Long-Horizon Expectations: a lab experiment

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Outline of the presentation

1. Motivations
2. The underlying model
3. Implementation in the lab
4. Experimental Results
5. Conclusions

Motivations

Expectations, Horizons and Macro Dynamics

- Macro-finance models are micro-founded and mostly expectation-driven → **infinite horizon expectations**:

$$X_t = \mathcal{F}\left(E_t\{X_{t+\tau}\}_{\tau=1,2,3,\ldots}\right) \quad (1)$$

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- Under **rational** and **homogeneous expectations**, the reduced-form models boil down to **one-step ahead expectations**:

$$X_t = \mathcal{M}\left(E_t(X_{t+1})\right) \tag{2}$$

  This is true for asset pricing models (e.g. Lucas tree model), micro-founded growth models (e.g. the Ramsey model) and DSGE models (e.g. the NK model).

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- Under RE, the dynamics under (1) and (2) are equivalent.
- With **non-RE** and **heterogeneous expectations**, not obvious.
- But the horizon of expectations may matter for a number of macro-finance questions: e.g. fiscal policy or forward-guidance.

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  - "Infinite horizon learning" (Preston 2005): $X_t = \mathcal{F}\left(\hat{E}\{X_{t+\tau}\}_{\tau=1,\dots}\right)$
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- Most macro-finance "**learning-to-forecast**" **lab experiments** use one-step-ahead reduced form models:
  - Within cob-web model, mean-variance asset pricing models, NK model, etc. (see Hommes (2011) for a survey).
  - At longer horizons: Haruvy et al. 2007, Hirota & Sunder 2007, Hirota et al. 2015.

Main objectives of this paper

1. **Develop a theoretical framework**:
   - which is expectation-driven,
   - where we can tune the horizon of expectations,
   - which is rich enough to allow for heterogeneous expectations, and different, co-existing forecast horizons,
   - but simple enough to be implemented in a laboratory experiment with human subjects.

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2. Obtain **theoretical predictions** on the market behavior under different configurations of expectation horizons;
3. Use the lab experiment to provide an **empirical test** of those theoretical predictions:

   Q1 : Can participants' predictions and the price converge to the fundamental value?

   Q2 : If so, how does it depend on the horizon of expectations?

   Q3 : How does heterogeneity in expectations and horizons affect the price dynamics?

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- Each agent maximizes her discounted utility flow over an **infinite horizon**.
- **Stationary** environment.

The standard formulation of the Lucas tree model

- Formally, for each farmer i:

$$\max E_0 \sum_{t \geq 0} \beta^t u(c_{i,t})$$

$$c_{i,t} + p_t q_{i,t} = (p_t + y_{i,t}) q_{i,t-1}, \text{ with } q_{i,-1} \text{ given.}$$

with c: egg consumption, p: price of a chicken, q: endowment of chickens, y: dividend (eggs).

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- The FOC is the standard Euler equation:

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- At the symmetric REE, there is no trade, $c^* = q^* \cdot y$ and $p^* = \frac{\beta y}{1-\beta}$.

The Lucas tree model under finite horizon learning

- With a given forecasting horizon T, for each farmer i:

$$\max E_0 \sum_{k=0}^{T} \beta^k u(c_{i,t+k})$$

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- Linearizing and iterating the FOC and T-period budget constraint, we obtain **individual demand schedules** (in deviation from steady state):

$$\begin{aligned} dq_{i,t} =& \alpha_1(\beta, T) dq_{i,t-1} - \alpha_2(\beta, T, \sigma, p^*, Q^*) dp_t \\ & + \alpha_3(\beta, T) dq_{i,t+T} + \alpha_4(\beta, T, \sigma, p^*, Q^*) \frac{\sum_{k=1}^{T} dp^e_{i,t+k}}{T} \end{aligned}$$

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with $dq_{i,t+T}$ and $dq_{i,t-1}$ given

- Market clearing ($\sum_i dq_{i,t} = 0$) gives p_t.

Dynamics under learning

- The price law of motion has **positive expectation feedback**:

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Predictions under learning:

1. The equilibrium is **stable**: the feedback parameter is always < 1.
2. The higher the **feedback parameter**, the higher **price volatility**.
3. **Increasing** the forecasting **horizon** T **is stabilizing** (the strongest feedback occurs with $T = 1$ and equals $\beta < 1$).
4. If there are two types of agents, **increasing** the proportion of **shorter-horizon forecasters** is **destabilizing**.

Near-unit root behavior and self-fulfilling expectations

With only short-horizon forecasters ($\alpha = 100\%$ and $T = 1$), the feedback parameter equals $\beta = 0.95$.

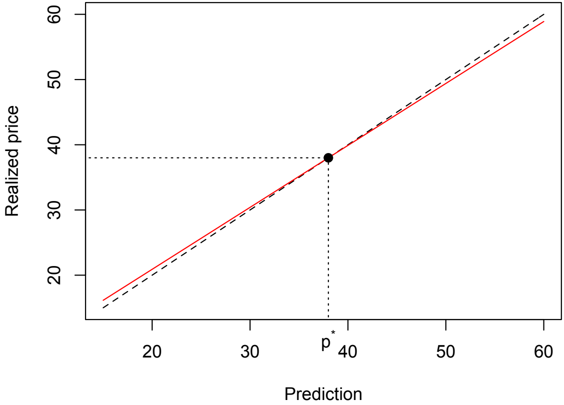

Figure: Positive feedback: $p_t - p^* = +0.95(\bar{p}_t^e - p^*)$

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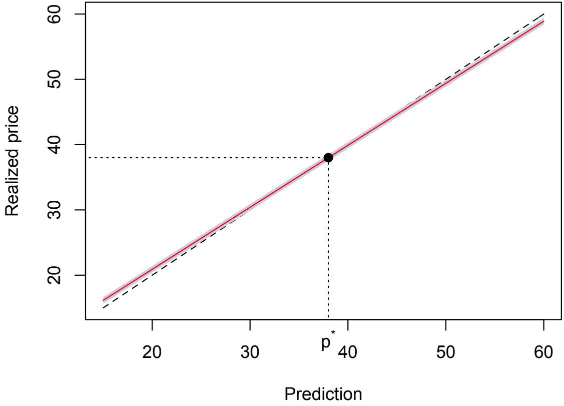

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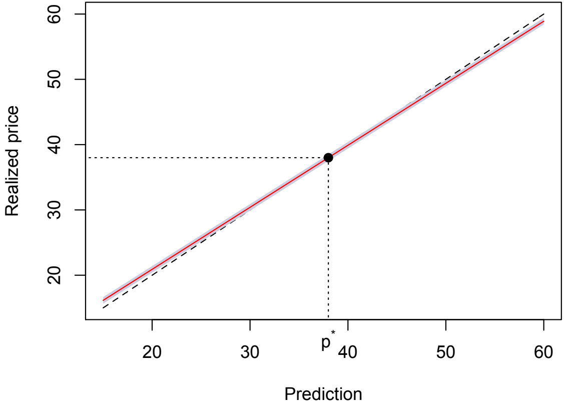

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"*Almost self-fulfilling equilibria*" may lead to price indeterminacy.

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- **Trade and price dynamics**: the motive for trade is heterogeneous price expectations, price is expectation-driven (up to a small noise process).
- No borrowing and no short selling constraints.
- **What do subjects know?**: *instructions* with the whole structure of the game, dividend, horizon, initial **individual** endowment of chickens, market clearing process, **qualitative information on the feedback, demand schedule** and consumption smoothing, pay-off, example, quiz and end questionnaire.

Challenges in the lab and specific features

- **Emulating an infinite horizon environment with discounting**: standard random termination method with a constant probability $1-\beta$ of ending the market (Roth & Murnighan 1978). In case of termination ("avian flu outbreak"), all the chickens die and become worthless.

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- The fundamental price (the dividend and the endowment of chickens) must vary between markets (minimizing the risk of learning effect, while keeping the same equilibrium consumption level).

Pay-off

- At the end of **each** market, with **equal** probability, paid on forecast accuracy **or** a linear transformation of a CRRA **utility** function:
  - To **induce consumption smoothing**, eggs are perishable (Crockett & Duffy 2013);
  - To avoid "hedging" and maintain equal incentives towards the two tasks.
  - The last rewarded forecast is rewarded T times (equal number of payments between consumption and forecasting).
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  - If the chickens die before $T+1$ periods, pay-off on utility.
- **Forecasting payoff**: $\max\left(1100 - \frac{1100}{49}(\text{forecast error})^2, 0\right)$
- **Consumption payoff**: $250 \cdot \ln(c)$ $(\sigma = 1,\ c \geq 1)$

Timing of events

... → **Subjects are asked to forecast the average future price over periods $[t+1, t+T]$.** ($t+\frac{0}{4}$) → **Compute individual demand schedule q_i.** ($t+\frac{1}{4}$) → **Solve for market clearing price : $\sum_i dq_i = 0$** ($t+\frac{2}{4}$) → ...

... → **Compute individual traded chickens, egg consumption and utility level.** ($t+\frac{3}{4}$) → **Subjects are asked to forecast the average future price over periods $[t+2, t+1+T]$.** ($t+1$) → ...

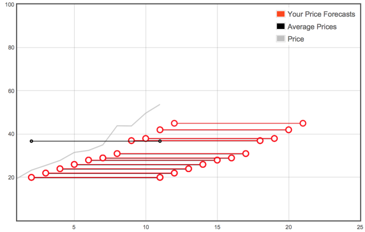
Example of the computer interface

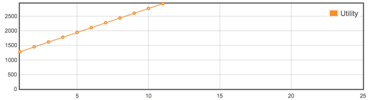
Long-horizon forecasters

You are player Player-0

You have got 121789 chicken(s). In each period, a chicken produces 1 egg(s).

Plots





Information table

Period	Price	Average price	Your Forecast	Fore-casting Points	Traded chickens	Nb. of chickens	Consump-tion	Utility Points
21			45.00					
20			42.00					
19			38.00					
18			37.00					
17			31.00					
16			29.00					
15			28.00					
14			26.00					
13			24.00					
12			22.00					
11	53.83	36.76	20.00	0	58706	121789	121789	2928
10	49.77				30409	63083	63083	2763
9	43.84				15751	32674	32674	2599
8	43.92				8159	16923	16923	2434
7	35.13				4227	8764	8764	2270
6	32.56				2189	4537	4537	2105
5	31.61				1134	2348	2348	1940
4	27.92				588	1214	1214	1775
3	25.63				304	626	626	1610
2	23.42				158	322	322	1443
1	19.61				82	164	164	1275

Player Actions

You are now at the beginning of period 12.

Enter your forecast of the average price between period 13 and period 22.

Submit

Player Information

Your total payoff so far in the experiment is: 58365 points.

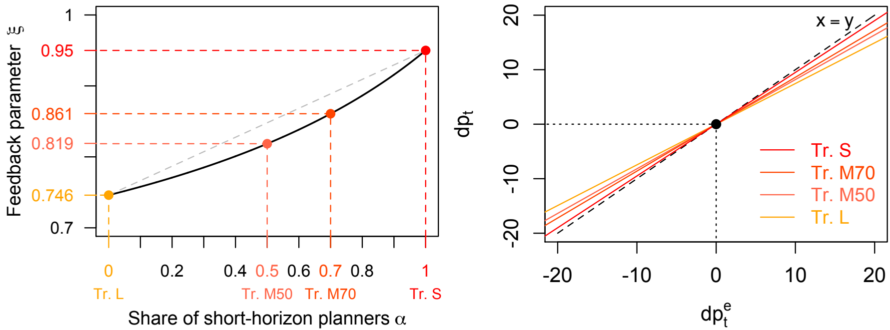
Please submit your forecast.

The four experimental treatments

Horizons and expectation feedback

	Treatments			
	Tr. `L`	Tr. `M50`	Tr. `M70`	Tr. `S`
Share α (and number of forecasters) with horizon $T = 1$	0	0.5 (5 subjects)	0.7 (7 subjects)	1 (10 subjects)
Share $1 - \alpha$ (and number of forecasters) with horizon $T = 10$	1 (10 subjects)	0.5 (5 subjects)	0.3 (3 subjects)	0

The four experimental treatments
Horizons and expectation feedback



(a) Feedback parameter (b) Expectation dynamics

The four experimental treatments

Hypotheses

1. Participants' predictions and the price converge towards the fundamental value in all treatments (E-stability).
2. Increasing the share of long-horizon forecasters fosters convergence.
3. Increasing the share of long-horizon planners reduces price volatility.
4. Participants coordinate their predictions. As a consequence, trade is eliminated (corollary).

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3. Increasing the share of long-horizon planners reduces price volatility.
4. Participants coordinate their predictions. As a consequence, trade is eliminated (corollary).
5. One period-ahead predictions are more homogeneous than long-horizon predictions (survey data).
6. Increasing the share of long-horizon forecasters increases trade volume (corollary).
7. The distance to fundamental value is decreasing with the number of the market (previous experimental works).

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3. Emulation of an **infinite** horizon (random termination) and **stationary** environment (with repetition of markets during a given period of recruitment);
4. **Payoff** function with subjects' payment depending on *both* utility and forecasting (economic/trading decisions resulting from the subjects' forecasts count towards their earnings).

Implementation

- **Software**: Programmed using the Java-based PET software.

Implementation

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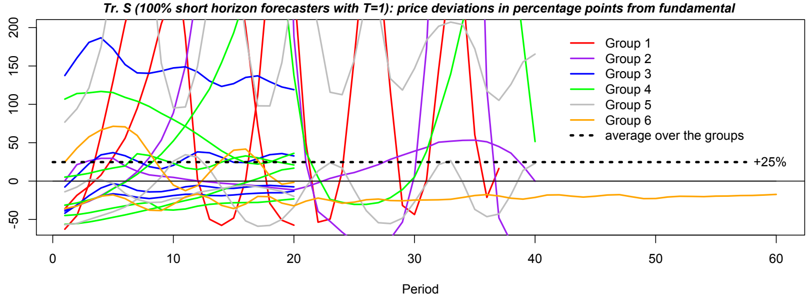
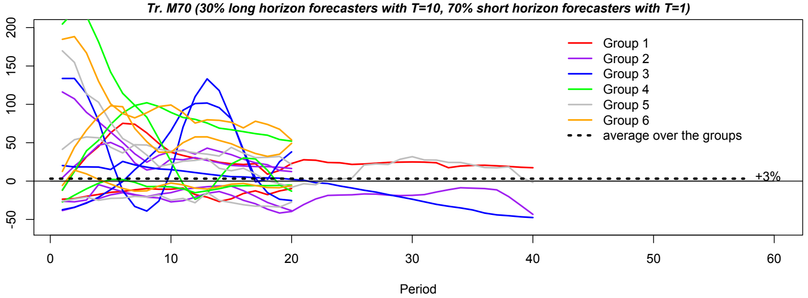
- **Further information**: 4 treatments, 6 groups of 10 subjects each, i.e. **240 subjects**, for a total of 63 markets, ranging from 20 to 60 periods. Most sessions lasted for less than two hours. The average earnings per participant amount to **22.9 euros** (ranging from 10.8 to 36.6 euros).

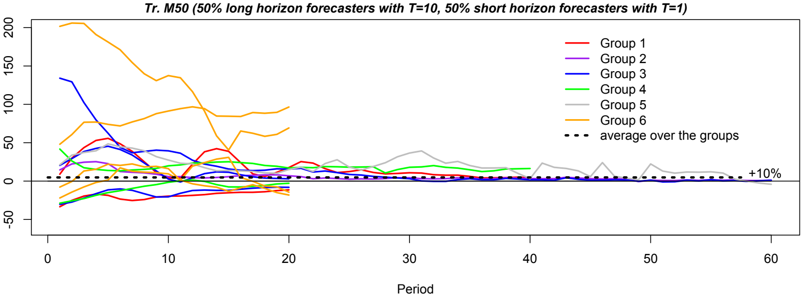
Overview of Tr. S: 100% of $T = 1$



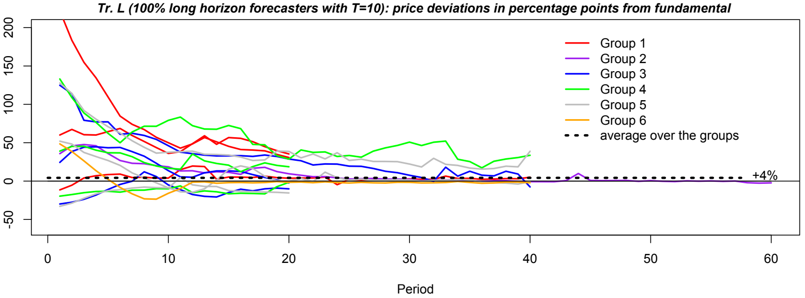
Overview of Tr. M70: 70% of $T = 1$, 30% of $T = 10$



Overview of Tr. M50: 50% of $T = 1$, 50% of $T = 10$



Overview of Tr. L: 100% of $T = 10$



Cross-treatment comparisons

	Diff-diff treatments					
	L-S	*L-M70*	*L-M50*	*M70-S*	*M50-S*	*M50-M70*
Price deviation	**-0.564**	**-0.111**	0.012	**-0.453**	**-0.576**	**-0.123**
(p-value)	(0.000)	(0.000)	(0.205)	(0.000)	(0.000)	(0.000)
Trade volume	0.001	0.001	**0.002**	**0.001**	**-0.001**	**-0.000**
(p-value)	(0.071)	(0.817)	(0.000)	(0.001)	(0.000)	(0.012)
Price volatility	**-2.12**	**-0.111**	-0.029	**-2.013**	**-2.094**	**-0.082**
(p-value)	(0.000)	(0.000)	(0.315)	(0.000)	(0.000)	(0.000)
Forecast dispersion	**0.149**	0.072	0.108	**0.077**	0.04	-0.037
(p-value)	(0.028)	(0.555)	(0.063)	(0.009)	(0.565)	(0.061)
EER (forecasts)	-0.071	-0.026	-0.083	-0.045	0.012	0.057
(p-value)	(0.231)	(0.924)	(0.452)	(0.304)	(0.5)	(0.622)
EER (utility)	0.01	-0.003	0.002	0.013	0.008	-0.01
(p-value)	(0.984)	(0.492)	(0.614)	(0.663)	(0.754)	(0.414)

Cross-treatment comparisons: bottom lines

Increasing the share of **long-horizon** forecasters strongly and significantly improves **convergence** of the price level towards the fundamental value and **decreases its volatility**. A modest share of long-horizon forecasters (less than half of the market) is enough to trigger stabilization and convergence.

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There is weak evidence that increasing the share of **short-horizon** forecasters improves the **coordination** of individual forecasts and **decreases trade**.

Earnings efficiency ratios are not significantly different across treatments, neither on utility nor on forecasting.

Collecting evidence of convergence for each market

For each treatment, estimate:

$$\frac{p_{g,m,t} - p_{g,m}}{p_{g,m}} = \frac{1}{t}\sum_{g=1}^{6}\sum_{m\in\Omega_{M_g}} D_{g,m} b_{1,g,m} + \frac{t-1}{t}\sum_{g=1}^{6}\sum_{m\in\Omega_{M_g}} D_{g,m} b_{2,g,m},$$

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$\rightarrow$ If $\hat{b}_{1,ij,} > \hat{b}_{2,ij,}$ (significantly), **weak convergence of market** j **of Group** i to the fundamental price.

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→ If $\hat{b}_{1,ij,} > \hat{b}_{2,ij,}$ (significantly), **weak convergence of market** j **of Group** i to the fundamental price.

→ If $\hat{b}_{2,ij,}$ not sign. different from zero, **strong convergence of market** j **of Group** i to the fundamental price.

Collecting evidence of convergence for each market

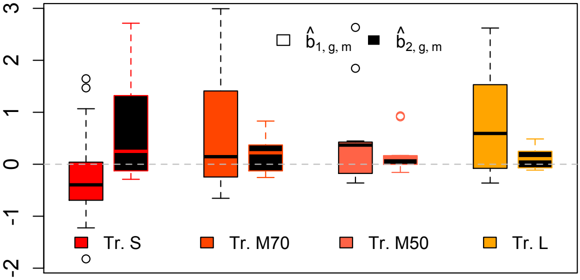

Figure: Coefficients $\hat{b}_{1,i,j}$ (initial estimated deviation from fundamental) and $\hat{b}_{2,i,j}$ (final estimated deviation from fundamental) per treatment.

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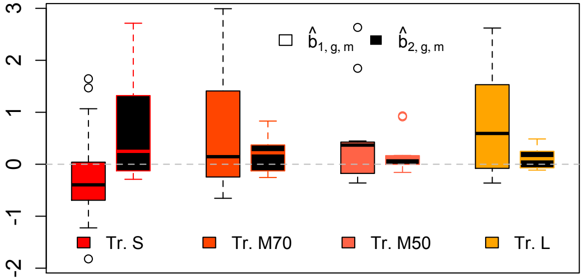

Figure: Coefficients $\hat{b}_{1,i,j}$ (initial estimated deviation from fundamental) and $\hat{b}_{2,i,j}$ (final estimated deviation from fundamental) per treatment.

Clear decrease in the estimated distance of the price to fundamental in Tr. `M70`, `M50` and `L`, not for Tr. `S`.

Collecting evidence of convergence for each market

	Market level	
	Weak convergence: $\mid \hat{b}_{1,g,m} \mid > \mid \hat{b}_{2,g,m} \mid$	Strong convergence: $\mid \hat{b}_{2,g,m} \mid = 0$
Tr. S	$7/18 \simeq 39\%$	$3/18 \simeq 17\%$
Tr M70	$11/18 \simeq 61\%$	$2/18 \simeq 11\%$
Tr. M50	$10/13 \simeq 77\%$	$3/13 \simeq 23\%$
Tr. L	$13/14 \simeq 93\%$	$4/14 \simeq 29\%$

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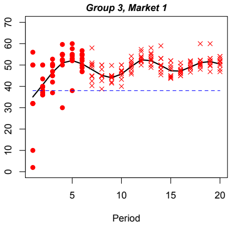
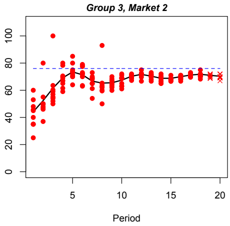
All markets exhibit weak convergence in Tr. `L`, most of them in Tr. `M50`, while the lowest share of convergence is obtained in Tr. `S`.

Does a wrong anchor drive convergence failures?

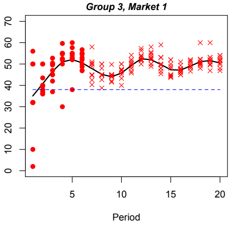


(a) Tr. S, Gp. 3, M. 1

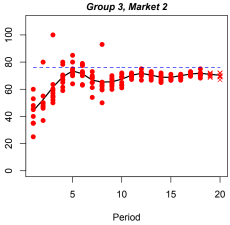


(b) Tr. S, Gp. 3, M. 2

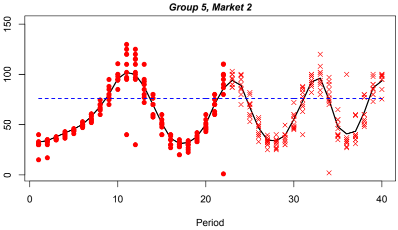
Does a wrong anchor drive convergence failures?



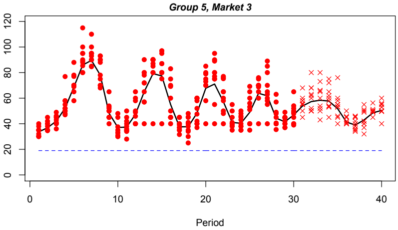
(e) Tr. S, Gp. 3, M. 1



(f) Tr. S, Gp. 3, M. 2



(g) Tr. S, Gp. 5, M. 2



(h) Tr. S, Gp. 5, M. 3

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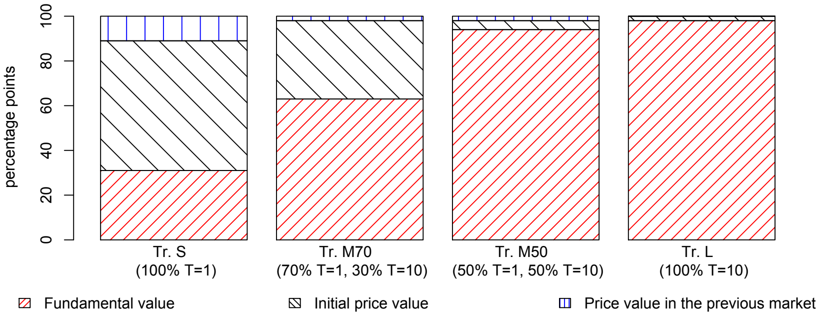

Figure: Analysis of variance of $\{\hat{b}_2\}_{i,m}$

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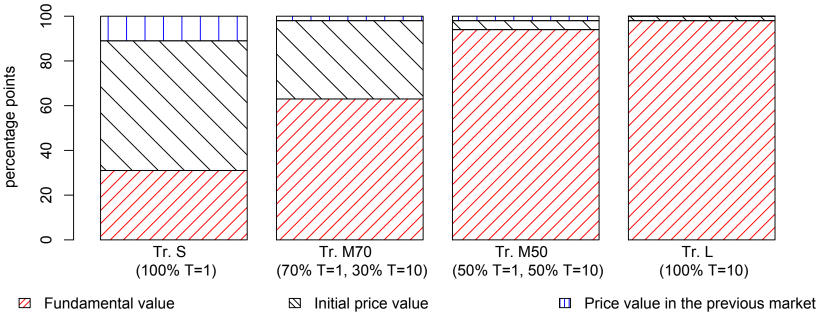

Figure: Analysis of variance of $\{\hat{b}_2\}_{i,m}$

With enough long-horizon forecasters, the asymptotic market price is driven by **fundamentals** only, while it becomes partly driven by **non-fundamental factors, namely past observed price levels**, when short-horizon forecasters dominate.

From micro to macro

- LtFEs: "*clean*" data on expectations, in a **fully controlled** environment, where
  - the available **information**,
  - the participants' incentives,
  - and the underlying **structure** of the economy

  are perfectly known.

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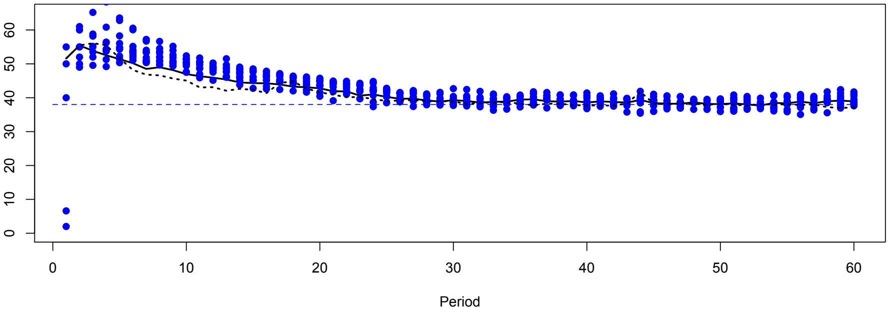
- Explaining the aggregate picture by looking at individual forecasting behaviors: estimating individual forecasting models.

Fitting the experiments: illustrations

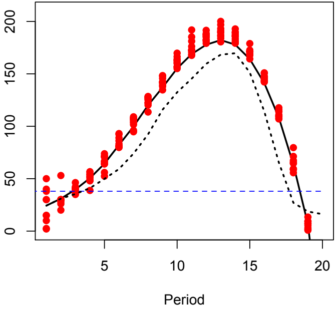


(a) 100% $T = 10$ adaptive ($\delta = 0.1$) vs. Gp. 2, M1, Tr. L

Figure: Simulated vs. experimental data

NB: the dotted line is the price in the experiment, the dots are the individual simulated forecasts and the black line is the resulting simulated price.

Fitting the experiments: illustrations



(d) 100% $T = 1$ with trend-extrapolation ($\gamma = 1.3$) vs. Gp. 1, M1, Tr. $\mathbb{S}$

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Estimation of individual forecasting models

$$P^e_{j,t} - P^* = \beta_0 + \beta_1(P_{t-1} - P^*) + \beta_2(P_{t-2} - P^*) + \delta_1(P^e_{i,t-1} - P^*)$$

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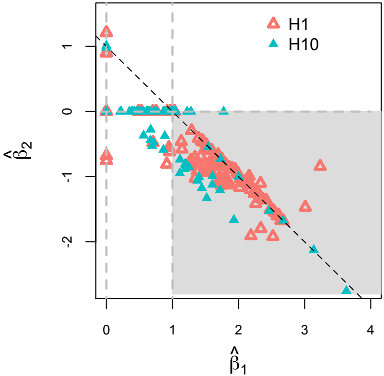

(a) Trend-chasing behavior in short-horizon forecasts

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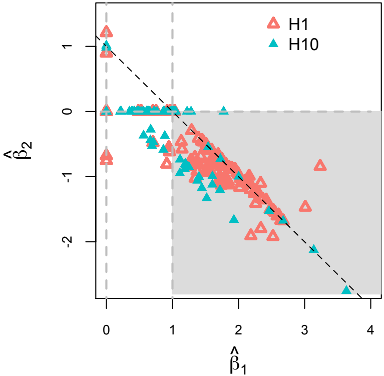

(a) Trend-chasing behavior in short-horizon forecasts

→ For more than half of the short-horizon forecasters:
$P^e_{j,t} \simeq P_{t-1} + (\beta_1 - 1) \cdot (P_{t-1} - P_{t-2})$.

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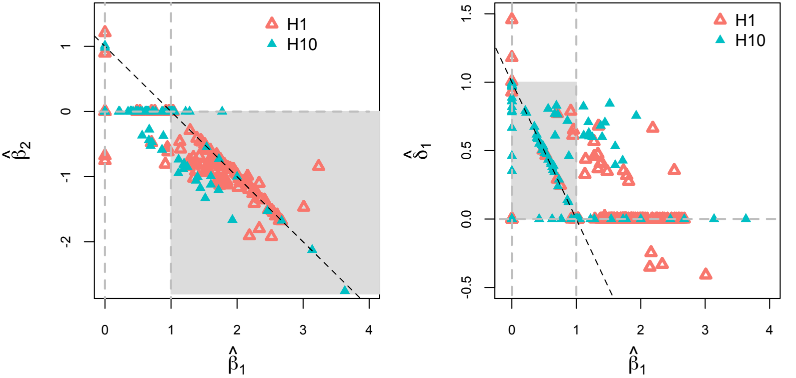

(a) Trend-chasing behavior in short-horizon forecasts

(b) Adaptive learning in long-horizon forecasts

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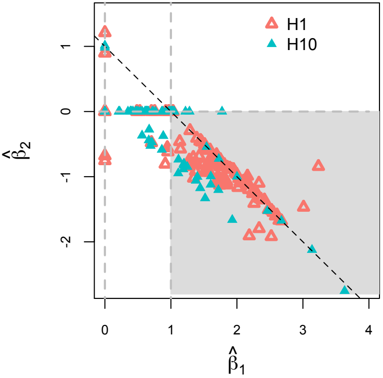

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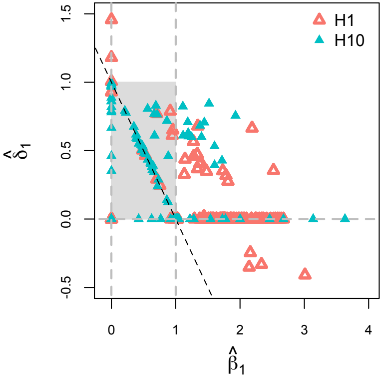

(b) Adaptive learning in long-horizon forecasts

→ For more than a third of the long-horizon forecasters, $P^e_{j,t} \simeq \beta_1 P_{t-1} + (1 - \beta_1) \cdot P^e_{j,t-1}$.

Conclusions

Coming back to our hypotheses, in our model:

1. The horizon of the forecasts matters for price dynamics.
2. A small share of long horizon forecasters induces convergence.
3. Short-horizon markets are prone to excess volatility due to coordination on wrong anchors (trend-chasing behaviors). Long-horizon markets exhibit adaptive convergent dynamics.
4. Short-horizon forecasts are more homogeneous, trade is more frequent under long-horizon forecasting.

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4. Short-horizon forecasts are more homogeneous, trade is more frequent under long-horizon forecasting.
5. One period-ahead predictions are more homogeneous than long-horizon predictions.
6. There is (weakly) significantly more trade with a higher share of long-horizon forecasters.
7. In unstable treatments, participants tend to reproduce past price patterns, repetition does not help convergence.

Opening remarks

- Under learning and heterogeneous expectations, **the horizon of expectations matters**. Learning dynamics predict well the behaviors of markets with long-horizon expectations (even a small share of them). This is not the case with short-horizon expectation markets that can be prone to price indeterminacy.

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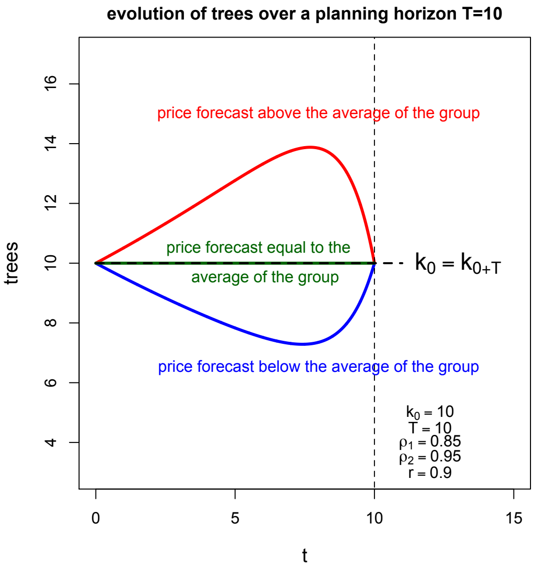
  Heterogeneity of beliefs may be beneficial.
- The underlying model is simple. Would this result survive in a multi-dimensional system?
- **Trading is computerized** given the forecasts. Would this result survive if participants had to "learn-to-optimize"?

Thank you for your attention

Questions welcome

Intuition on the dynamics of wealth

under the assumption of naive expectations of the final period wealth



back