Learning in a Complex World Insights from an OLG lab experiment

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EEA 2022 30 August 2023



Mode

- 3 Theoretical analysis
- 4 Experimental Protocol
- 5 Main results
- 6 Explanation of the results

- Many macro models have multiple equilibria
 indeterminacy under rational expectations
- Need for equilibrium selection devices
 - theory **x**
 - theoretical selection criteria like learning x any equilibrium can be learnt under an appropriately designed mechanism
 - $\circ~$ laboratory experiments might offer a solution $\checkmark~$
- Additional advantage of lab experiments: accounting for heterogeneity

Which equilibria are empirically relevant in complex/non-linear environments?

- Learning-to-forecast (Ltf) + learning-to-optimize (LtO) Experiments
- Model with multiple equilibria (Araujo et al., 2000)
- Goal: study equilibria selection
- Preview of the results:
 - Convergence to the simplest equilibria in both LtF and LtO
 - Non-monotonicity as complexity increases, both in LtF and LtO, both at the individual and aggregate levels
 - LtO: less efficient behavior, many non-optimal savings decisions

- Indeterminacy and adaptive learning (homogeneous beliefs): Grandmont(1985), Grandmont and Laroque (1986), Woodford (1990), Guesnerie and Woodford (1991), Evans and Honkapohja (1995a,b)
- Indeterminacy and GA learning (heterogeneous beliefs): Dawid (1996), Bullard and Duffy (1998), Arifovic (1998)
- Experimental evidence: Marimon and Sunder (1993), Marimon, Spear and Sunder (1993), Van Huyck, Cook and Battalio (1994), Arifovic et al. (2019)

Arifovic et al. 2019. Model Arifovic et al. 2019. Results

- Extending work by Arifovic et al. (2019)
- Exploring parameter values in the chaotic region / behavior in a more complex and non-linear environment
- LtOE:
 - o 2 tasks: forecast return and make savings decisions
 - 2-cycle Pareto dominates the steady state in terms of payoff
- Online experiment
- Group size increased to 7 (to incorporate potential dropouts)



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OLG economy à la Araujo et al. (2000, ET) General features

• OLG structure: Households live for 2 periods (young, old)

Household Choices

- Choosing hours worked n_{i,t} and consumption when old c_{i,t+1}
- Selling production *y_{i,t}* and saving (by money transfers)

Simplifying Assumptions

- Linear production function $y_{i,t} = n_{i,t}$
- Constant money supply M > 0

OLG economy à la Araujo et al. (2000, ET)

Behavioural and equilibrium equations

Maximizing expected lifetime utility

$$U(c_{t+1}, y_t) = \lambda c_{t+1} - \frac{\lambda}{2} c_{t+1}^2 - y_t$$
(1)

subject to

$$\begin{cases} P_{t+1}^{e} c_{t+1} & \leq P_{t} y_{t} \\ y_{t} & \leq \frac{M}{P_{t}} \end{cases}$$

• Model parameter λ of interest

OLG economy à la Araujo et al. (2000, ET)

Working/consumption decision depends on expected price (FOC):

$$\lambda \frac{P_t}{P_{t+1}^e} - \lambda (\frac{P_t}{P_{t+1}^e})^2 y_t - 1 = 0$$
⁽²⁾

• FOC + Money market equilibrium:

$$\lambda \frac{M/y_t}{M/y_{t+1}} - \lambda (\frac{M/y_t}{M/y_{t+1}})^2 y_t - 1 = 0$$
(3)

$$y_t = \lambda y_{t+1} (1 - y_{t+1})$$
 (4)

Solution for individual output (y_{i,t}):

$$y_{i,t} = P_{i,t+1}^{e} y_t (\lambda M - P_{i,t+1}^{e} y_t)$$
 (5)

• Complex, non-monotonic feedback of forecasts

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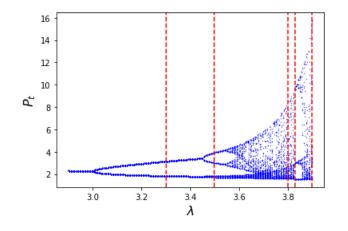


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Dynamics under perfect foresight/naive expectations Bifurcation diagram of the price map $f_{\lambda}(p) = \frac{1}{\lambda}p^2/(p-M)$, $p_0 = 1.55$, M = 1.5



Theoretical selection criteria

 \rightarrow *Perfect foresight*: cycles and chaotic behaviour

RQ 1

Can subjects coordinate on an equilibrium of a complex model in the lab? If yes, which equilibria are more likely be selected?

RQ 2

Which forecasting strategies are used most often?

RQ 3

Will the learning-to-optimize design yield the same results?



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Procedure and Subject Pool

- Subjects: undergraduate students; CREED lab at UvA (average age: 21.7; 52.5% women and 47.5% men)
- LtFE: 20 sessions with 7 participants each, total of 140 participants
- LtO: 16 sessions with 6/7 participants each, total of 108 participants
- Duration: 2 hours (LtFE)/ 2.5 hours (LtO), a session consists of 100 rounds
- Average payoff: 27 euro (including 5 euro participation fee)

The learning-to-forecast Experiment (LtFE)

- Task of subjects: N = 7 subjects have one task; act as private forecasters advising young individuals in work/leisure decision.
- Prediction: price level of next period (2-period ahead forecast)
- Available information in period t: price levels, own forecasts, forecast errors, and payoffs (up to period t 1).
- Consumption/leisure decision: market clearing in *t* given price forecasts for *t*+1 → consistent with micro-foundations.
- Timeline of Experiment Timeline

Learning-to-optimize Experiment (LtOE)

- Tasks of subjects: N = 7 subjects have two tasks; make private forecasts on saving return and take saving decision.
 - predict return on savings in the current period $\left(\frac{P_t}{P_{t+1}}\right)$
 - o decide on the amount of savings for the current period

Payoff/Incentives:

- Both tasks are incentivized
- Forecasting task: quadratic payoff function as in LtFE
- Savings task: according to utility function
- Payoff: random selection of one of the two task
- Note: 2-cycle pareto dominates steady state in terms of payoff



Mode

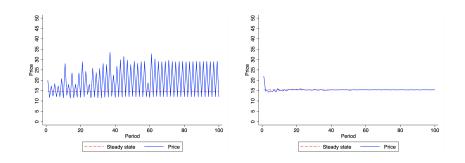
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Summary (LtFE)

- Convergence to an equilibrium in all sessions
- Only simplest equilibria are chosen (Steady State and 2-cycle)
- 2-cycles are observed in intermediate parameter range only (non-monotonicity in parameters)
- Non-monotonicity around $\lambda = 3.83$ for all indicators (convergence, coordination, time to converge, forecast errors)
- Anchoring and adjustment is the most popular forecasting strategy
- More trend-following and adaptive rules in sessions converging to the 2-cycle

Convergence (LtFE)

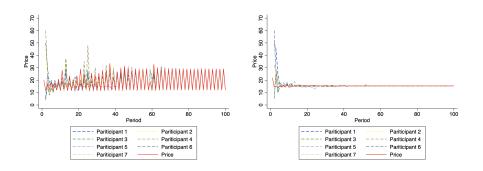
- Three sessions converged to the 2-cycle ($\lambda = 3.8, 3.83$)
- 17 session converged to steady state



all sessions

Coordination (LtFE)

- Coordination is high, and it happens fast
- It is more difficult to coordinate on the 2-cycle



all sessions

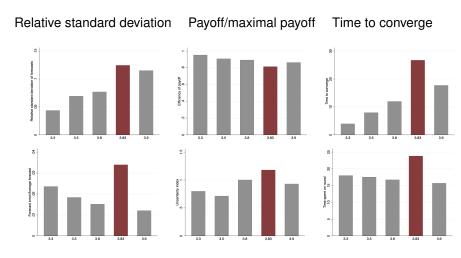
Additional Indicators (LtFE)

Non-monotonicity in all indicators

- convergence
- relative standard deviation
- payoffs
- forecast error
- uncertainty
- time spent on round
- $\bullet\,$ Significant differences between $\lambda=$ 3.83 and all other treatments

Summary statistics

Additional Indicators by Treatment (LtFE)



Forecast error

Uncertainty index

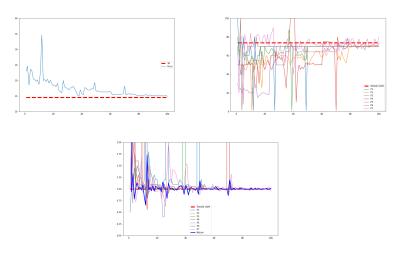
Time spent on round

- Convergence is harder to achieve, in many sessions price converges (approximately) to Steady State
- Many sub-optimal savings decisions, high variance of decisions
- Pareto dominant 2-cycles are not observed
- Return forecasts are accurate

Summary (LtOE). Graphs

Price vs SS

Savings decisions



Return forecasts All sessions

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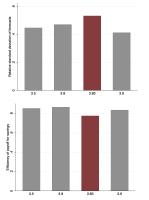
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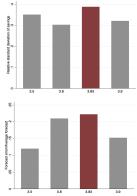
25/62

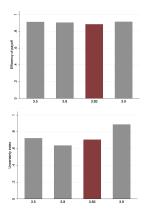
- Non-monotonicity in the following indicators
 - Relative standard deviation of savings
 - Payoffs
 - Forecast error
- $\bullet\,$ Significant differences between $\lambda=3.83$ and all other treatments

Additional Indicators by Treatment (LtO)

Relative standard deviation of forecasts of savings Payoff for forecasts /maximal payoff







Payoff for savings /maximal payoff

Forecast error

Uncertainty index

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Decision rules (LtOE)



- Most popular rule: weighted average of last two savings decisions
- More complex rules for higher λ treatments

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Why is the treatment $\lambda = 3.83$ so special?

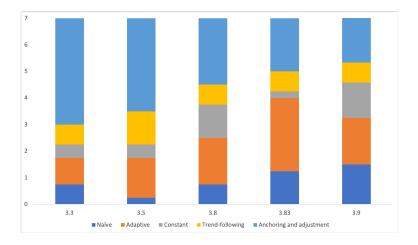
Forecasting rules (LtFE)

Do subjects use different forecasting rules across treatments?

- The following forecasting rules are estimated:
 - naive expectations: $p_{t+1}^e = p_{t-1}$
 - (2) trend-following: $p_{t+1}^e = \beta p_{t-1} + \delta(p_{t-1} p_{t-2})$
 - **③** adaptive: $p_{t+1}^e = wp_{t-1} + (1 w)p_{t-1}^e$, 0 < w ≤ 1
 - sample average: $p_{t+1}^e = \frac{1}{t-1} \sum_{j=1}^{t-1} p_j$
 - So anchoring and adjustment heuristic: $p_{t+1}^e = \beta_1 p_{t-1} + \beta_2 p_t^e + \alpha + \gamma (p_{t-1} - p_{t-2}) + \varepsilon_t$

Notes: Rule is chosen based on nested model comparison (for each subject).

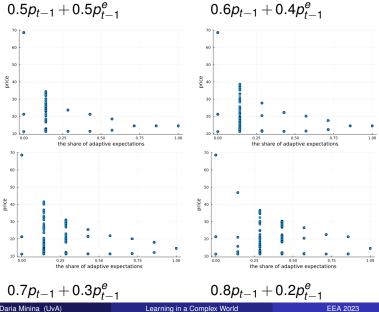
Distribution of Forecasting rules (LtFE)



More adaptive forecasts in sessions in the region with 2-cycles

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Adaptive expectations result in 2-cycles



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- LtfE and LtOE based on OLG model by Araujo et al.(2000)
- **Goal:** explore equilibrium selection and coordination in highly complex environments
- Results:
 - LtFE and LtOE: behavior is non-monotonic function of model parameters
 - LtFE: price converges to the simplest equilibria in every session (Steady State or 2-cycle)
 - LtOE: only approximate convergence of price, many non-optimal savings decisions
 - LtOE: 2-cycle not observed, although it Pareto dominated the steady state in terms of payoff

Thank you for your attention.

Arifovic et al. 2019 model

back

• The representative agent born in period *t* maximizes:

$$U = \frac{c_t(t)^{1-\rho_1}}{1-\rho_1} + \frac{c_t(t+1)^{1-\rho_2}}{1-\rho_2}$$
(6)

subject to:

$$egin{cases} c_t(t) &\leq e_1-s_t(t)\ c_t(t+1) &\leq e_2+rac{P(t)}{P(t+1)}s_t(t) \end{cases}$$

(7)

Arifovic et al. 2019 model

back

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(7)

• Savings/consumption decision depends on *expected price* (FOC):

$$c_t(t) + c_t(t)^{(\rho_1/\rho_2)} \frac{P_t^e(t+1)}{P(t)}^{[(\rho_2-1)/\rho_2]} = e_1 + e_2 \frac{P_t^e(t+1)}{P(t)}$$
(8)

Arifovic et al. 2019 model

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(8)

• Money market equilibrium: $S(t) = \frac{M}{P(t)}$ and $S(t+1) = \frac{M}{P(t+1)}$.

back

- **Finding 1**: In all LtF experimental economies, the price converged towards a perfect-foresight equilibrium.
- **Finding 2**: In all LtF experimental economies, the price converged towards either the monetary steady state or the 2-cycle.
- **Finding 3**: In the LtOE, the monetary steady state is the only selected perfect-foresight equilibrium.

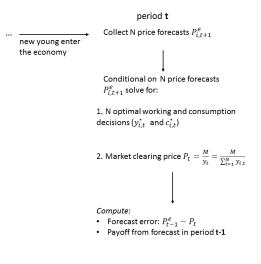
Stability

	Forward	Backward	r		
Treatment			Strong	Weak	Adaptive
Stability concept	perfect	perfect	E-stability	E-stability	Expectations
	foresight	foresight	,		
	Grandmo	ont (1985)		s and	Guesnerie and
	Granunic	JIII (1903)	Honkapol	hja (2001)	Woodford (1991)
$\lambda = 2.9$	None	SS	SS	SS	SS
				SS	SS
$\lambda = 3.3$	SS	2-cycle	2-cycle		
			-	2-cycle	2-cycle
				SS	SS
	ss				
$\lambda = 3.5$		4-cycle	4-cycle	2-cycle	2-cycle
<i>n</i> = 0.0	2-cycle		. 0,00	2 0)0.0	2 0,010
	2 Cyclc			4-cycle	4-cycle
				4 Cycle	SS
	SS				33
	33			SS	
				55	2-cycle
$\lambda = 3.8$	All cycles	none	none		
	except			2-cycle	All cycles
	period 3				except period 3
					(if w is low enough)
					SS
	SS			SS	
	55			55	2-cycle
$\lambda = 3.83$	All cycles	3-cycle	3-cycle	2-cycle	3-cycle
	except				,
	period 3			3-cycle	All cycles
					(if w is low enough)
					SS
			1		33
	SS			SS	0 avala
$\lambda = 3.9$		none	none		2-cycle
	All cycles		1	2-cycle	
	.,		1	.,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	All cycles
					(if w is low enough)

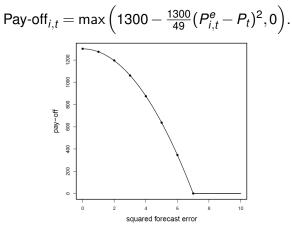
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The learning-to-forecast experiment

Timeline



Subjects' pay-off depends on the accuracy of their price forecast:



return

LtO. Payoff table

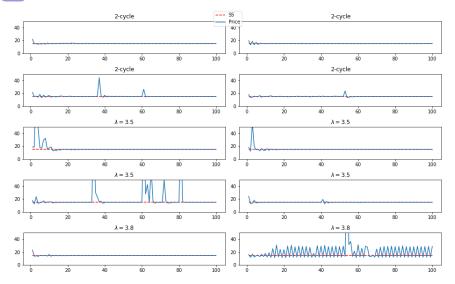
					Your		ecision					
	1	5	10	20	30	40	50	60	70	80	90	100
0.05	117	109	100	83	69	57	46	38	30	24	19	15
0.075	117	110	102	87	73	62	52	43	36	30	24	20
0.1	118	111	104	90	78	67	58	50	42	36	30	25
0.2	118	116	113	107	100	94	87	81	75	69	63	58
0.3	119	121	122	125	126	127	126	125	123	120	116	111
0.4	120	126	132	145	156	167	175	182	187	189	189	187
0.5	121	131	143	167	191	214	235	253	267	277	282	282
0.6	122	136	154	192	231	270	306	338	363	380	388	387
0.7	123	142	166	219	276	334	388	434	470	492	499	490
0.8	124	147	178	248	326	405	479	541	585	607	604	577
0.9	125	153	191	280	381	484	578	653	700	713	691	635
1	126	159	205	315	441	569	683	768	810	803	749	655
1.1	127	165	219	352	505	660	792	879	906	869	772	635
1.2	129	171	234	391	575	756	901	983	984	903	758	577
1.3	130	177	250	433	648	854	1008	1074	1036	903	706	490
1.4	131	184	266	478	725	954	1110	1148	1060	869	625	387
1.5	132	190	283	525	805	1054	1202	1201	1053	803	523	282
1.6	133	197	301	574	888	1152	1282	1231	1017	713	413	187
1.7	134	204	319	626	972	1247	1347	1235	953	607	305	111
1.8	135	211	338	680	1058	1335	1396	1214	867	492	208	58
1.9	136	219	358	735	1144	1416	1426	1168	764	380	130	25
2	137	226	378	793	1229	1487	1436	1101	651	277	73	9
2.5	142	266	492	1103	1617	1661	1202	578	157	16	0	0
3	148	311	622	1427	1866	1487	683	143	6	0	0	0
4	160	414	930	1983	1720	569	36	0	0	0	0	0
5	172	536	1284	2204	944	47	0	0	0	0	0	0
6	185	676	1652	1983	261	0	0	0	0	0	0	0
7	199	834	1996	1427	21	0	0	0	0	0	0	0
8	213	1006	2278	793	0	0	0	0	0	0	0	0
9	229	1191	2463	315	0	0	0	0	0	0	0	0
10	244	1383	2527	76	0	0	0	0	0	0	0	0
15	335	2301	1284	0	0	0	0	0	0	0	0	0
20	445	2703	96	0	0	0	0	0	0	0	0	0

Your return forecast

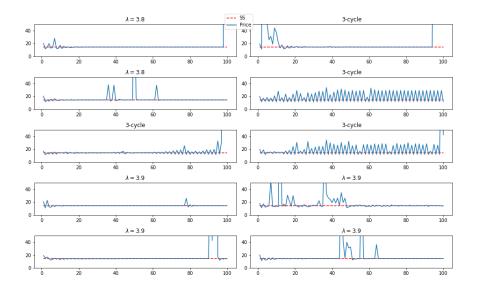
- Tr. 1 $\lambda = 3.5$: convergence to a **4-cycle** under naive expectations/perfect foresight.
- Tr. 2 $\lambda = 3.8$: chaotic region under naive expectations/perfect foresight.
- Tr. 3 $\lambda =$ 3.83: convergence to a **3-cycle** under naive expectations/perfect foresight.
- Tr. 4 $\lambda = 3.9$: chaotic region under naive expectations/perfect foresight.

Learning-to-forecast. Price vs SS

back

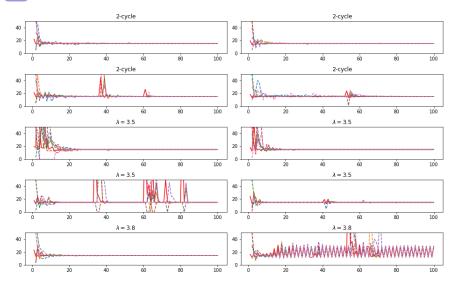


Aggregate behavior. Price vs SS cont.



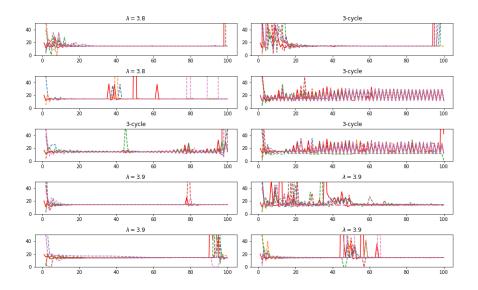
Learning-to-forecast. Price forecasts

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Individual behavior. Forecasts cont.



Indicators by treatment (Summary Table)

Treatment	$\lambda = 3.3$	$\lambda = 3.5$		$\lambda = 3.8$		$\lambda = 3.8$	$\lambda = 3.9$		
Design	LtFE	LtFE	LtO	LtFE	LtO	LtFE	LtO	LtFE	LtO
Equilibrium	4 SS	4 SS	2 SS*	3 SS,1 2-c	2 SS*	2 SS, 2 2-c	1 SS*	4 SS	3 SS*
ARDE	0.3	0.1	26.4	0.6	27.2	5.6	38.3	1.6	12.2
TTC_{10}	4.5	36.3	84.8	38.3	92.5	67.5	98.3	51.0	97.0
RSD _f	0.4	0.9	28.3	0.6	18.3	7.8	56.7	2.8	22.8
RSD _s	0.24	0.7	25.4	0.4	24.0	2.6	30.7	2.6	25.4
EERf	95.4	91.0	91.3	89.3	90.5	81.5	88.5	86.5	91.5
EERs	-	-	85.5	-	86.8	-	77.8	-	83.8

Notes: all numbers are averages over all groups of a given treatment. * approximate convergence occurs where the average price stayed within 25% from the steady state in the last 25 rounds. Outlier price values due to subjects' drop-outs, typos or experimentation are excluded. ARDE: average price is x% away from the equilibrium for the last 25 rounds. TTC: time to converge to an equilibrium and stay within 10% from it until the end of the experiment. In the case of no convergence, TTC is set to 100 periods. RSD_i : standard deviation of the forecasts divided by the average forecast over the last 25 rounds. For the LtF we use savings derived from the first-order conditions of the model given price forecasts. EER_f à average payoff for the forecasting task relative to the maximum possible payoff. EER_s - average payoff for the savings task relative to the maximum possible payoff.

✓ return

Treatment Difference (LtFE) at group level

$$Y_j = eta_0 + eta_1' Tr_{3.83} + eta_j$$

- *Y_i*: indicator of group *j* (average over time, periods 1–100)
- $Tr_{3.83}$: dummy equal to one if treatment $\lambda = 3.83$.
- ε_i: robust standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	EER	TTC	RSD	RMSE	ARDE	Uncertainty
$\lambda = 3.83$	-0.0903**	16.31*	0.0659	16.93	0.0740	0.318**
(dummy)	(0.0316)	(6.623)	(0.0427)	(18.25)	(0.0663)	(0.114)
Ν	20	20	20	20	20	20
R^2	0.255	0.261	0.319	0.136	0.189	0.225

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses. EER - average payoff relative to the maximum possible payoff; TTC - time to converge to equilibrium and stay within 5% from it for at least 10 rounds; RSD - relative standard deviation of the forecasts; ARDE - average relative distance to the equilibrium; Uncertainty - uncertainty index based on rounding of forecasts.

Treatment Difference (LtFE) at individual level

$$Y_{i,j} = eta_0 + eta_1' Tr_{3.83} + F_j + arepsilon_{i,j}$$

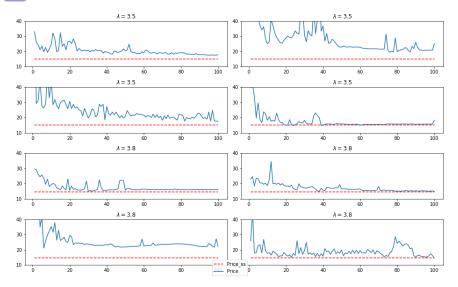
- $Y_{i,j}$: indicator for individual *i*, belonging to group *j*.
- $Tr_{3.83}$: dummy equal to one if treatment $\lambda = 3.83$.
- *F_j*: group fixed effects.
- $\varepsilon_{i,j}$: clustered standard errors at group level

	(1)	(2)	(3)	(4)
	Time on round	Payoff	RMSE	Uncertainty
$\lambda = 3.83$	11.16***	-296.2***	37.31***	0.720***
	(3.452)	(45.25)	(8.697)	(0.182)
Group FE	+	+	+	+
N	70	140	140	140
R^2	0.264	0.863	0.657	0.324

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses. Payoff - average payoff; RMSE - root mean squared error; Uncertainty - uncertainty index based on rounding of forecasts; Time on round - average time spent on experimental round.

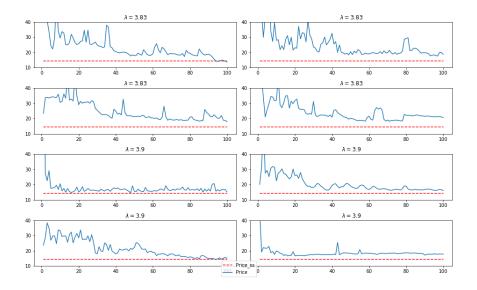
Learning-to-optimize. Price vs steady state

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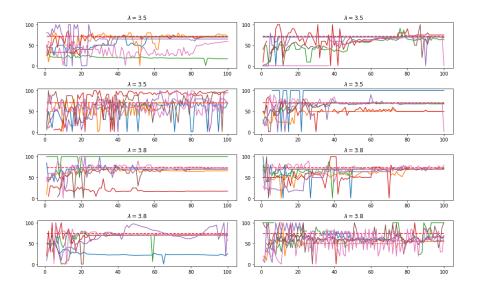
Learning-to-optimize. Price vs steady state



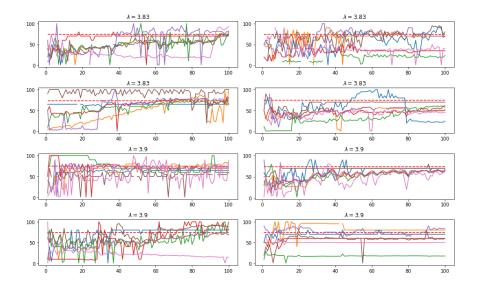
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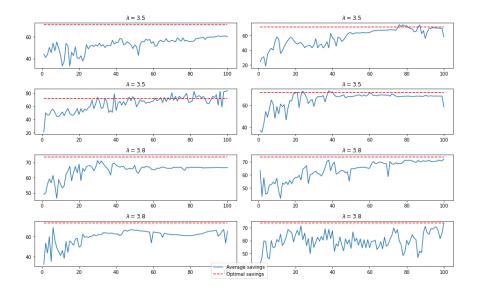
Learning-to-optimize. Savings decisions



Learning-to-optimize. Savings decisions



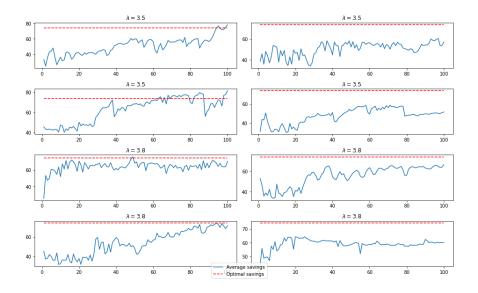
Learning-to-optimize. Average savings



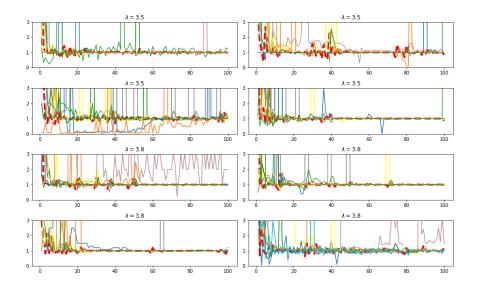
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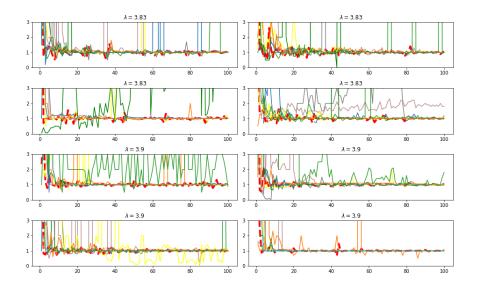
Learning-to-optimize. Average savings



Learning-to-optimize. Return forecasts



Learning-to-optimize. Return forecasts



All regressions

	RD	EERs	FEr	RSD _s
	(1)	(2)	(3)	(4)
$\lambda = 3.83$	3.670***	-0.0758***	-0.7309***	0.0892*
	(1.158)	(0.0243)	(0.2753)	(0.127)
Group FE	-	-	+	-
N	16	16	108	16
R^2	0.207	0.434	0.406	0.031

Notes: Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. *EER*_s - average payoff for the savings task relative to the maximum possible payoff; *EER*_t - average payoff for the forecasting task relative to the maximum possible payoff; *RSD*_s - relative standard deviation of the forecasts; *RSD*_s - relative standard deviation of the forecasts; *RSD*_s - relative standard deviation of the savings decisions; RD - average relative distance to the equilibrium; Uncertainty - uncertainty index based on rounding of forecasts; *FE*_r - forecast error divided by the mean forecast.

	RD	EE	R _s	EE	ER _f	1	FEr	RSD _s	RSD _f	Unce	rtainty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\lambda = 3.83$	3.670***	-0.0758***	-0.0685	-0.0258	-0.0799	0.0617	-0.7309***	0.0892*	0.0635	-0.0427	-0.0357
	(1.158)	(0.0243)	(0.0846)	(0.0176)	(0.0577)	(0.0527)	(0.2753)	(0.127)	(0.0345)	(0.0972)	(0.1864)
constant	6.127*** (1.101)	0.853*** (0.0113)	0.824*** (0.0715)	0.911*** (0.0108)	0.944*** (0.0176)	0.161*** (0.0276)	0.445*** (0.0685)	0.826*** (0.2739)	0.326*** (0.0232)	0.750*** (0.0860)	0.694*** (0.1247)
Group FE	-	-	+	-	+	-	+	-	-		+
N	16	16	108	16	108	16	16	108	16	16	108
R^2	0.207	0.434	0.104	0.103	0.135	0.084	0.406	0.031	0.136	0.006	0.232

Notes: Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. EER_5 - average payoff for the savings task relative to the maximum possible payoff; EER_7 - average payoff for the forecasting task relative to the maximum possible payoff; RSD_8 - relative standard deviation of the forecasts; RSD_8 - relative standard deviation of the savings decisions; RD - average relative distance to the equilibrium; Uncertainty - uncertainty index based on rounding of forecasts; FE_7 - forecast error divided by the maxime and forecast.

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