	0.3051	0.0397	-0.4595	575.91
l51	1.5134	0.0000	0.8063	64.57
l52	1.4454	0.0000	0.4944	132.11
l53	0.9800	0.0000	0.4041	121.80
l54	1.2981	0.0000	0.7551	72.13
l55	1.9847	0.0000	0.7761	62.61
l56	1.8417	0.0000	0.5675	128.81
l57	1.6607	0.0000	0.7158	77.25
l58	0.8958	0.0000	0.5452	201.31
l59	1.5538	0.0000	0.7871	47.59
l510	1.7686	0.0000	0.7318	78.20

Table 10: Above is the result of estimating $p^e_{h,t+1} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$ (adaptive rule) for the treatment L. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.

sub no.	coefficient	p-value	R-squared	MSE
h11	1.3640	0.0000	0.6136	23.42
h12	1.5519	0.0000	0.5616	22.18
h13	1.8027	0.0000	0.8224	9.32
h14	1.1696	0.0000	0.7082	15.49
h15	1.0576	0.0000	0.5227	15.68
h16	1.2825	0.0000	0.8100	7.93
h17	1.4679	0.0000	0.8787	4.56
h18	1.3931	0.0000	0.6565	10.20
h19	1.4350	0.0000	0.7977	9.16
h110	1.2810	0.0000	0.7603	9.75
h21	1.4494	0.0000	0.8305	6.31
h22	1.1443	0.0000	0.6566	8.69
h23	1.6587	0.0000	0.6545	13.85
h24	1.3726	0.0000	0.5843	16.60
h25	1.9535	0.0000	0.6139	10.61
h26	1.2840	0.0000	0.6315	19.41
h27	1.2394	0.0000	0.6708	16.06
h28	1.5541	0.0000	0.8500	6.02
h29	1.3863	0.0000	0.6722	9.31
h210	1.6976	0.0000	0.4589	17.04
h31	1.6872	0.0000	0.8385	15.96
h32	1.4222	0.0000	0.7084	26.56
h33	1.5704	0.0000	0.7472	23.38
h34	1.7744	0.0000	0.6864	40.15
h35	1.6109	0.0000	0.8098	23.34
h36	1.3935	0.0000	0.7081	23.71
h37	2.0169	0.0000	0.6464	30.03
h38	1.3292	0.0000	0.7347	26.67
h39	1.3551	0.0000	0.8454	22.35
h310	1.4018	0.0000	0.6712	36.45
h41	1.5589	0.0000	0.8385	3.80
h42	1.3693	0.0000	0.7231	6.16
h43	1.2472	0.0000	0.7903	3.38
h44	1.3350	0.0000	0.9345	1.18
h45	1.4940	0.0000	0.7541	7.25
h46	1.8161	0.0000	0.4540	11.56
h47	1.5178	0.0000	0.7255	7.75
h48	1.2274	0.0000	0.8661	2.91
h49	1.3224	0.0000	0.7609	4.37
h410	1.1065	0.0000	0.6785	6.47
h51	1.0471	0.0000	0.8885	2.60
h52	1.3454	0.0000	0.8200	4.50
h53	1.3053	0.0000	0.5441	12.09
h54	1.0929	0.0000	0.7168	6.55
h55	0.9028	0.0000	0.4788	9.78
h56	1.1615	0.0000	0.8630	3.19
h57	1.0298	0.0000	0.7382	7.03
h58	0.8944	0.0000	0.8636	4.22
h59	0.6798	0.0000	0.4475	43.58
h510	1.0864	0.0000	0.8865	2.72
h61	1.0969	0.0000	0.6187	2.33
h62	1.2260	0.0000	0.7980	0.71
h63	1.0794	0.0000	0.7986	0.47
h64	0.9364	0.0000	-1.6900	4.00
h65	1.2449	0.0000	0.7339	0.49
h66	1.0313	0.0000	0.7531	0.71
h67	1.0760	0.0000	0.8758	0.37
h68	1.2682	0.0000	0.4142	1.63
h69	0.7364	0.0000	0.9612	0.18
h610	0.9935	0.0000	0.7012	0.98

Table 11: Above is the result of estimating $p^e_{h,t+1} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$ (adaptive rule) for the treatment H. The second and third column shows the estimated coefficients and associated $p-$value. The fourth and fifth columns show the R^2 and MSE of the regressions.