When Speculators Meet Constructors: Positive versus 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 housing 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 are well described by a behavioral heuristics switching model. Our results suggest that negative feedback policies may stabilize speculative asset bubbles.

JEL Classification: C91, C92, D83, D84, R30

Keywords: Rational Expectations, Learning, Housing Bubble, Experimental Economics.

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1 Introduction

Are housing price bubbles and crashes less likely to arise 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 (e.g., Gjerstad and Smith, 2014). Many previous studies focused on speculative asset pricing models on the demand side of the market, but real estate assets also distinguish 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".

An 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.

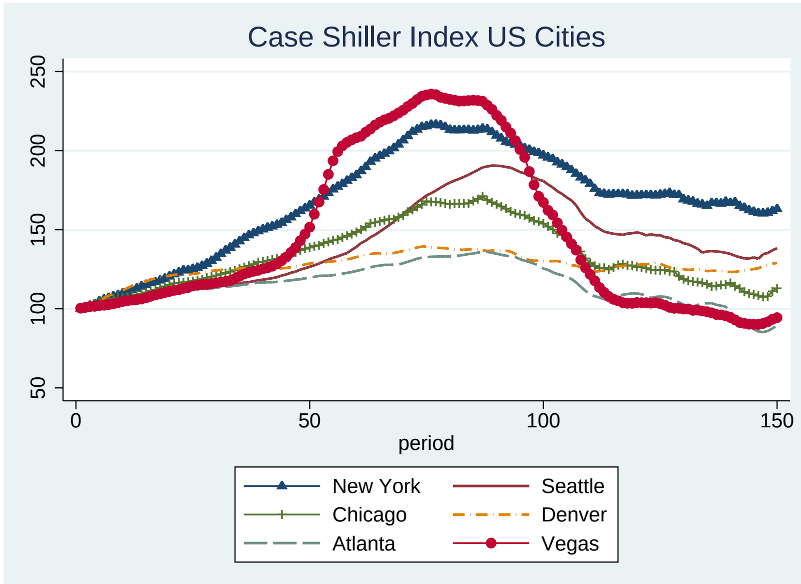

Figure 1: Case-Shiller index in 6 US major cities. New York, Seattle and Chicago are considered as low elasticity cities, and Denver, Atlanta and Las-Vegas are considered as high elasticity cities according to Saiz (2008). The time series are monthly data from January 2000 to June 2012.

In this paper, we run a laboratory experiment on how the elasticity of housing supply affects 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). 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.

Our experiment may be the first laboratory experiments on the 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.

Our paper makes a second, more fundamental contribution to the understanding of the (de)stabilizing effect of positive versus negative expectations feedbacks in markets. In terms of the relation between individual expectations and aggregate market outcomes, the housing market is a positive expectation feedback system to investors/speculators, but a negative feedback system to the housing developers/constructors. When investors predict that the price will go up, their 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 houses, 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, Sutan and Willinger (2009), Sonnemans and Tuinstra, 2010, Bao et al, 2012)[1]. The current paper designs the first experimental market combining both positive and negative feedback 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. In contrast, in markets with positive feedback the price generally does not converge to the REE, but rather price bubbles and crashes are more likely to occur in positive feedback markets[2].

[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.

[2]Gjerstad and Smith (2014) stress the difference between experimental markets for perishable versus durable goods. Perishable good markets are rather stable (Smith, 1962), while experimental markets for durable goods exhibit bubbles and crashes (Smith et al., 1988). Perishable good markets may be dominated by negative production feedback, while durable good markets may exhibit strong

An important question to ask then is: can bubbles in positive feedback markets be stabilized by adding negative feedback to the market? An experimental housing market is a natural framework to study this question by investigating the potential emergence of bubbles for different values of the the supply elasticity. Our experimental results show that stronger supply elasticity leads to more stable housing markets. This result has important policy implications: speculative bubbles may be mitigated by negative feedback policies that weaken the overall positive feedback in markets.

A third 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 in our experimental data. The results of former learning to forecast experiments suggest that agents learn to use different expectation rules in the positive and negative feedback markets. In positive feedback markets, subjects are more likely to coordinate on trend-following expectations, while in negative feedback markets coordination of expectations across agents is weaker, and subjects are more likely to become users of adaptive or contrarian expectations (Anufriev and Hommes, 2012b; Bao et al., 2012). Our results for the housing market show that under strong positive feedback bubbles emerge, amplified by trend-following coordination, while more negative feedback promotes coordination on adaptive expectations and a stable housing market. These results are consistent with empirical work estimating endogenous heterogeneous expectations switching models, where agents switching between destabilizing trend-following and stabilizing mean reverting fundamentalists strategies (Bolt et al., 2015, Eicholz et al. 2014).

Our paper fits into 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.

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

positive feedback speculative demand.

heuristics switching model explaining individual as well as aggregate behavior. Finally, Section 5 concludes.

2 Experimental Design

We employ a "learning-to-forecast" experimental design, where participants submit price expectations and their optimal demand and supply decisions are computerized and derived from maximization of profit and utility, given these subjective individual forecasts. For discussions about differences between the learning-to-forecast versus learning-to-optimize" designs, see the surveys of Duffy (2008) and Assenza et al. (2014)[3].

2.1 The Housing Market

To keep the design simple and to focus on two different types of expectations feedback, we consider a housing market with I constructors, who build houses, and H owners/investors, who buy houses for speculative investment. Let $z^s_{i,t}$ be the housing supply by constructor i in period t, and $z^d_{h,t}$ the housing demand of speculative investor h at period t. Housing supply is derived from expected profit maximization with a quadratic cost function (see Appendix A). The supply of constructor i is then a linear function of individual price expectations:

$$z^s_{i,t} = \frac{cp^e_{i,t+1}}{I},$$

where c is the coefficient of the quadratic cost function and the supply is normalized by the number of constructors I[4].

Housing demand is derived from maximization of a myopic mean-variance utility

[3]Bao et al. (2015) study the emergence of asset bubbles in experimental market comparing learning-to-forecast versus learning-to-optimize market designs. It appears that learning-to-optimize is even more difficult than learning-to-forecast and may lead to even larger emerging bubbles and crashes.

[4]We have chosen a quadratic cost function, and hence a linear supply function to keep the design as simple as possible. Normalization with respect to I will render a pricing function depending on average expectations.

maximization (see Appendix A)[5]. The housing demand of individual investor h for period t is given as

$$z^d_{h,t} = \frac{p^e_{h,t+1} + E_t y_{t+1} - Rp_t}{a\sigma^2},$$

where $R = 1 + r$ is the gross interest rate for a risk free investment (i.e. a bond), and y_{t+1} is the dividend paid by the risky asset (i.e., the imputed housing rent in our case). We assume $E_t y_{t+1} = \overline{y}$ is constant over time. For simplicity, we let $a\sigma^2 = H$, so that the demand is normalized by the number of investors H. By imposing market clearing condition we have:

$$\sum_i z^s_{i,t} = \sum_h z^d_{h,t}$$

$$\sum_i z^s_{i,t} = c\frac{\sum_i p^e_{i,t+1}}{I} = c\overline{p}^e_{i,t+1}$$

$$\sum_h z^d_{h,t} = \frac{\sum_h (p^e_{h,t+1} + E_t y_{t+1} - Rp_t)}{a\sigma^2} = \overline{p}^e_{h,t+1} + E_t y_{t+1} - Rp_t,$$

where $\overline{p}^e_{i,t+1}, \overline{p}^e_{h,t+1}$ are the average expected housing price by constructors and investors. By substituting in these conditions, the reduced form equation for equilibrium housing 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 small demand or supply shocks that may influence the housing price. As can be seen from (1), the housing price will increase when the average price prediction $\overline{p}^e_{h,t+1}$ made by the investors goes up, and decrease when the average price prediction $\overline{p}^e_{i,t+1}$ by the constructors goes up. Therefore the housing market exhibits *positive expectations feedback* from the speculative investors, and *negative expectation feedback* from the constructors.

[5] This setup follows the user cost of capital model, which has become a standard tool for studying housing demand and for analyzing the equilibrium value of the imputed rental income accruing to homeowners (Himmelberg et al., 2005; Poterba and Sinai, 2008). This design is also used in the asset pricing experiments in Hommes et al (2005), based on the standard asset pricing model in Cuthbertson and Nitzsche (2005) or Campbell, Lo and MacKinlay (1997). Our experimental design is similar to the theoretical housing model in Dieci and Westerhoff (2012) and the empirically estimated heterogeneous expectations housing model in Bolt et al. (2015).

2.2 Rational expectations

If the constructors and speculators have homogeneous expectations, equation (1) becomes

$$p_t = \frac{1}{R}[(1-c)\overline{p}^e_{t+1} + \overline{y}] + \nu_t, \tag{2}$$

where $\overline{p}^e$ is the average price expectation of all speculators and constructors. By substituting in $\overline{p}^e_{t+1} = p^*$, a rational expectation steady state equilibrium of the system is:

$$p^* = \frac{\overline{y}}{R-1+c} \tag{3}$$

The rational expectation equilibrium p^* 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.

It should be noted that there are other rational bubble solutions growing at rate $R/(1-c)$. In the absence of noise, along these bubble solutions agent have perfect foresight. These bubble solutions, however, are usually excluded because they do not satisfy the transversality condition. The rational steady state p^* is the only *bounded* rational solution of (2). See e.g. Cuthbertson and Nitsche (2005).

2.3 Treatments

We use $R = 1.05$, which is a gross interest rate commonly used in the experimental literature. This means according to (1) 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. We call the slope $\frac{1-c}{R}$ of (1) the "overall strength of expectation feedback". In this experiment, we consider three different treatments by three different values of the supply elasticity c, namely $c = 0, 0.1$ and 0.25:

- Treatment with no supply (**treatment N**); $c = 0$; $\lambda = \frac{1-c}{R} = 0.95$:
  There are no constructors in the market. We let 6 investors/forecasters participate in each market, and the market price only depends on the average price expectation of the investors.

- Treatment with low supply elasticity (**treatment L**); $c = 0.1$; $\lambda = \frac{1-c}{R} = 0.86$: There are 5 investors and 5 constructors in each market. The market price depends on both expectations by the investors and constructors, but the influence from the constructors is relatively small.

- Treatment with high supply elasticity (**treatment H**): $c = 0.25$; $\lambda = \frac{1-c}{R} = 0.71$: There are 5 investors and 5 constructors in each market. The market price depends on both expectations by the investors and constructors, and the influence from the constructors is larger than in treatment L.

The slope $\frac{1-c}{R}$ is always positive and measures the overall positive feedback, that is, how much the realized price changes when the overall average expected price in the market goes up by 1 unit. Hence, in the three treatments the overall positive feedback varies from an eigenvalue $\lambda = 0.95$ (Treatment N), to $\lambda = 0.86$ (Treatment L), and finally to $\lambda = 0.71$ (Treatment H). Our main research question is: *does a decrease of the overall positive expectation feedback make the market price more stable*?[6].

We impose that in all three treatments, the rational expectations steady state is the same, $p^* = 60$. According to equation (3), this means that 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 $c = 0.25$.

[6] Sonnemans and Tuinstra (2010) study the price behavior in positive feedback markets $p_t = 60 + \lambda(p_t^e - 60)$, with two different "strengths of feedback" (i.e., slope of the price feedback map) $\lambda = 0.67$ and $\lambda = 0.95$. 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 light on the price behavior when the slope is between 0.67 and 0.95. An important difference is that they use a one-period ahead price expectations feedback system, while our temporary equilibrium setup requires two-period ahead forecasts and exhibits rational bubble solutions. 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 market to converge is that the slope of the price feedback map is less than or equal to 0.7.

2.4 Design

Subjects in the experiments play the role of professional forecasters, either for constructors or for investors. The underlying price equation is given by Eq. (1). Subjects do not know the price generating law of motion, but only receive qualitative information about the housing market. In particular, subjects are informed that price determination in the housing market is driven by expectations feedback (see Appendix B for detailed experimental instructions):

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.

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 groups 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 a housing market instead of a stock market to check whether the bubble/crashe patterns in the data of Hommes et al. (2008) is not affected by the change of framing. Given that we indeed observe bubbles in TN, four observations may be considered a representative sample to make comparison with the markets in the other treatments. The duration of a typical session is 1 hour and 5 minutes, including instructions reading and payment. The experiment uses a 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).

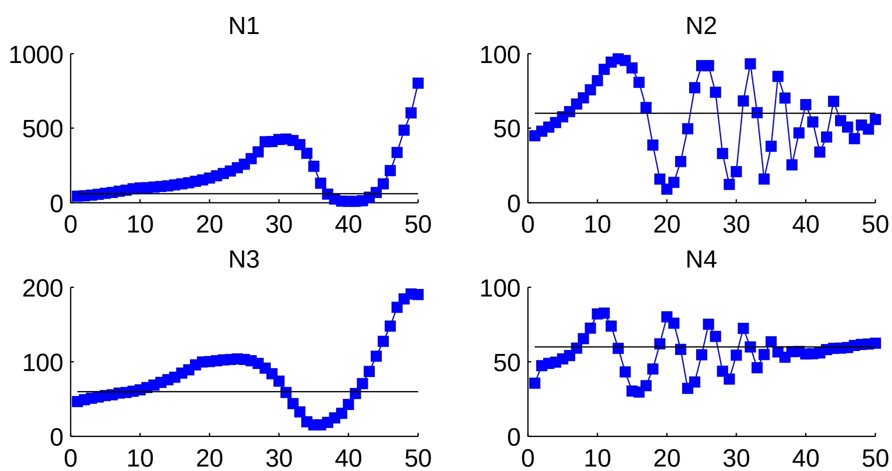

Figure 2: The market prices against the REE price in treatment N.

To quantify the deviation of the market price from the REE, we calculate the

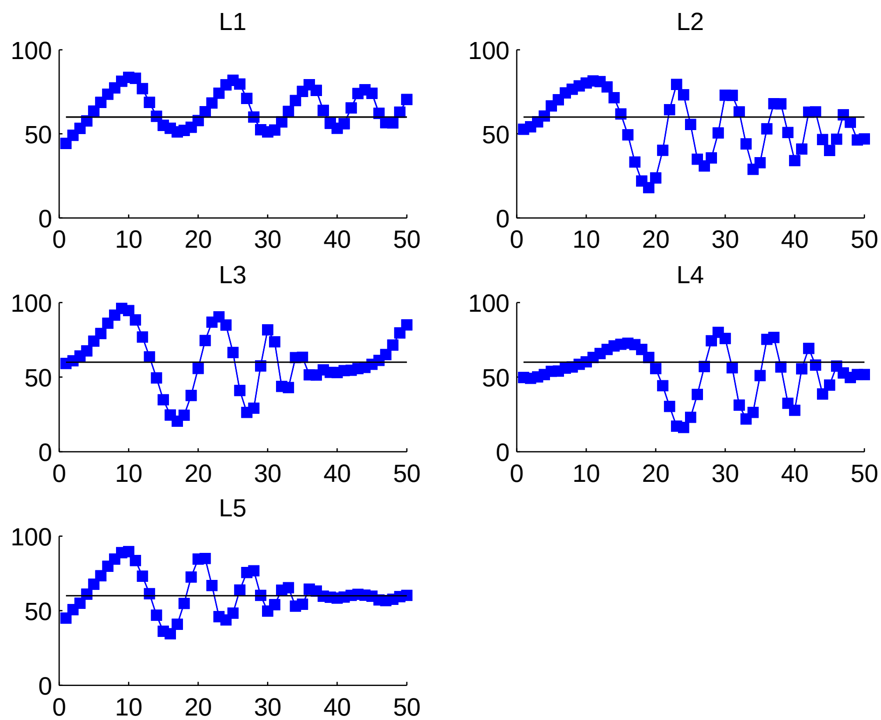

Figure 3: The market prices against the REE price in treatment L.

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 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-

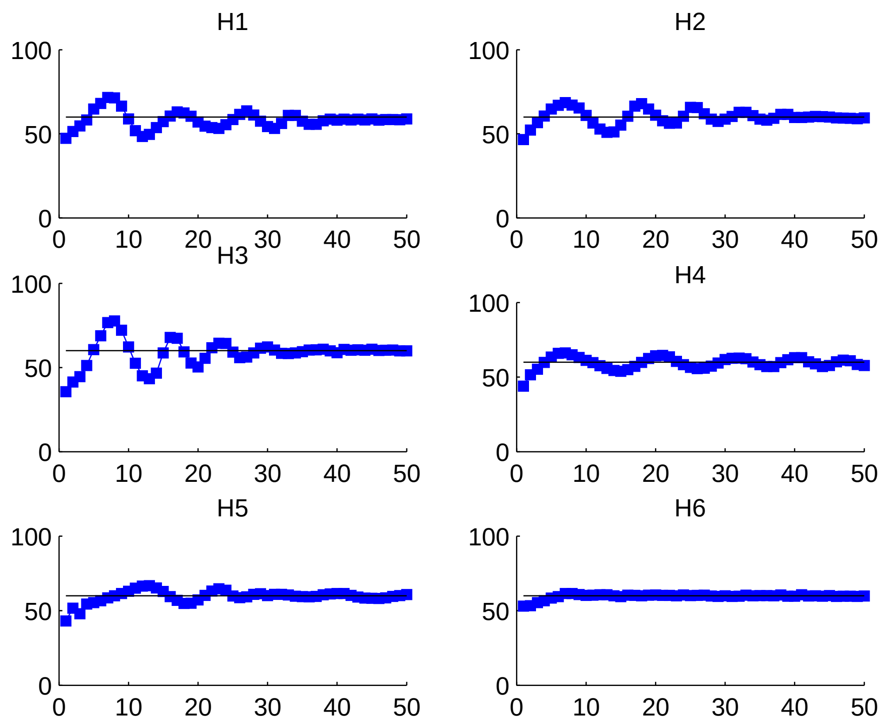

Figure 4: The market prices against the REE price in treatment H.

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 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

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.

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 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.

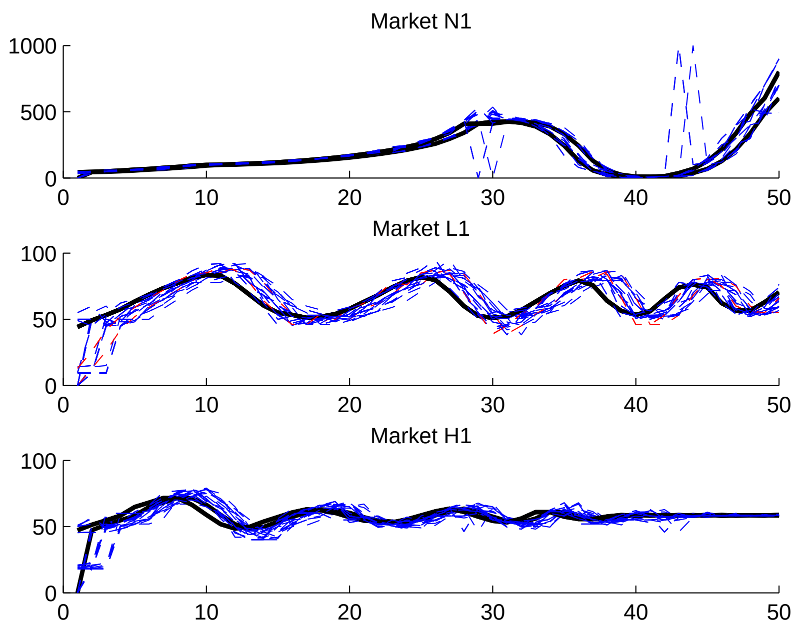

Figure 5: The individual predictions (dashed lines) plotted against the market price (thick line) in a typical market in each of treatment N (market N1, upper panel), L (market L1, middle panel) and H (market H1, lower panel).

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 significantly different at the 5% level in any of the markets in treatment L and H.

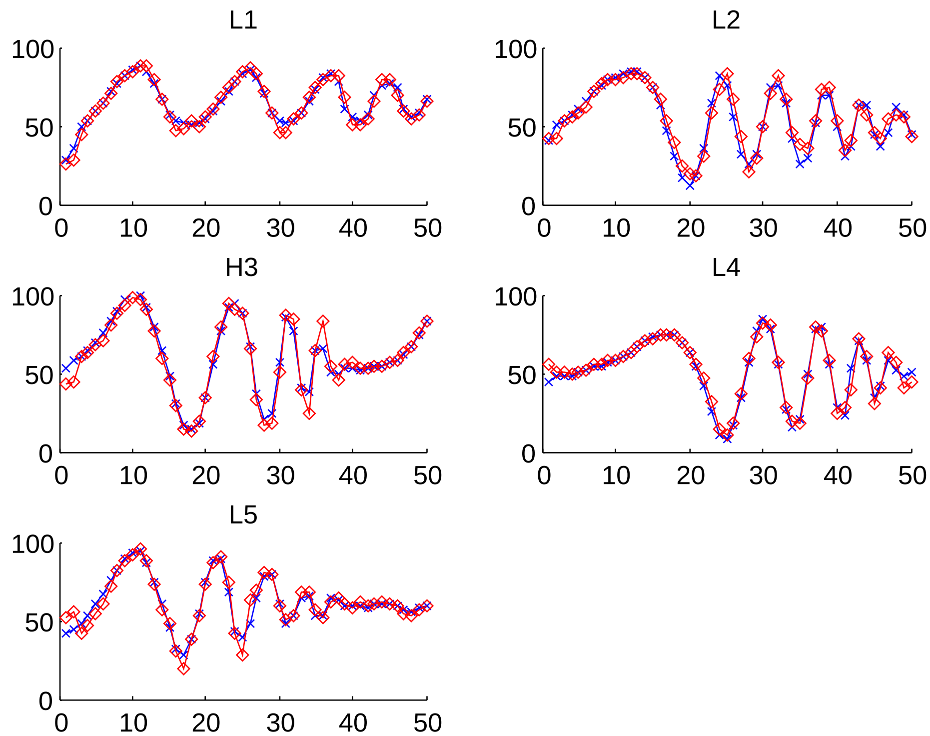

Figure 6: The average predictions by the speculators (Xs) and constructors (diamonds) in each market in treatment L.

3.3 Estimation of Individual Forecasting Strategies

We consider a general form of individual prediction strategy, the "first order heuristic" as considered in Heemeijer et al. (2009). This rule has a behavior interpretation: it is a specification of the anchoring and adjustment heuristic in Tversky and Kahneman (1974). This forecasting rule uses a time varying anchor as a weighted average of past price p_{t-1}, own past prediction p^e_{t-1} and the rational expectation equilibrium price 60, and extrapolate the last price change $(p_{t-1} - p_{t-2})$.

We run the model with three parameters first, and drop the coefficient with the largest $p-value$ iteratively until all remaining coefficients are significant at 5% level.

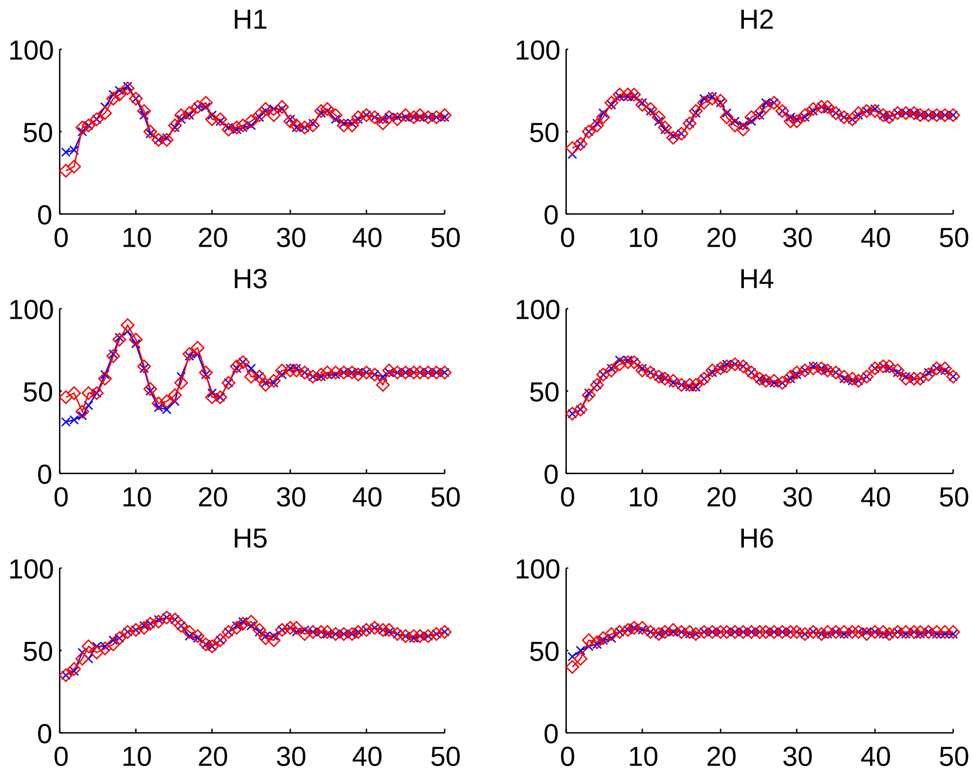

Figure 7: The average predictions by the speculators (Xs) and constructors (diamonds) in each market in treatment H.

We also drop the regressions with autocorrelation in the error term within 10 lags as indicated by LjungBox Q-test. It turns out among 134 subjects in the experiment, the strategy of 43 of them can be successfully estimated using the first order heuristic under these criteria. The estimation results are reported in Table 6 in the appendix and plotted in Figure 8.

$$p^e_{h,t+1} = \alpha_1 p^e_{t-1} + \alpha_2 p^e_{h,t-1} + (1 - \alpha_1 - \alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2}) \tag{7}$$

The result of our estimation is similar to the result for the positive feedback treatment in Heemeijer et al. (2009). The coefficient for the trend term is significant for all except one subjects. Most of the estimated βs are larger than 0.5, and the average value is 1.121. The sum $\alpha_1 + \alpha_2$ is close to 1 for the majority of the cases ($\alpha_1 + \alpha_2 > 0.9$ for 25 out of 43 regressions, among which $\alpha_1 > 0.9$ for 24 out of 25 regressions). This means the rational expectation equilibrium gets little weight in

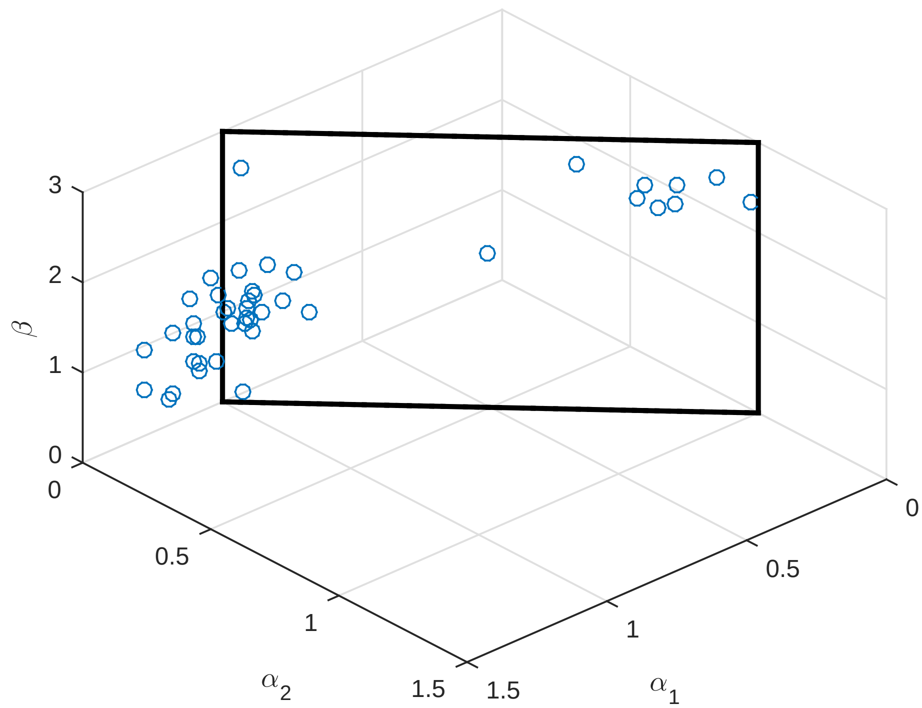

Figure 8: Prism of first-order heuristics containing the parameter vectors of the prediction rules $p^e_{h,t+1} = \alpha_1 p^e_{t-1} + \alpha_2 p^e_{h,t-1} + (1 - \alpha_1 - \alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2})$. Positive β is associated with trend following prediction rule. α_1 close 1 is associated to naive prediction strategy. $\alpha_2 > 0$ is associated with usage of some general form of adaptive expectations.

the anchor. The price prediction behavior of subjects in this experiment can be also described as "naive and adaptive trend following".

4 The 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), extending the model of Brock and Hommes (1997, 1998). The 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 unstable oscillations with large bubbles in treatment L, persistent oscillations in treatment N and dampened oscillations in treatment L converging to the fundamental price. The HSM assumes that the subjects chose between a finite menu of four simple forecasting 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:

$$p^e_{t+1,1} = p^e_t + 0.65(p_t - p^e_{t,1}). \tag{8}$$

The weak trend rules (WTR) given by:

$$p^e_{t+1,2} = p_t + 0.4(p_t - p_{t-1}). \tag{9}$$

The strong trend extrapolating rule (TRE) given by:

$$p^e_{t+1,2} = p_t + 1.3(p_t - p_{t-1}). \tag{10}$$

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

$$p^e_{t+1,4} = 0.5(p^{av}_t + p_t) + (p_t - p_{t-1}). \tag{11}$$

We use $w = 0.65$ for the adaptive rule because it is about the median of the estimated coefficient using equation (7). 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:

$$U_{t,h} = -(p_t - p^e_{t,h})^2 + \eta U_{t-1,h}, \tag{12}$$

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):

$$n_{t,h} = \delta n_{t-1,h} + (1-\delta)\frac{\exp(\beta U_{t-1,h})}{\sum_{i=1}^{4}\exp(\beta U_{t-1,i})}. \tag{13}$$

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 with the original setting. The result turns out to be very good. The simulated prices fit the experimental data very well. The weights of the different forecasting heuristics show different patterns in the three different treatments. A typical market in treatment N is mostly dominated by the strong trend rule, which leads to large bubbles and sharp price fluctuations. A typical market in treatment L is firstly dominated by the strong trend rule, but after the reversal of the price trend the anchoring and adjustment rule increases its share and becomes dominating in later periods, which leads to persistent price oscillations. The typical market in treatment H is firstly dominated by the anchoring and adjustment rule, but after period 30 the adaptive rule becomes more popular towards the end of the experiment, which eventually leads to dampening of

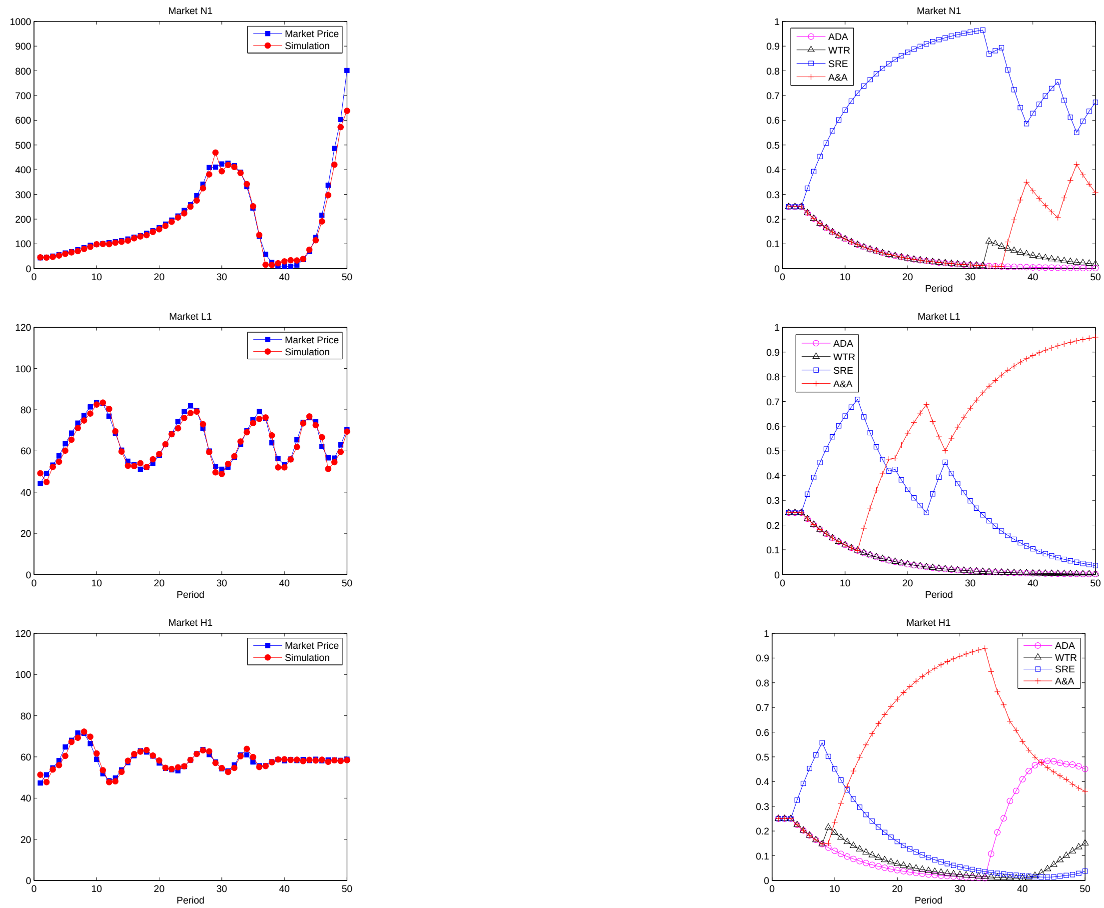

Figure 9: The simulated and experimental market price (left panel) and the simulated fractions of users of different heuristics (right panel) in a typical market in treatment N (upper panel), L (middle panel) and H (lower panel).

the oscillations and convergence to the fundamental price.

Table 4 reports the mean squared error (MSE) 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 12 markets.

Besides HSM Benchmark, we also conducted a grid search of optimal values of β, η, δ that minimizes 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 typically 10, η and δ are 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 but one 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 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 to H, the average weight of the strong trend (STR) heurisitic declines substantially, while the weight of the adaptive (ADA) rule and Anchoring and Adjustment (LAA) rule increase.

Figure 4 shows the time evolution of the average weight (i.e. averaged over all groups) of each heurisitic in each treatment. In general, this figure confirms that on average there are more users of the strong trend rule in treatment N, more of the LAA heuristic and adaptive heurisitic in treatment L and H. More precisely, in treatment N, the strong trend rule dominates the market for 40 periods, explaining large bubbles in the first half of this treatment. In treatment L, the strong trend rule STR dominates in the first 10 periods, explaining the occurrence of a bubble in the initial phase of the experiment. After the price trend reverses, the anchor and adjustment rule LAA starts improving and dominates the market between periods 18-35 with the market price oscillating; in the last 10 periods the LAA together with adaptive expectations (ADA) dominate the market leading to slowly stabilizing oscillations. In treatment H, the strong trend rule dominates in the first 15 periods, the LAA rule slightly dominating between periods 15-35, and adaptive expectations (ADA) slightly dominating in the final phase, periods 36-50, causing prices to stabilize towards the fundamental value.

			Treatment N			
Fundamental	46297.37	596.94	2192.08	169.55		
Naive	3371.91	369.22	99.02	102.50		
ADA heuristic	8397.89	404.06	316.81	124.42		
WTR heuristic	1800.98	328.69	44.97	81.51		
STR huristic	**398.23**	456.04	10.61	147.19		
LAA heuristic	6183.74	281.46	363.62	54.87		
HSM Benchmark	878.53	**190.26**	**10.41**	**42.68**		
HSM Optimal	398.48	136.19	10.29	34.91		
β	10.00	0.10	10.00	10.00		
η	0.90	0.60	0.90	0.40		
δ	0.50	0.70	0.90	0.80		
			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	28.98	119.57	119.82	119.51	61.80	
ADA heuristic	59.95	174.41	201.27	174.84	103.72	
WTR heuristic	15.46	78.02	77.03	78.59	38.18	
STR huristic	11.67	97.60	90.56	99.97	45.08	
LAA heuristic	17.73	60.84	79.56	54.45	29.84	
HSM Benchmark	**6.65**	**35.25**	**45.16**	**30.27**	**17.20**	
HSM Optimal	6.62	33.41	25.71	24.94	12.50	
β	10.00	0.40	10.00	10.00	10.00	
η	0.70	0.60	0.30	0.50	0.30	
δ	0.80	0.80	0.60	0.80	0.70	
			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	7.39	5.81	17.29	3.30	**3.32**	0.16
ADA heuristic	14.52	11.51	32.80	7.62	5.17	0.36
WTR heuristic	4.11	3.19	9.56	1.86	3.61	**0.14**
STR huristic	1.89	1.75	5.10	1.46	7.06	0.37
LAA heuristic	4.38	3.12	8.76	2.72	6.54	0.40
HSM Benchmark	**2.59**	**1.75**	**4.60**	**1.41**	4.12	0.15
HSM Optimal	2.27	1.14	2.66	1.04	3.63	0.10
β	10.00	0.30	10.00	0.10	0.10	10.00
η	0.60	0.90	0.70	0.90	0.40	0.70
δ	0.60	0.40	0.60	0.00	0.00	0.80

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	21.12%	22.60%	24.96%
WTR	6.51%	4.81%	9.90%
STR	55.57%	29.76%	19.06%
LAA	16.80%	42.82%	46.08%

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

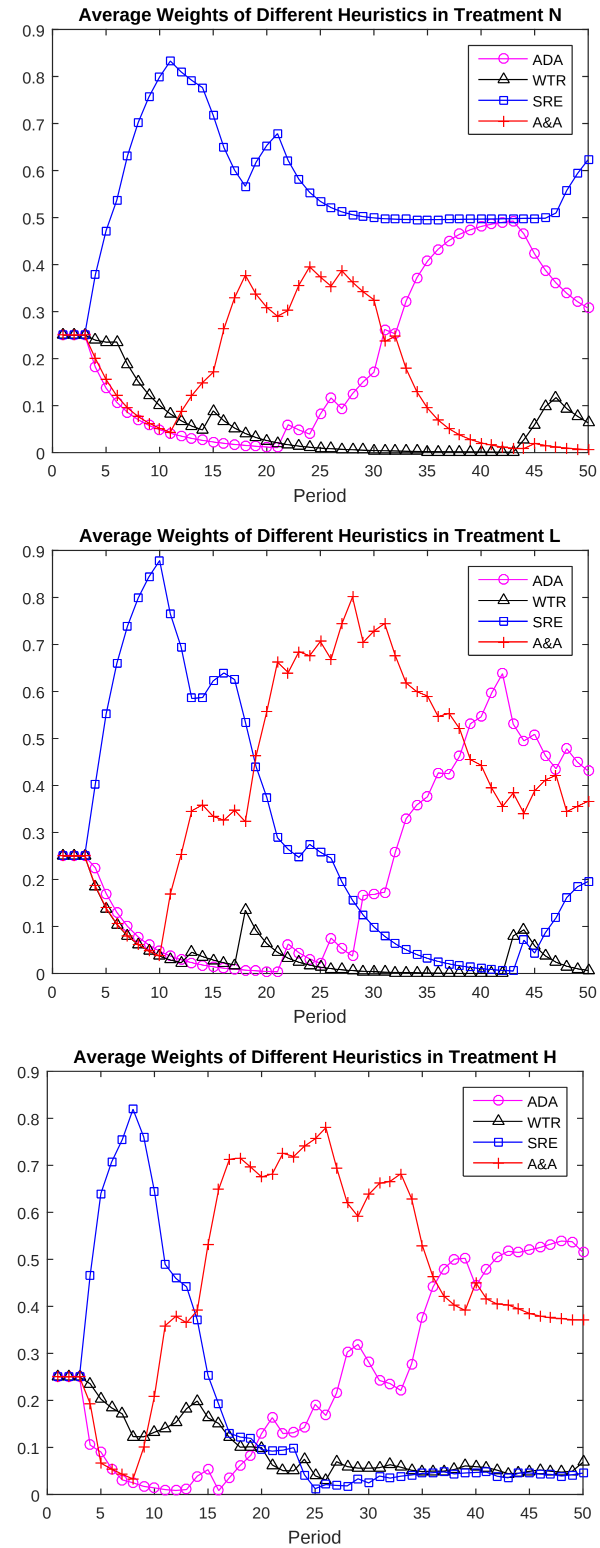

Figure 10: The average simulated fractions of users of different heuristics in treatment N (upper panel), L (middle panel) and H (lower panel).

5 Conclusion

We study the relationship between supply elasticity and price dynamics in experimental housing markets using a "learning to forecast" design. Our results show that when the supply elasticity increases, the housing price becomes more stable.

The housing market exhibits both positive feedback through speculative demand and negative feedback from endogenous housing supply. The market is a positive feedback system to the investors and a negative feedback system to the constructors, but 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; near unit root) trend-following rules dominate the market leading to housing bubbles and crashes; for intermediate supply elasticity (medium positive feedback) an anchoring and adjustment rule dominates the market 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 by preventing or making coordination on trend-following strategies less likely.

Many interesting questions for future research remain. For simplicity we studied only a stylized 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. Another stylized feature of our housing market model is that the expectations feedback is essentially one-dimensional and characterized by a single real eigenvalue. When that single eigenvalue moves away from a near unit root (e.g. $\lambda = 0.95$) to stronger mean reversion (e.g. $\lambda = 0.7$ the market stabilizes. It would be interesting to study negative feedback policies in more complex, higher dimensional systems. An example may already be found in the lab experiments in the New Keynesian framework of Assenza et al. (2014), where a Taylor interest rate rule adds negative feedback to the inflation-output dynamics in the NK framework. It would be of interest to study the effectiveness of negative feedback policies in more general, higher dimensional settings and, for example, study the relation between the eigenvalues and market stability in laboratory group experiments.

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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:

$$\pi^e_{i,t+1} = p^e_{i,t+1} q_{i,t} - c(q_{i,t}), \tag{14}$$

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:

$$U_{h,t}(z^d_{h,t}) = E_{h,t} W_{h,t+1} - \frac{a}{2} V_{i,t}(W_{h,t+1}), \tag{15}$$

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

$$W_{h,t+1} = RW_{h,t} + z^d_{h,t}(p_{t+1} + y_{t+1} - Rp_t), \tag{16}$$

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,

$$z^d_{h,t} = \frac{p^e_{h,t+1} + \overline{y} - Rp_t}{a\sigma^2} \tag{17}$$

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 First Order Heuristic

sub no.	α_1	p-value	α_2	$p-value$	β	$p-value$	R-squared	MSE	Label
N12			0.8373	0.00	2.3821	0.00	0.6940	10211.90	Adaptive Trend Follower
N15	0.9349	0.00			2.4976	0.00	0.4946	22856.85	Naive trend Follower
N31			0.9695	0.00	2.3010	0.00	0.9599	77.46	Adaptive Trend Follower
N32	0.9245	0.00					0.9032	114.94	Naive trend Follower
N34	0.9847	0.00			1.0225	0.00	0.9649	58.80	Naive trend Follower
N36	1.0434	0.00			1.4407	0.00	0.9763	49.97	Naive trend Follower
N43			0.5575	0.00	1.8714	0.00	0.8106	58.59	Adaptive Trend Follower
L51			0.6818	0.00	2.0555	0.00	0.8451	50.96	Adaptive Trend Follower
L54			0.6714	0.00	1.8423	0.00	0.7535	71.64	Adaptive Trend Follower
L56			0.2886	0.00	1.7164	0.00	0.6984	88.23	Adaptive Trend Follower
L57			0.5246	0.00	1.6735	0.00	0.6863	83.25	Adaptive Trend Follower
L59			0.6118	0.00	1.7096	0.00	0.7719	50.87	Adaptive Trend Follower
H12	0.8399	0.00			1.3143	0.00	0.6828	15.4654	Naive trend Follower
H13	0.9385	0.00			1.3826	0.00	0.8651	6.7829	Naive trend Follower
H15	0.4020	0.01	0.3785	0.00	1.3943	0.00	0.7557	7.6697	Adaptive Trend Follower
H16	0.9932	0.00			0.9804	0.00	0.9083	3.7163	Naive trend Follower
H17	0.9698	0.00			0.8223	0.00	0.9090	3.2570	Naive trend Follower
H18	0.7417	0.00			1.0895	0.00	0.8507	4.4216	Naive trend Follower
H19	1.1025	0.00			0.8575	0.00	0.8565	6.2766	Naive trend Follower
H110	0.8945	0.00			1.0884	0.00	0.9012	3.7862	Naive trend Follower
H27	1.1148	0.00			1.3011	0.00	0.8518	6.6502	Naive trend Follower
H28	1.1023	0.00			1.0120	0.00	0.8768	4.5202	Naive trend Follower
H31	0.8868	0.00			1.0246	0.00	0.8416	13.8022	Naive trend Follower
H39	1.2806	0.00			0.9545	0.00	0.9377	7.9126	Naive trend Follower
H310	0.9084	0.00			0.9948	0.00	0.7252	28.2834	Naive trend Follower
H41	1.0186	0.00			1.2136	0.00	0.8902	2.1754	Naive trend Follower
H43	1.0818	0.00			0.5365	0.00	0.8879	1.7499	Naive trend Follower
H44	1.0195	0.00			0.4754	0.00	0.8980	1.3710	Naive trend Follower
H45	1.1809	0.00			0.9979	0.00	0.7638	5.9444	Naive trend Follower
H48	1.0910	0.00			0.8507	0.00	0.9288	1.2215	Naive trend Follower
H49	0.9128	0.00			0.9115	0.00	0.8176	2.8091	Naive trend Follower
H410	0.8968	0.00			0.7664	0.00	0.7343	4.0303	Naive trend Follower
H51	1.1902	0.00			0.2853	0.00	0.8961	1.9220	Naive trend Follower
H52	1.2828	0.00			0.5173	0.00	0.8773	2.8011	Naive trend Follower
H53	0.9233	0.00			0.7551	0.00	0.5265	10.1676	Naive trend Follower
H54	1.1019	0.00			0.5904	0.00	0.7657	4.6846	Naive trend Follower
H55	0.8619	0.00			0.8161	0.00	0.6712	5.4887	Naive trend Follower
H56	1.0864	0.00			0.4637	0.00	0.8241	3.0843	Naive trend Follower
H510	1.1766	0.00			0.3354	0.00	0.8810	2.2224	Naive trend Follower
H61	0.7857	0.00			0.8248	0.00	0.6597	0.5647	Naive trend Follower
H64	0.6926	0.00			0.5723	0.00	0.3551	0.7171	Naive trend Follower
H65	0.8923	0.00			0.6286	0.00	0.8830	0.1779	Naive trend Follower
H610	0.9115	0.00			0.8119	0.00	0.70	0.61	Naive trend Follower

Table 6: Above is the result of estimating $p^e_{h,t+1} = \alpha_1 p^e_{t-1} + \alpha_2 p^e_{h,t-1} + (1-\alpha_1-\alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2})$ for the all treatments. The second to the seventh column shows the estimated coefficients and associated $p-$value. The eighth and ninth columns show the R^2 and MSE of the regressions. We only report the estimation results when there is no autocorrelation in the error term.