When speculators meet suppliers: Positive versus negative feedback in experimental housing markets

Bao, T.; Hommes, C.

DOI
10.1016/j.jedc.2019.103730

Publication date
2019

Document Version
Final published version

Published in
Journal of Economic Dynamics and Control

Journal of Economic Dynamics & Control 107 (2019) 103730

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

When speculators meet suppliers: Positive versus negative feedback in experimental housing markets[☆]

Te Bao[a], Cars Hommes[b,c,*]

[a] Division of Economics, School of Social Sciences, Nanyang Technological University, Singapore
[b] CeNDEF, Amsterdam School of Economics, University of Amsterdam and Tinbergen Institute, Amsterdam, the Netherlands
[c] Bank of Canada, Ottawa, Canada

ARTICLE INFO

Article history:
Received 13 November 2018
Revised 10 July 2019
Accepted 13 August 2019
Available online 18 August 2019

JEL classification:
C91
C92
D83
D84
R30

Keywords:
Rational expectations
Learning
Housing bubble
Experimental economics

ABSTRACT

Asset markets like stock markets are characterized by positive feedback through speculative demand. But the supply of housing is endogenous, and adds negative feedback to the housing market. We design an experimental housing market and study how the strength of the negative feedback, i.e., the price elasticity of supply, 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 are well described by the heuristics switching model. Our results suggest that negative feedback policies may stabilize speculative asset bubbles.

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 to be a main contributor to the recent financial crisis (e.g., Gjerstad and Smith, 2014). Many previous studies focused on the demand side of speculative asset markets, but real estate assets distinguish themselves from other speculative assets in that the supply of housing is endogenous and responds to (expected) price changes. As Glaser et al. (2008) observed "models of housing price volatility that ignore supply miss a fundamental part of the housing market".

☆ We thank the editor, an associate editor and two anonymous referees for their helpful comments. Discussion form participants of the CEF 2014 conference, Oslo, the workshop "Learning in Macroeconomics and Finance" 2014, Barcelona, the CEF 2017 conference, New York, Barcelona GSE Summer Forum (CEE) 2019 and in particular Jess Benhabib, Roberto Dieci, Alan Kirman, Thomas Lux and Rosemarie Nagel is gratefully acknowledged. We also thank the financial support by INET Project "Heterogeneous Expectations and Financial Crises", the Research Priority Area Behavioural Economics at the University of Amsterdam, the National Science Foundation of China (No. 71803201, No. 71773013, and No. 71873149) and Tier 1 Grant from MOE of Singapore.

* Corresponding author.
E-mail addresses: baote@ntu.edu.sg (T. Bao), c.h.hommes@uva.nl (C. Hommes).

https://doi.org/10.1016/j.jedc.2019.103730
0165-1889/

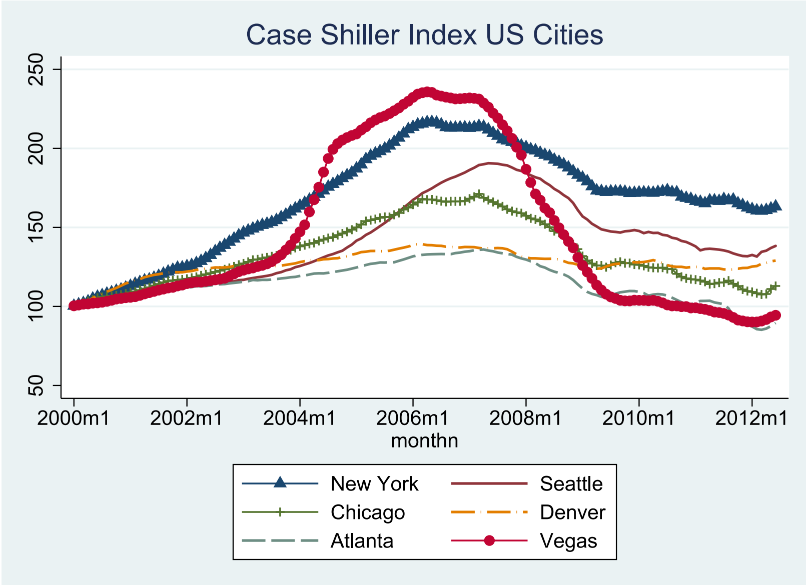

Fig. 1. Case-Shiller index in 6 US major cities. New York, Seattle and Chicago are considered as low price elasticity cities, and Denver, Atlanta and Las-Vegas are considered as high elasticity cities according to Saiz (2008). The time series are monthly data from January 2000 to June 2012.

An answer to this 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 price 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 a 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. Fig. 1 plots the Case-Shiller index in some major cities in the US. Among these, 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 price elasticity of supply 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 fluctuations of the housing price.

In this paper, we run a laboratory experiment to study how the price 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 price elasticity of supply *alone*. For example, Glaeser 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 experiments is that it takes full control over other variables, and therefore singles out the effect of a change in one condition 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 price elasticity and (3) of high price elasticity. We find strong evidence that, *ceteris paribus*, the market price is less volatile and deviates less from the REE in markets with high price elasticity of supply.

Our experiment may be the first laboratory experiments on the housing market. Stephens and Tyran (2012) studied nominal loss aversion in the housing market using a 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 the 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 influence of individual expectations on the market (in)stability. Asparouhova et al. (2016) consider housing bubble as an result of tension between social and individual rationality. Huber et al. (2016) conduct a laboratory experiment on the housing market within an OLG framework. Different from our work, the supply of housing in their paper is exogenous.

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/suppliers. 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 suppliers predict that the price will increase, they will tend to build more houses, which increases the supply, and has a tendency to drive the price down.[1] 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., 2017). There have also been experimental studies comparing positive and negative feedback markets (Heemeijer et al., 2009, Sutan and Willinger (2009), Bao et al., 2012; Sonnemans and Tuinstra, 2010).[2] The current paper designs the first experimental market *combining* both positive and negative feedback features in a single market. 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.[3] Our results show that the stronger the overall positive feedback in the experimental housing market, the more likely housing bubbles occur.

A third contribution of our paper is that we use a behavioral heuristics switching model (Anufriev and Hommes, 2012a; Anufriev and Hommes, 2012b; Brock and Hommes, 1997) to explain individual expectation formation and aggregate price dynamics in the experimental housing market. 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 on trend-extrapolating expectations across agents is weaker, and subjects are more likely to become users of adaptive or contrarian expectations (Anufriev and Hommes, 2012b; Anufriev et al., 2017; Bao et al., 2012). Our results for the housing market show that under strong positive feedback bubbles emerge, amplified by coordination on trend-following rules, while more negative feedback, or equivalently weaker overall positive feedback, promotes coordination on adaptive expectations and a stable housing market. These results are consistent with empirical work estimating heterogeneous expectations models, where agents switch between destabilizing trend-following and stabilizing mean reverting fundamentalists strategies (Bolt et al., 2016; Eichholtz et al., 2015), as well as the results of the theoretical, agent based modeling studies (Dieci et al., 2017; Dieci and Westerhoff, 2012, 2013, 2016). Finally, coordination on trend-extrapolating expectations is consistent with studies of survey data on housing market expectations (Case et al., 2012; Cheng et al., 2014; Shiller, 2007).

Our paper fits into a literature in real estate economics that finds that the rational expectation hypothesis may not provide a 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.

Our results lead to an important policy question to ask: can asset 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 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*.

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

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,

[1] The combined positive and negative feedback system is a feature for markets of investment assets that also serve as consumption goods. Similar situation may also apply to gold, silver, tulip bulbs historically, or cocoa, oil and sugar in modern commodity markets. We use the framing of housing market because the US housing cycle in 2000s has been the most prominent financial phenomenon recently. To some extent, our main result that the price of the asset will be more stable when the supply of it is more elastic may also generalize to other assets traded in commodity markets. Recently, in a related paper de Jong et al. (2019) combined negative and positive feedback in a commodity market coupled with a speculative futures market for the commodity.

[2] Fehr and Tyran (2001, 2005, 2008) also show that 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 Soros (2003). Hommes (2013) provides a detailed discussion about the relation between these concepts.

[3] 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 positive feedback speculative demand.

see the surveys of Duffy (2008), Assenza et al. (2014a,b) and Arifovic and Duffy (2018). Learning to forecast experiments can also be viewed as a repeated version of beauty contest games (Duffy and Nagel, 1997; Mauersberger and Nagel, 2018; Nagel, 1995).

2.1. The housing market

The housing model combines the mean-variance speculative asset pricing model and the supply driven cobweb model. The speculative demand part of the model is based on the asset pricing model in Brock and Hommes (1997) and the version of that used in the laboratory in Hommes et al. (2008). The housing supply model in Treatment L and H is similar to the cobweb type model used in the experimental negative feedback markets in Hommes et al. (2007) and Bao et al. (2013). To our knowledge, this paper is the first one that combines these two types of markets in laboratory experiments. The combination of positive and negative feedback markets in the laboratory is a novel methodological contribution of this paper.

To keep the design simple and to focus on two different types of expectations feedback, we consider a housing market with I suppliers, who build houses, and H owners/investors, who buy houses for speculative investment. There have been only few finance or macroeconomic experiments with heterogeneity of subjects in terms of their roles. In the experimental literature on New Keynesian economies, Petersen (2012) and Mauersberger (2018) introduce similar type of heterogeneity with human subjects playing the role of households and firms in the economy. Let $z^s_{i,t}$ be the housing supply by builder 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 builder 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 suppliers I.[4]

Housing demand is derived from maximization of a myopic mean-variance utility 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 $E_t y_{t+1} = \bar{y}$ is constant over time. For simplicity, we set $a\sigma^2 = H$, so that the demand is normalized by the number of investors H and will depend on investor's average price forecasts. By imposing a 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 $\overline{p}^e_i$, $\overline{p}^e_{h,t+1}$ are the average expected housing price by suppliers and investors. By substituting in these conditions, the reduced form equation for equilibrium housing prices is given by:

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

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 suppliers goes up. Therefore the

[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 price expectations.

[5] This setup follows the recent works that address the interplay between the demand and supply sides of housing markets, within a framework with behavioral heterogeneity close in spirit to the model outlined in the present paper, e.g. Dieci and Westerhoff (2012, 2016) and Zheng et al. (2017). 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 et al. (1997). Our experimental design is also similar to the empirically estimated heterogeneous expectations housing model in Bolt et al. (2016). We acknowledge that in real life, many houses are not bought for speculative purposes. We use this setting because the focus of this paper is the speculative demand in the housing market. In addition, our result is not going to be very different if the demand by consumers is introduced. For example, if we introduce a standard demand function $z^C_t = l - mp_t$ to the demand side, the equilibrium price is going to become $p_t = \frac{1}{(1+m)R}(\overline{p}^e_{h,t+1} + \bar{y} - c\overline{p}^e_{i,t+1} + l) + \nu_t$, which is the not different from the price determination function in our paper in the way the average expectation influences the aggregate price if we do some normalization.

housing market exhibits *positive expectations feedback* from the speculative investors, and *negative expectation feedback* from the suppliers.

2.2. Rational expectations

If the suppliers and speculators have homogeneous expectations, Eq. (1) becomes

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

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

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

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 slope of the supply function c as a proxy of price elasticity of housing supply.

It should be noted that there are other 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, do not satisfy the transversality condition and are therefore considered as non-rational. The rational steady state p^* is the only *bounded* fully rational solution of (2). See e.g. Cuthbertson and Nitzsche (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 suppliers 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 suppliers 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 expectation feedback". In this experiment, we consider three different treatments by three different values of the price elasticity of supply 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 suppliers in the market. We let 6 investors/forecasters participate in each market, and the market price only depends on the average price expectation of these investors/forecasters.
- Treatment with low price elasticity of supply (**treatment L**); $c = 0.1$; $\lambda = \frac{1-c}{R} = 0.86$:
  There are 5 investors and 5 suppliers in each market. The market price depends on both expectations by the investors and suppliers, but the influence from the suppliers 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 suppliers in each market. The market price depends on both expectations by the investors and suppliers, and the influence from the suppliers 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; strong positive FB), to $\lambda = 0.86$ (Treatment L; medium positive FB), and finally to $\lambda = 0.71$ (Treatment H; weak positive FB). 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 Eq. (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 $c = 0.25$.

2.4. Design

Subjects in the experiments play the role of professional forecasters, either for suppliers 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

[6] Sonnemans and Tuinstra (2010) study the price behavior in positive feedback markets $p_t = 60 + \lambda(p^e_t - 60)$, 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. The two-period ahead temporary equilibrium framework is inherently more unstable, because it exhibits rational bubble solutions growing exponentially at rate $R/(1-c)$. We find that the market price converges to the REE when the overall slope is 0.71 (i.e., when the supply coefficient $c = 0.25$)and the positive FB is weak. Given that there is no systematic difference between the price expectations by the suppliers 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.

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 given in Eq. (4) below. It is a decreasing function of their prediction error. The subjects earn 0 points if their prediction error is larger than 7:

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

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 results

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 fluctuations in the number of groups is due to show up rates of subjects. We use slightly fewer observations 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/crash patterns in the data of Hommes et al. (2008) are not affected by the change of framing. Given that we indeed observe bubbles in treatment N, 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 h and 5 min, 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

Figs. 2–4 report the market price in different treatments. Generally, the prices are more stable in the treatment with higher supply slopes/elasticities, that is, when the positive feedback is weak. 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).

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 Stöckl 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 definitions are as follows:

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

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

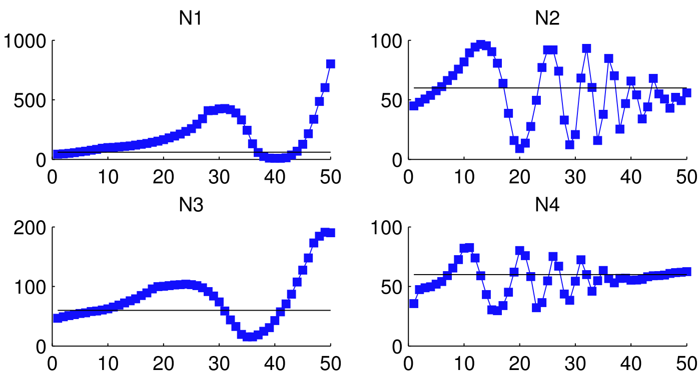

Fig. 2. The market prices against the REE price in treatment N.

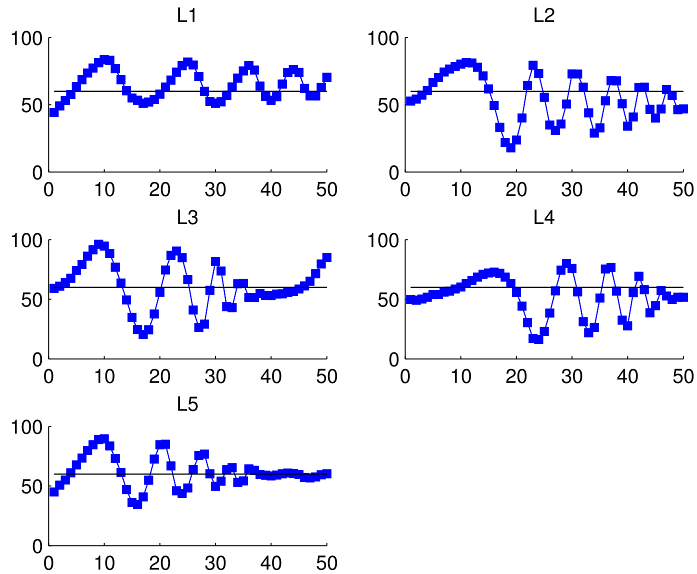

Fig. 3. The market prices against the REE price in treatment L.

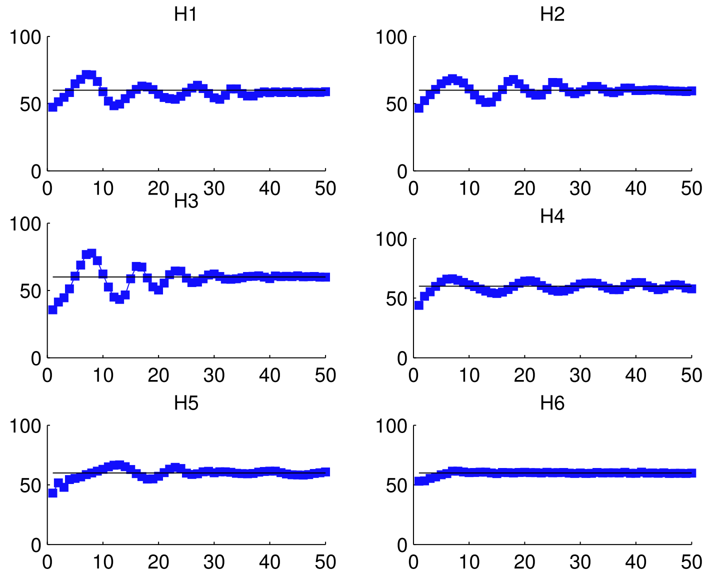

Fig. 4. The market prices against the REE price in treatment H.

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 treatments N and L is significant at 5% level, while the difference between other pairs of treatments is not significant ($z = 1.715$ for N and L, $z = 2.558$ for N and H, and $z = 2.739$ for L and H). The difference between the RD in different pairs of treatments is not significant at 5% level ($z = 0.980$ for N and L, $z = 0.000$ for N and H, and $z = 0.548$ for L and H). The result is in general robust if we restrict the analysis for the last 25 periods when the price tends to be more stable in Treatment L and H. A Wilcoxon-Mann-Whitney test suggests that the difference between the RAD in different pairs of treatments is always significant at 5% level ($z = 2.460$ for N and L, $z = 2.66$ for N and H, and $z = 2.751$ for L and H). The difference between the RD in different pairs of treatments is not significant at 5% level ($z = 1.107$ for N and L, $z = 0.912$ for N and H, and $z = 0.575$ for L and H).

Table 2 shows the variance of market prices in each market. The variance is very large for markets in treatment N (strong positive feedback), and much smaller for markets in treatment L (medium positive feedback) and H (weak positive feedback).

Table 1
The RAD and RD in each market.

Treatment All Periods	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%
Last 25 Periods						
Market 1	375.59%	341.15%	14.07%	7.60%	3.91%	−2.83%
Market 2	377.89%	−12.93%	30.26%	−12.64%	2.07%	0.28%
Market 3	87.93%	39.13%	30.17%	−4.81%	1.67%	−0.49%
Market 4	78.96%	−3.49%	22.13%	−16.55%	3.30%	−0.68%
Market 5			25.93%	0.84%	1.49%	−0.08%
Market 6					0.46%	−0.13%
Mean	230.09%	90.97%	24.51%	−5.11%	2.15%	−0.65%
Median	231.76%	17.82%	26.15%	−8.73%	2.68%	−0.58%

Table 2
The variance of market price 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

Overall, the observed aggregate behaviour supports the conclusion that housing markets with higher supply elasticities or, equivalently, with weaker positive feedback are more stable.

3.2. Individual predictions

Fig. 5 shows the individual predictions in a typical market (market 1) in each of treatments N, L and H (namely, N1, L1 and H1). Previous studies (Bao et al., 2012; Heemeijer et al., 2009) show that agents have high level of coordination of expectations (expectations are more 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 suppliers, 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 suppliers have low level of coordinations between themselves, and with the speculators. The results generally confirm the first hypothesis. There is high level of coordination between the price expectations of both speculators and suppliers. After a few initial periods, all prediction time series tend to follow the same pattern, which is generally follows 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. These results are consistent with the observations that for all treatments N, L and H, the housing market is a positive feedback system, with only the strength of the positive feedback varying.

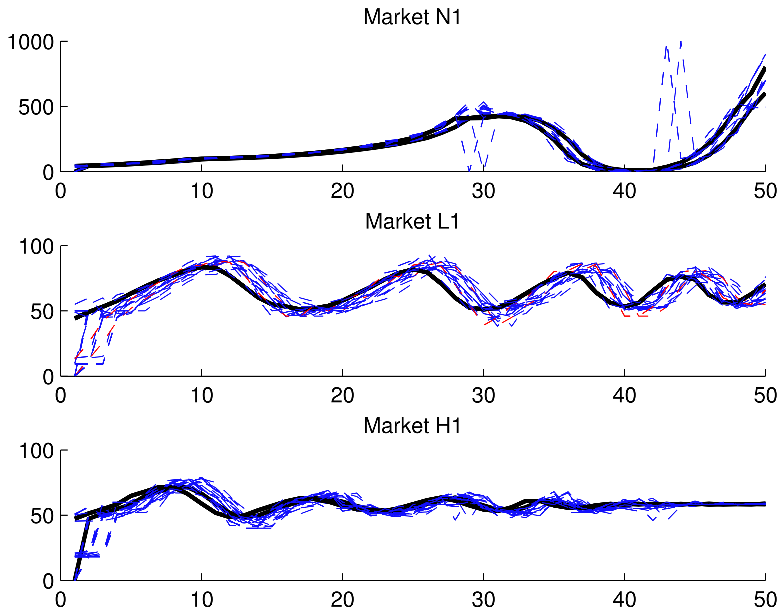

Fig. 5. The individual predictions (dashed lines) plotted against the market price (thick line) in a typical market in each of treatments N (market N1, upper panel), L (market L1, middle panel) and H (market H1, lower panel).

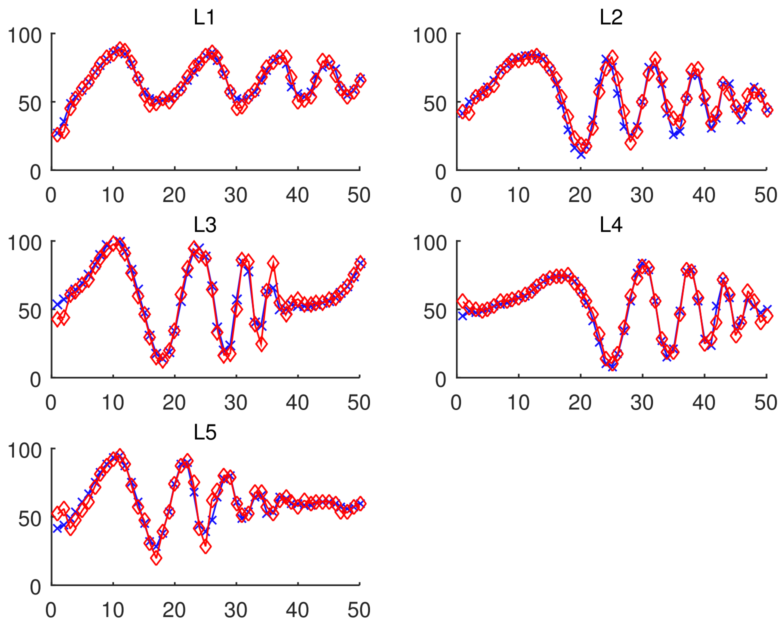

Fig. 6. The average predictions by the speculators (Xs) and suppliers (diamonds) in each market in treatment L.

Previous studies show that people tend to follow adaptive expectations in negative feedback markets, and trend extrapolating expectations in positive feedback markets. In our experiment, would suppliers and speculators use different types of expectation rules based on their roles? Or would they coordinate on one type of rule that depends on the overall sign of the expectation feedback of the market? To better examine whether there is a systematic difference between the predictions made by the speculators and suppliers in the same market, Figs. 6 and 7 show the average price forecast by the investors (Xs) and suppliers (diamonds). The graphs suggest that there is no systematic difference between the average predictions by the two types of agents in the same market. The average expectation is 58.84 for suppliers and 56.64 for speculators in treatment L, and 58.64 for suppliers and 58.48 for speculators for treatment H. It appears the average expectations are close to the REE in both treatments, and slightly higher for suppliers than for speculators. We test the difference in the mean

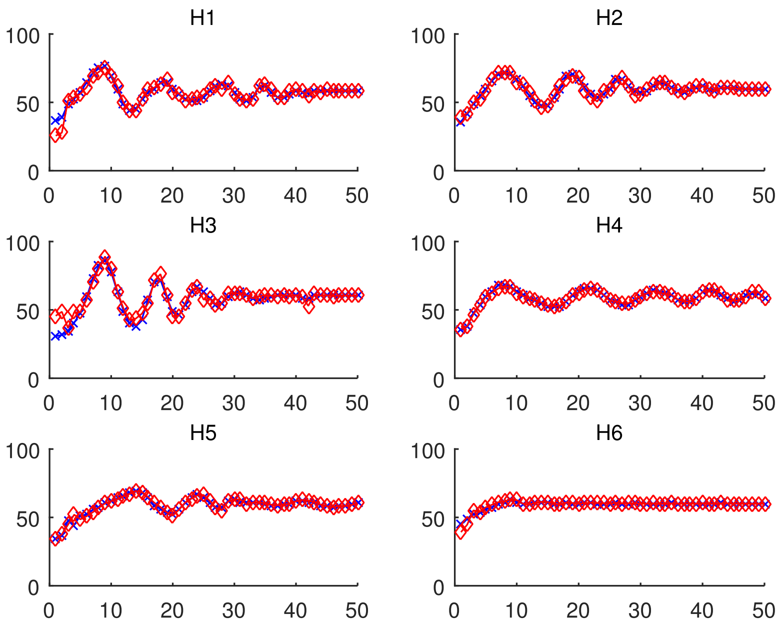

Fig. 7. The average predictions by the speculators (Xs) and suppliers (diamonds) in each market in treatment H.

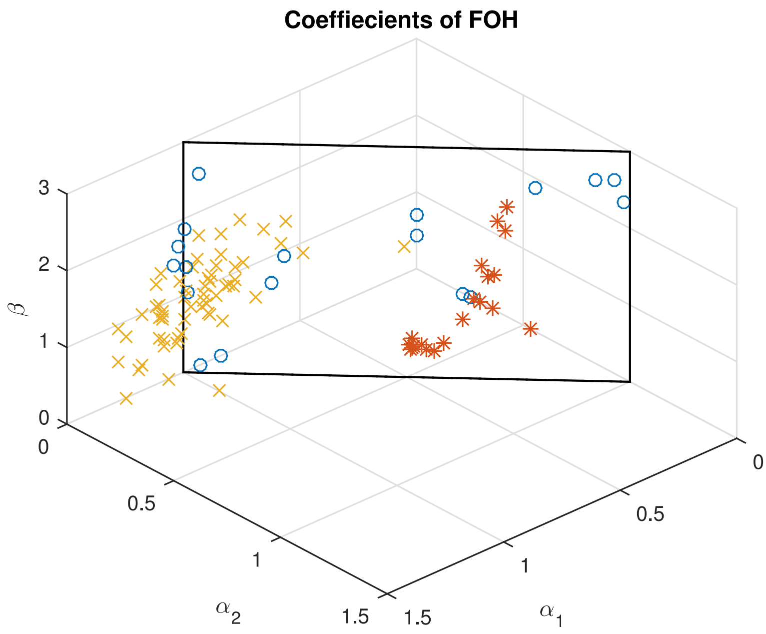

Fig. 8. Prism of first-order heuristics containing the parameter vectors of the prediction rules $p^e_{h,t+1} = \alpha_1 p_{t-1} + \alpha_2 p^e_{h,t-1} + (1-\alpha_1-\alpha_2)\times 60 + \beta(p_{t-1} - p_{t-2})$. Positive β is associated with trend following behaviour. α_1 close 1 is associated to a naive anchor of the prediction rule, while $\alpha_2 > 0$ is associated with usage of some general form of adaptive expectations. Circles represent observations from treatment N, characterized by strong trend-following behaviour, stars represent treatment L and Xs represent treatment H, characterized by weak trend-following behaviour.

using t-test and the result suggests that the different is significant at 5% level in treatment L ($t = 3.200$), and not significant in treatment H ($t = 1.217$).

3.3. Estimation of individual forecasting strategies

We consider a simple, but general form of individual prediction strategies, the “first order heuristic” as studied in Heemeijer et al. (2009). This rule has a simple behavioral interpretation: it is a specification of an anchoring and adjustment heuristic as in Tversky and Kahneman (1974). This forecasting rule uses a time varying anchor, a weighted

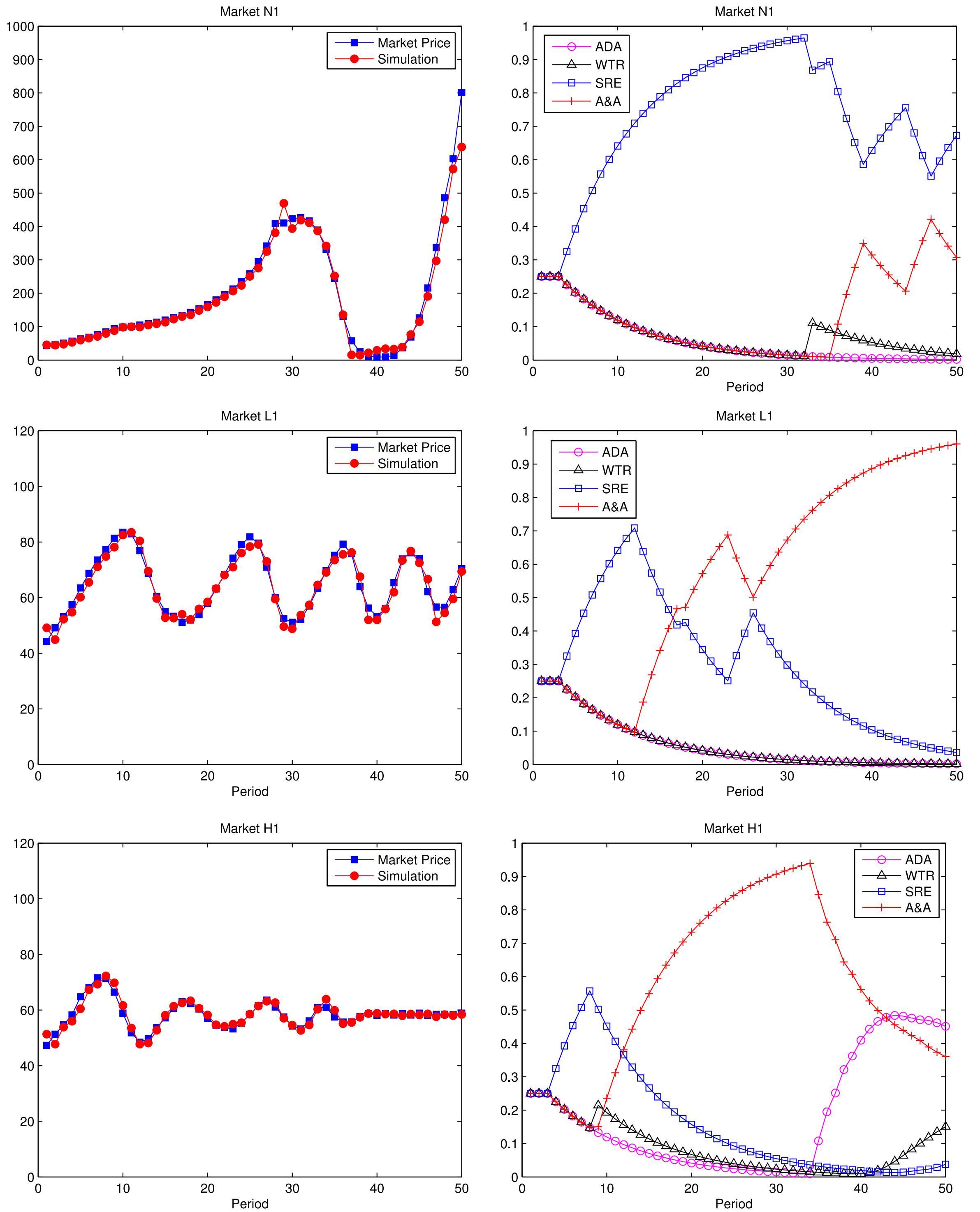

Fig. 9. The simulated and experimental market price (left panel) and the simulated fractions of users of different heuristics (right panel) in a typical market in treatment N (upper panel), L (middle panel) and H (lower panel).

average of the past price p_{t-1}, the own past prediction p^e_{t-1} and the fundamental equilibrium price 60, and extrapolates the last price change $(p_{t-1} - p_{t-2})$:

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

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. It turns out that among 134 subjects in the experiment, the strategy of 108 of them (80.60%) can be successfully estimated using the first order heuristic under these criteria. The estimation results are reported in Tables 4–6 in the appendix and plotted in Fig. 8.

The results 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 most subjects. Most of the estimated βs are larger than 0.5, and the average value is 1.107. The average estimated β is 1.8141 in treatment N, 1.1971 in treatment L, and 0.8895 in treatment H. This suggests that subjects extrapolate trends in a stronger way when the supply elasticity is smaller. The sum $\alpha_1 + \alpha_2$ is close to 1 for a large fraction of cases ($\alpha_1 + \alpha_2 > 0.9$ for 45 out of 108 regressions, among which $\alpha_1 > 0.9$ for 43 out of 45 regressions). This means that the rational expectation equilibrium gets little weight in the anchor, while the last observed price gets much weight in 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 (2012a,b), extending the model of Brock and Hommes (1997). The HSM is able to explain the *different* types of price dynamics, monotonic convergence, persistent oscillations and dampened oscillations, observed in the experimental asset markets in Hommes et al. (2005) and Hommes et al. (2008). In our experiment, we also see all these types of price dynamics. 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.

More details about the model can be found in Appendix E. Fig. 9 shows the simulated market price by the HSM model against the experimental market price in a typical market (market 1) in each treatment, using the benchmark parameterization $\beta = 0.4, \eta = 0.7, \delta = 0.9$, as in Anufriev and Hommes (2012a,b). Since we have similar patterns of price dynamics, we can check whether the same HSM can be applied to our housing market experiment. 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 unstable 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 the oscillations and convergence to the fundamental price.The HSM thus provides simple and intuitive explanations of our experiments. The large housing bubbles in treatment N are explained by coordination on a strong trend-following rule (STR). The oscillations in treatment L are explained by coordination on an anchor and adjustment rule (LAA). The stable price behaviour in treatment H is explained by coordination on adaptive expectations.

5. Conclusion

We study the relationship between price elasticity of supply and price dynamics in experimental housing markets using a "learning to forecast" design. Our results show that when the price elasticity of supply 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 suppliers, 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 will tend to coordinate on 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 price elasticity of supply (strong positive feedback; near unit root) trend-following rules dominate the market leading to housing bubbles and crashes; for intermediate price elasticity of supply (medium positive feedback) an anchoring and adjustment rule dominates the market leading to (non-exploding) price oscillations; for high price elasticity of supply (weak positive feedback) housing prices converge to REE fundamental through coordination on adaptive expectations. This confirms the observation by Glaeser and Nathanson (2015) 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. Recently, Paciorek (2013) conducts a structural estimation on the US housing market and find that US constraints on housing supply indeed lowers the elasticity of new housing supply and larger price volatility. Our result is in line with these empirical findings and suggests that removing constraints on housing supply may help to reduce housing price volatility. In addition, a higher interest may lower the strength of the positive feedback of the market, and lead to less price deviation and enhanced market stability. Hennequin and Hommes (2018) test whether a Taylor type interest rate policy of leaning against the wind, i.e., the interest rate is an increasing function of the degree of the mispricing of the asset, may lead to market stability and they find supportive experimental evidence for that. Bao and Zong (2019) find that an interest rate policy that is not responsive to small mispricing, but strongly responsive to larger price deviations can reduce asset bubbles substantially.

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 price elasticity of supply 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 of the underlying system and market stability in laboratory group experiments. Finally, recent studies (Akiyama et al., 2017; Hanaki et al., 2017) find that subjects' cognitive ability and strategic uncertainty may also play an important role in determining the price stability of experimental stock markets. It will be interesting how cognitive ability and strategic uncertainty may influence the stability of experimental housing markets.

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

$$\pi^e_{i,t+1} = p^e_{i,t+1} q_{i,t} - c(q_{i,t}), \tag{8}$$

where $p^e_{i,t+1}$ is the expected housing price by builder i for period $t+1$. 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 $\frac{Iq_{i,t}}{c} = p^e_{t+1,i}$, $q_{i,t} = \frac{cp^e_{i,t}}{I}$, or $z^s_{i,t} = \frac{cp^e_{i,t+1}}{I}$.

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

$$U_{h,t}(z^d_{h,t}) = E_{h,t}W_{h,t+1} - \frac{a}{2}V_{i,t}(W_{h,t+1}), \tag{9}$$

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

$$W_{h,t+1} = RW_{h,t} + z^d_{h,t}(p_{t+1} + y_{t+1} - Rp_t), \tag{10}$$

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 parameter for risk aversion. 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 $a\sigma^2 z^d_{h,t} = E_{h,t}(p_{t+1} + y_{t+1} - Rp_t)$. Moreover, we assume the expected value of y_{t+1} is also a constant over time, which equals to $\bar{y}$. This will lead to $a\sigma^2 z^d_{h,t} = E_{h,t}(p_{t+1} + y_{t+1} - Rp_t) = p^e_{h,t+1} + \bar{y} - Rp_t$, namely,

$$z^d_{h,t} = \frac{p^e_{h,t+1} + \bar{y} - Rp_t}{a\sigma^2} \tag{11}$$

Appendix B. Experimental instructions

This section shows the experimental instructions for suppliers 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 suppliers 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.

B1. 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. 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 convex 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 risk-free 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 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 construction 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 $t+1$, 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.

B2. 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 p_{t+1} in period $t+1$, 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.

Appendix C. Payoff Table

Table 3 is the payoff table used in this experiment.

Table 3
Payoff Table for Forecasters.

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 4
Estimation results for $p^e_{h,t+1} = \alpha_1 p_{t-1} + \alpha_2 p^e_{h,t-1} + (1 - \alpha_1 - \alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2})$ for Treatment N. 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.

sub no.	α_1	p-value	α_2	$p - value$	β	$p - value$	R-squared	MSE	Label
L11	0.221	0.031	0.458	0.000	0.311	0.025	0.289	109.89	Adaptive Trend Follower
L12	0.351	0.000	0.350	0.000			0.357	106.75	Adaptive Expectations
L13	0.367	0.000	0.371	0.000			0.359	113.97	Adaptive Expectations
L14	0.358	0.000	0.367	0.001			0.357	114.23	Adaptive Expectations
L15	0.317	0.000	0.431	0.000			0.359	96.70	Adaptive Expectations
L16	0.346	0.000	0.362	0.000			0.334	135.87	Adaptive Expectations
L17	0.263	0.000	0.411	0.000			0.376	74.10	Adaptive Expectations
L18	0.320	0.000	0.325	0.000			0.340	110.52	Adaptive Expectations
L19	0.323	0.000	0.376	0.001			0.330	109.39	Adaptive Expectations
L110	0.332	0.000	0.408	0.000			0.335	120.11	Adaptive Expectations
L21			0.304	0.024	0.482	0.043	0.061	411.48	Adaptive Trend Follower
L22			0.333	0.011	0.393	0.047	0.101	309.03	Adaptive Trend Follower
L25			0.535	0.000			0.169	314.96	Adaptive Expectations
L29			0.366	0.006	0.460	0.040	0.111	384.61	Adaptive Trend Follower
L31			0.425	0.000	1.439	0.004	0.311	403.76	Adaptive Trend Follower
L34			0.377	0.002	1.165	0.015	0.262	385.95	Adaptive Trend Follower
L37			0.419	0.001	1.118	0.021	0.289	397.96	Adaptive Trend Follower
L41			0.298	0.011			0.011	397.83	Adaptive Expectations
L43			0.356	0.004			−0.027	412.83	Adaptive Expectations
L45			0.268	0.028			−0.065	416.71	Adaptive Expectations
L46			0.256	0.033			−0.121	406.24	Adaptive Expectations
L48			0.287	0.020			−0.026	405.02	Adaptive Expectations
L49			0.313	0.012			0.082	306.01	Adaptive Expectations
L51			0.682	0.000	2.055	0.000	0.845	50.96	Adaptive Trend Follower
L54			0.671	0.000	1.842	0.000	0.753	71.64	Adaptive Trend Follower
L56			0.289	0.000	1.716	0.000	0.698	88.23	Adaptive Trend Follower
L57			0.525	0.000	1.674	0.000	0.686	83.25	Adaptive Trend Follower
L59			0.612	0.000	1.710	0.000	0.772	50.87	Adaptive Trend Follower

Table 5
Estimation results for $p^e_{h,t+1} = \alpha_1 p_{t-1} + \alpha_2 p^e_{h,t-1} + (1 - \alpha_1 - \alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2})$ for Treatment L. 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.

sub no.	α_1	p-value	α_2	$p - value$	β	$p - value$	R-squared	MSE	Label
L11	0.221	0.031	0.458	0.000	0.311	0.025	0.289	109.89	Adaptive Trend Follower
L12	0.351	0.000	0.350	0.000			0.357	106.75	Adaptive Expectations
L13	0.367	0.000	0.371	0.000			0.359	113.97	Adaptive Expectations
L14	0.358	0.000	0.367	0.001			0.357	114.23	Adaptive Expectations
L15	0.317	0.000	0.431	0.000			0.359	96.70	Adaptive Expectations
L16	0.346	0.000	0.362	0.000			0.334	135.87	Adaptive Expectations
L17	0.263	0.000	0.411	0.000			0.376	74.10	Adaptive Expectations
L18	0.320	0.000	0.325	0.000			0.340	110.52	Adaptive Expectations
L19	0.323	0.000	0.376	0.001			0.330	109.39	Adaptive Expectations
L110	0.332	0.000	0.408	0.000			0.335	120.11	Adaptive Expectations
L21			0.304	0.024	0.482	0.043	0.061	411.48	Adaptive Trend Follower
L22			0.333	0.011	0.393	0.047	0.101	309.03	Adaptive Trend Follower
L25			0.535	0.000			0.169	314.96	Adaptive Expectations
L29			0.366	0.006	0.460	0.040	0.111	384.61	Adaptive Trend Follower
L31			0.425	0.000	1.439	0.004	0.311	403.76	Adaptive Trend Follower
L34			0.377	0.002	1.165	0.015	0.262	385.95	Adaptive Trend Follower
L37			0.419	0.001	1.118	0.021	0.289	397.96	Adaptive Trend Follower
L41			0.298	0.011			0.011	397.83	Adaptive Expectations
L43			0.356	0.004			−0.027	412.83	Adaptive Expectations
L45			0.268	0.028			−0.065	416.71	Adaptive Expectations
L46			0.256	0.033			−0.121	406.24	Adaptive Expectations
L48			0.287	0.020			−0.026	405.02	Adaptive Expectations
L49			0.313	0.012			0.082	306.01	Adaptive Expectations
L51			0.682	0.000	2.055	0.000	0.845	50.96	Adaptive Trend Follower
L54			0.671	0.000	1.842	0.000	0.753	71.64	Adaptive Trend Follower
L56			0.289	0.000	1.716	0.000	0.698	88.23	Adaptive Trend Follower
L57			0.525	0.000	1.674	0.000	0.686	83.25	Adaptive Trend Follower
L59			0.612	0.000	1.710	0.000	0.772	50.87	Adaptive Trend Follower

Table 6
Estimation results for $p^e_{h,t+1} = \alpha_1 p_{t-1} + \alpha_2 p^e_{h,t-1} + (1-\alpha_1-\alpha_2) \times 60 + \beta(p_{t-1} - p_{t-2})$ for Treatment H. 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.

sub no.	α_1	p-value	α_2	$p - value$	β	$p - value$	R-squared	MSE	Label
H11	0.933	0.000			1.701	0.000	0.902	5.82	Naive Trend Follower
H12	0.840	0.000			1.314	0.000	0.683	15.47	Naive Trend Follower
H13	0.939	0.000			1.383	0.000	0.865	6.78	Naive Trend Follower
H14	1.244	0.000			0.790	0.000	0.818	9.48	Naive Trend Follower
H15	0.402	0.014	0.378	0.000	1.394	0.000	0.756	7.67	Adaptive Trend Follower
H16	0.993	0.000			0.980	0.000	0.908	3.72	Naive Trend Follower
H17	0.970	0.000			0.822	0.000	0.909	3.26	Naive Trend Follower
H18	0.742	0.000			1.090	0.000	0.851	4.42	Naive Trend Follower
H19	1.103	0.000			0.857	0.000	0.856	6.28	Naive Trend Follower
H110	0.895	0.000			1.088	0.000	0.901	3.79	Naive Trend Follower
H21	1.089	0.000			0.820	0.000	0.834	5.56	Naive Trend Follower
H22	0.831	0.000			0.436	0.002	0.655	7.52	Naive Trend Follower
H23	0.964	0.000			1.316	0.000	0.817	7.18	Naive Trend Follower
H24	0.862	0.000			1.215	0.000	0.719	10.71	Naive Trend Follower
H25	0.584	0.000			1.112	0.000	0.709	7.08	Naive Trend Follower
H26	1.095	0.000			1.411	0.000	0.823	8.76	Naive Trend Follower
H27	1.115	0.000			1.301	0.000	0.852	6.65	Naive Trend Follower
H28	1.102	0.000			1.012	0.000	0.877	4.52	Naive Trend Follower
H29	0.817	0.000			0.877	0.000	0.736	7.04	Naive Trend Follower
H210	0.655	0.000			1.392	0.000	0.815	5.71	Naive Trend Follower
H31	0.887	0.000			1.025	0.000	0.842	13.80	Naive Trend Follower
H32	0.808	0.000			0.874	0.000	0.738	20.74	Naive Trend Follower
H33	0.778	0.000			1.072	0.000	0.824	13.95	Naive Trend Follower
H34	0.755	0.000			1.652	0.000	0.885	13.40	Naive Trend Follower
H35	0.988	0.000			1.048	0.000	0.788	22.64	Naive Trend Follower
H36	0.780	0.000			0.909	0.000	0.810	13.40	Naive Trend Follower
H37	0.558	0.000			1.380	0.000	0.825	14.05	Naive Trend Follower
H38	0.880	0.000			1.110	0.000	0.877	10.97	Naive Trend Follower
H39	1.281	0.000			0.954	0.000	0.938	7.91	Naive Trend Follower
H310	0.908	0.000			0.995	0.000	0.725	28.28	Naive Trend Follower
H41	1.019	0.000			1.214	0.000	0.890	2.18	Naive Trend Follower
H42	0.998	0.000			0.684	0.000	0.696	5.48	Naive Trend Follower
H43	1.082	0.000			0.536	0.000	0.888	1.75	Naive Trend Follower
H44	1.019	0.000			0.475	0.000	0.898	1.37	Naive Trend Follower
H45	1.181	0.000			0.998	0.000	0.764	5.94	Naive Trend Follower
H46	0.838	0.000			1.585	0.000	0.908	1.90	Naive Trend Follower
H47	1.117	0.000			1.018	0.000	0.747	6.03	Naive Trend Follower
H48	1.091	0.000			0.851	0.000	0.929	1.22	Naive Trend Follower
H49	0.913	0.000			0.912	0.000	0.818	2.81	Naive Trend Follower
H410	0.897	0.000			0.766	0.000	0.734	4.03	Naive Trend Follower
H51	1.190	0.000			0.285	0.001	0.896	1.92	Naive Trend Follower
H52	1.283	0.000			0.517	0.000	0.877	2.80	Naive Trend Follower
H53	0.923	0.000			0.755	0.000	0.527	10.17	Naive Trend Follower
H54	1.102	0.000			0.590	0.000	0.766	4.68	Naive Trend Follower
H55	0.862	0.000			0.816	0.000	0.671	5.49	Naive Trend Follower
H56	1.086	0.000			0.464	0.000	0.824	3.08	Naive Trend Follower
H57	1.063	0.000					0.740	6.99	Naive Expectations
H58	1.246	0.000					0.886	3.54	Naive Expectations
H59	1.676	0.000			−1.574	1.000	0.592	32.09	Naive Trend Follower
H510	1.177	0.000			0.335	0.000	0.881	2.22	Naive Trend Follower
H61	0.786	0.000			0.825	0.000	0.660	0.56	Naive Trend Follower
H62	1.089	0.000			0.905	0.000	0.789	0.54	Naive Trend Follower
H63	0.883	0.000			0.589	0.000	0.809	0.31	Naive Trend Follower
H64	0.693	0.000			0.572	0.002	0.355	0.72	Naive Trend Follower
H65	0.892	0.000			0.629	0.000	0.883	0.18	Naive Trend Follower
H66	1.010	0.000			0.524	0.002	0.744	0.59	Naive Trend Follower
H67	1.031	0.000			0.432	0.000	0.857	0.30	Naive Trend Follower
H68	0.483	0.000			0.856	0.000	0.428	0.60	Naive Trend Follower
H69	0.997	0.000	0.169	0.000			0.972	0.13	Adpative Expectations
H610	0.912	0.000			0.812	0.000	0.700	0.61	Naive Trend Follower

Appendix D. Estimated Forecasting Rules

D1. First order heuristic

Appendix E. The Details about 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 (2012a,b), extending the model of Brock and Hommes (1997). The HSM is able to explain the *different* types of price dynamics, monotonic convergence, persistent oscillations and dampened oscillations, observed in the experimental asset markets in Hommes et al. (2005) and Hommes et al. (2008). In our experiment, we also see all these types of price dynamics. 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). The four rules in the model are therefore as follows:

An adaptive expectation (ADA) rule:

$$p^e_{1,t+1} = p^e_{t,1} + 0.65(p_{t-1} - p^e_{t,1}). \tag{12}$$

The weak trend rules (WTR) given by:

$$p^e_{2,t+1} = p_{t-1} + 0.4(p_{t-1} - p_{t-2}). \tag{13}$$

The strong trend extrapolating rule (STR) given by:

$$p^e_{3,t+1} = p_{t-1} + 1.3(p_{t-1} - p_{t-2}). \tag{14}$$

The fourth rule is called an anchoring and adjustment heuristic (A&A) where the anchor is equal to the price in the last period p_{t-1} and the sample average of past prices $p^{av}_{t-1} = (1/t)\sum_{j=0}^{t-1} p_j$, as in Tversky and Kahneman (1974):

$$p^e_{4,t+1} = 0.5(p^{av}_{t-1} + p_{t-1}) + (p_{t-1} - p_{t-2}). \tag{15}$$

Note that all these rules predict two periods ahead, using as the most recent observation p_{t-1} to forecast p_{t+1}. We use exactly the same rules and parameters as in Anufriev and Hommes (2012a,b), who used the HSM to fit the experimental asset markets in Hommes et al. (2005) and Hommes et al. (2008). The performance of the HSM is not very sensitive to these parameters, as long as the four rules represent the different types of behaviour observed in the experiments. The adaptive expectations rule leads to monotonic convergence to the fundamental price. The weak trend rule also leads to convergence to the fundamental, possibly with some small overshooting followed by mean reversion. The strong trend rule is unstable and leads to a large bubble with exploding prices. Finally, the learning, anchoring and adjustment (LAA) rule is in fact also a trend-following rule, but it uses a time varying anchor, $0.5(p^{av}_{t-1} + p_{t-1})$, 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 $p_{t-1} - p_{t-2}$. Because it includes a flexible time-varying anchor, the LAA rule is the only rule that can predict turning points of an observed price trend and therefore the LAA has been 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:

$$U_{h,t} = -(p_t - p^e_{h,t})^2 + \eta U_{h,t-1}, \tag{16}$$

where $n_{h,t}$ is the fraction of the agents using heuristic h. 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):

$$n_{h,t} = \delta n_{h,t-1} + (1-\delta)\frac{\exp(\beta U_{h,t-1})}{\sum_{i=1}^4 \exp(\beta U_{i,t-1})}. \tag{17}$$

$n_{h,t}$ is the weight for heuristic h at period t. 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, immediately switch to the most successful heuristic.

Fig. 9 shows the simulated market price by the HSM model against the experimental market price in a typical market (market 1) in each treatment, using the benchmark parameterization $\beta = 0.4$, $\eta = 0.7$, $\delta = 0.9$, as in Anufriev and Hommes (2012a,b). Since we have similar patterns of price dynamics, we can check whether the same HSM can be applied to our housing market experiment. 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

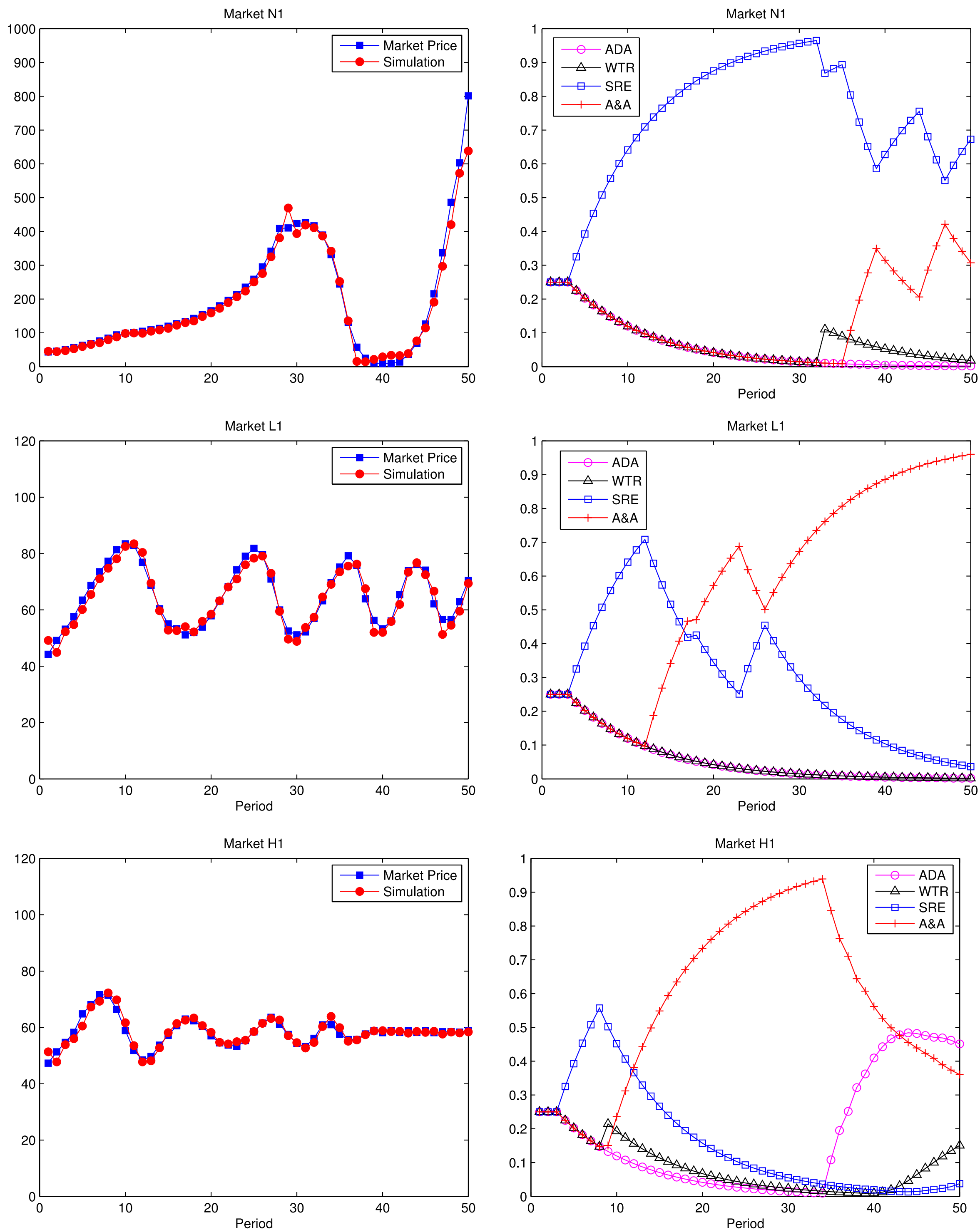

Fig. 10. The simulated and experimental market price (left panel) and the simulated fractions of users of different heuristics (right panel) in a typical market in treatment N (upper panel), L (middle panel) and H (lower panel).

Table 7
The fitness of different models to the experimental data. HSM benchmark means the heuristic switching model where $\beta = 0.4, \eta = 0.7, \delta = 0.9$.

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 heuristic	**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 heuristic	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 heuristic	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 8
The average weight of each heuristic over the markets in each treatment according to the HSM optimal model.

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%

in treatment N is mostly dominated by the strong trend rule, which leads to large bubbles and unstable 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 the oscillations and convergence to the fundamental price.The HSM thus provides simple and intuitive explanations of our experiments. The large housing bubbles in treatment N are explained by coordination on a strong trend-following rule (STR). The oscillations in treatment L are explained by coordination on an anchor and adjustment rule (LAA). The stable price behaviour in treatment H is explained by coordination on adaptive expectations.

Table 7 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. The exceptions are treatment N, market 1, where the strong trend rule provides a slightly better fit to the large bubble, and in treatment H, markets 5 and 6, where naive expectations and the WTR respectively provide a slightly better fit to the stable patterns and convergence to the fundamental price.

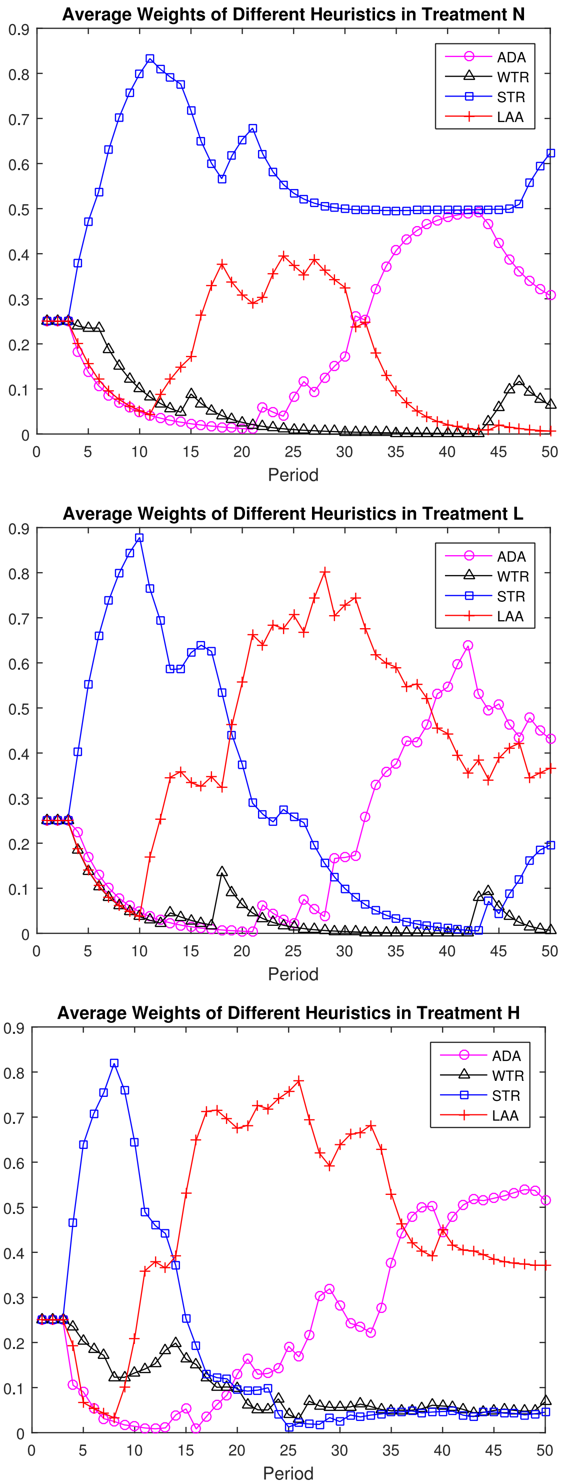

Fig. 11. The average simulated fractions of users of different heuristics in treatment N (upper panel), L (middle panel) and H (lower panel).

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, 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 high intensity in this experiment, and the inertia of choice is very high or, stated differently, subjects only gradually update their strategy. 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 8 reports the average weight of each heurisitic over all the markets and periods in each treatment. When the price elasticity of supply increases from treatment N to L to H, the average weight of the strong trend (STR) heurisitic declines substantially, from 55% to 30% to less than 20%. At the same time the weight of the adaptive (ADA) rule slightly increases from 21% to 25%, while the fraction of Anchoring and Adjustment (LAA) rule increases substantially from 17% to more than 40%.

Figure E shows the time evolution of the average weight (i.e. averaged over all groups) of each heuristic in each treatment. In general, this figure confirms that on average there are more users of the strong trend rule in treatment N, and more of the LAA heuristic and adaptive heuristic 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 (small) 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.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jedc.2019.103730

References

Akiyama, E., Hanaki, N., Ishikawa, R., 2017. It is not just confusion! strategic uncertainty in an experimental asset market. Econ. J. 127 (605), F563–F580.
Anufriev, M., Hommes, C., 2012a. Evolution of market heuristics. Knowl. Eng. Rev. 27 (2), 255–271.
Anufriev, M., Hommes, C., 2012b. Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments. Am. Econ. J. Microecon. 4 (4), 35–64.
Anufriev, M., Hommes, C., Makarewicz, 2017. Simple forecasting heuristics that make us smart. evidence from different market experiments. CeNDEF Working Paper, University of Amsterdam,.
Arifovic, J., Duffy, J., 2018. Heterogeneous agent modeling: experimental evidence. In: Handbook of Computational Economics Vol. 4. Elsevier, pp. 491–540.
Asparouhova, E., Bossaerts, P., Tran, A., 2016. Market Bubbles and Crashes as an Expression of Tension Between Social and Individual Rationality. University of Utah, Mimeo.
Assenza, T., Bao, T., Hommes, C., Massaro, D., 2014a. Experiments on expectations in macroeconomics and finance. Exper. Macroecon. Res. Exper. Econ. 17, 11–70.
Assenza, T., Heemeijer, P., Hommes, C., Massaro, D., 2014b. Managing Self-Organization of Expectations Through Monetary Policy: A Macro Experiment. University of Amsterdam, CeNDEF Working Paper.
Bao, T., Duffy, J., Hommes, C., 2013. Learning, forecasting and optimizing: An experimental study. Eur. Econ. Rev. 61, 186–204.
Bao, T., Hommes, C., Sonnemans, J., Tuinstra, J., 2012. Individual expectations, limited rationality and aggregate outcomes. J. Econ. Dyn. Control 36 (8), 1101–1120.
Bao, T., Hommes, C.H., Makarewicz, T., 2017. Bubble formation and (in)efficient markets in learning-to-forecast and -optimise experiments. Econ. J. 127 (605), F581–F609.
Bao, T., Zong, J., 2019. The impact of interest rate policy on individual expectations and asset bubbles in experimental markets. J. Econ. Dyn. Control. forthcoming.
Bolt, W., Demertzis, M., Diks, C., van der Leij, M., 2016. Identifying booms and busts in house prices under heterogeneous expectations. CeNDEF Working paper, University of Amsterdam.
Brock, W.A., Hommes, C.H., 1997. A rational route to randomness. Econometrica 65, 1059–1095.
Campbell, J.Y., Lo, A.W., Mickinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton University Press.
Case, K.E., Shiller, R.J., Thompson, A.K., Laibson, D., Willen, P., 2012. What have they been thinking? homebuyer behavior in hot and cold markets. Brook. Pap. Econ. Act. 2012, 265–315. Fall
Cheng, I.-H., Raina, S., Xiong, W., 2014. Wall street and the housing bubble. Am. Econ. Rev. 104 (9), 2797–2829.
Clayton, J., 1997. Are housing price cycles driven by irrational expectations? J. Real Estate Finance Econ. 14 (3), 341–363.
Cuthbertson, K., Nitzsche, D., 2005. Quantitative Financial Economics: Stocks, Bonds and Foreign Exchange. John Wiley and Sons.
Dieci, R., Schmitt, N., Westerhoff, F., 2017. Interactions Between Stock, Bond and Housing Markets. Working paper. University of Bamberg.
Dieci, R., Westerhoff, F., 2012. A simple model of the speculative housing market. J. Evolut. Econ. 22, 303–329.
Dieci, R., Westerhoff, F., 2013. Modeling house price dynamics with heterogeneous speculators. In: Global Analysis of Dynamic Models in Economics and Finance. Springer, Berlin Heidelberg, pp. 35–61.
Dieci, R., Westerhoff, F., 2016. Heterogeneous expectations, boom-bust housing cycles, and supply conditions: a nonlinear economic dynamics approach. J. Econ. Dyn. Control 71, 21–44.
Diks, C., Van Der Weide, R., 2005. Herding, a-synchronous updating and heterogeneity in memory in a CBS. J. Econ. Dyn. Control 29 (4), 741–763.
Duffy, J., 2008. Macroeconomics: a survey of laboratory research. Handb. Exper. Econ. 2.
Duffy, J., Nagel, R., 1997. On the robustness of behaviour in experimental beauty contest games. Econ. J. 107 (445), 1684–1700.
Eichholtz, P.M.A., Huisman, R., Zwinkels, R.C.J., 2015. Fundamentals or trends? a long-term perspective on house prices. Appl. Econ. 47 (2015), 1050–1059.
Fehr, E., Tyran, J.R., 2001. Does money illusion matter? Am. Econ. Rev. 91 (5), 1239–1262.
Fehr, E., Tyran, J.R., 2005. Individual irrationality and aggregate outcomes. J. Econ. Perspect. 19 (4), 43–66.
Fehr, E., Tyran, J.R., 2008. Limited rationality and strategic interaction: the impact of the strategic environment on nominal inertia. Econometrica 76 (2), 353–394.
Gjerstad, S.D., Smith, V.L., 2014. Rethinking Housing Bubbles. The Role of Household and Bank Balance Sheets in Modeling Economic Cycles. Cambridge University Press.
Glaeser, E.L., Gyouko, J., Saiz, A., 2008. Housing supply and housing bubbles. J. Urban Econ. 64, 198–217.
Glaeser, E. L., Nathanson, C.G., 2015. Housing bubbles. In: Handbook of regional and urban economics, Vol. 5. Elsevier, pp. 701–751.
Hanaki, N., Akiyama, E., Funaki, Y., Ishikawa, R., 2017. Diversity in cognitive ability enlarges mispricing in experimental asset markets, GREDEG Working Paper, University Cote d'Azur, WP No. 2017-08.

Heemeijer, P., Hommes, C., Sonnemans, J., Tuinstra, J., 2009. Price stability and volatility in markets with positive and negative expectations feedback: an experimental investigation. J. Econ. Dyn. Control. 33 (5), 1052–1072.
Hennequin, M., Hommes, C.H., 2018. Managing coordination on bubbles in experimental asset markets with monetary policy. mimeo. Available at: https://cendefone.feb.uva.nl/~mhenn/live/HennequinHommes2018.pdf.
Hirota, S., Suzuki-Loffelholz, K., Udagawa, D., 2015. When Owners Buy Higher, they Offer Higher Rents: Experimental Evidence. Waseda University, Working paper.
Hommes, C., 2013. Reflexivity, expectations feedback and almost self-fulfilling equilibria: economic theory, empirical evidence and laboratory experiments. J. Econ. Methodol. 20 (4), 406–419.
Hommes, C., Huang, H., Wang, D., 2005. A robust rational route to randomness in a simple asset pricing model. J. Econ. Dyn. Control. 29 (6), 1043–1072.
Hommes, C., Sonnemans, J., Tuinstra, J., Van de Velden, H., 2005. Coordination of expectations in asset pricing experiments. Rev. Finan. Stud. 18 (3), 955–980.
Hommes, C., Sonnemans, J., Tuinstra, J., Van De Velden, H., 2007. Learning in cobweb experiments. Macroecon. Dyn. 11 (S1), 8–33.
Hommes, C., Sonnemans, J., Tuinstra, J., Van de Velden, H., 2008. Expectations and bubbles in asset pricing experiments. J. Econ. Behav. Organ. 67 (1), 116–133.
Huber, S. J., Rott, C., Giusti, G., 2016. Preference for housing services and house price bubble occurrence evidence from a macro-experiment, Working paper.
de Jong, J., Sonnemans, J., Tuinstra, J., 2019. The effect of futures markets on the stability of commodity prices. CeNDEF Working Paper.
Mankiw, N.G., Weil, D.N., 1989. The baby boom, the baby bust, and the housing market. Reg. Sci. Urban Econ. 19 (2), 235–258.
Mauersberger, F., 2019. Monetary policy rules in a non-rational world: A macroeconomic experiment. SSRN Working Paper, Available at SSRN 3060341: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3060341.
Mauersberger, F., Nagel, R., 2018. Levels of reasoning in Keynesian beauty contests: a generative framework. In: Handbook of Computational Economics, Vol. 4. Elsevier, pp. 541–634.
Nagel, R., 1995. Unraveling in guessing games: an experimental study. Am. Econ. Rev. 85 (5), 1313–1326.
Paciorek, A., 2013. Supply constraints and housing market dynamics. J. Urban Econ. 77, 11–26.
Petersen, L., 2012. Nonneutrality of Money, Preferences and Expectations in Laboratory new Keynesian Economies. University of California, Santa Cruz. SIGFIRM, Working paper.
Saiz, A., 2008. On local housing supply elasticity. University of Pennsylvania, The Wharton School, Working paper.
Shiller, R. J., 2007. Understanding recent trends in house prices and home ownership. NBER National Bureau of Economic Research, Chicago, Working paper 13553.
Smith, V.L., 1962. An experimental study of competitive market behavior. J. Pol. Econ. 70 (111), 1–77.
Smith, V.L., Suchanek, G.L., Williams, A.W., 1988. Bubbles, crashes and endogenous expectations in experimental spot asset markets. Econometrica 56, 1119–1151.
Sonnemans, J., Tuinstra, J., 2010. Positive expectations feedback experiments and number guessing games as models of financial markets. J. Econ. Psychol. 31 (6), 964–984.
Soros, G., 2003. The Alchemy of Finance. John Wiley and Sons.
Stephens, T., 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.
Stöckl, T., Huber, J., Kirchler, M., 2010. Bubble measures in experimental asset markets. Exper. Econ. 13 (3), 284–298.
Sutan, A., Willinger, M., 2009. Guessing with negative feedback: an experiment. J. Econ. Dyn. Control 33, 1123–1133.
Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: Heuristics and biases. Science 185 (4157), 1124–1131.
Wheaton, W., 1999. Real estate "cycles": some fundamentals. Real Estate Econ. 27 (2), 209–230.
Zheng, M., Wang, H., Wang, C., Wang, S., 2017. Speculative behavior in a housing market: boom and bust. Econ. Model. 61, 50–64.