Microfoundations for Switching Behaviour in Heterogeneous Agent Models: An Experiment

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Heterogeneous Agent Models (HAMs)

Heterogeneous Agent Models, key characteristics:

1. agents use behavioral decision rules ("forecasting heuristics")
2. "switching": agents evaluate desirability of heuristics on the basis of their past performances (Brock and Hommes, 1997).

HAMs are empirically successful, tractable, intuitive...

But the dynamics depends both on the chosen heuristics and on the mechanism and parameters of switching.

Experiments with paid human subjects allow to investigate heuristics and switching in a controlled environment, estimate parameters, test hypotheses.

1. many Learning-to-Forecast Experiments
2. this paper: is the Switching Experiment

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General setup of switching models

- agents' choices are distributed over H different heuristics.
- past payoffs of heuristics are known:

$$\pi^h_{t-1}, \pi^h_{t-2}, \ldots, \pi^h_{t-\ell}, \ldots$$

- fraction of agents using heuristic h at time t, is given by discrete choice model (Manski and McFadden, 1981)

$$n_{h,t} = \frac{\exp\left[\beta \pi_{h,t-1}\right]}{\sum_{k=1}^{H} \exp\left[\beta \pi_{k,t-1}\right]},$$

where $\beta > 0$ is the Intensity of Choice

$$n_{h,t} = \frac{\exp\left[\alpha_h + \beta_{h,1}\pi_{h,t-1} + \ldots + \beta_{h,L}\pi_{h,t-L}\right]}{\sum_{k=1}^{H} \exp\left[\alpha_k + \beta_{k,1}\pi_{k,t-1} + \ldots + \beta_{k,L}\pi_{k,t-L}\right]}.$$

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Other Studies for HAMs Estimation and Calibration

- on financial data: Boswijk, Hommes and Manzan (2007), Goldbaum and Mizrach (2008), De Jong, Verschoor, and Zwinkels (2009), Kouwenberg and Zwinkels (2010), Franke and Westerhoff (2011), Chiarella, He and Zwinkels (2014);
- on survey data: Branch (2004);
- on experimental data: Anufriev and Hommes (2012), Anufriev, Hommes and Philipse (2013);

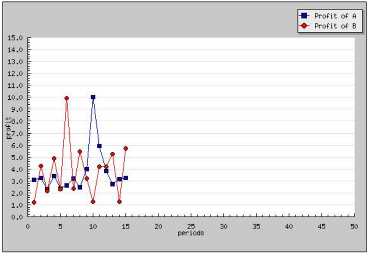
Experiment where the subjects choose between heuristics directly may be helpful!

Experiment: screen during one block

Your decision for period 16

Which fund do you choose? (A or B) ○A ○B

Send



Period	The fund you choose	Profit of fund A	Profit of fund B
15	**B**	**3.25**	**5.72**
14	B	3.16	1.23
13	A	2.72	5.23
12	B	3.82	4.21
11	A	5.91	4.21
10		10	1.23
9		3.96	3.21
8		2.48	5.43
7		3.17	2.37
6		2.64	9.91
5		2.35	2.31
4		3.42	4.87
3		2.32	2.16
2		3.25	4.26
1		3.1	1.21

Experiment: design

6 treatments, each consisting of 2 blocks of 40 decision periods

- Human subjects make discrete choice decisions by choosing between 2 (3 or 4) alternatives ('investment funds')
- Participants know that the performances ('returns') of the funds are exogenous to their decisions, but they don't know the data-generating process
- At each period participants observe past performances of all funds, choose a fund, and are paid the return of the chosen fund.
- This process is repeated 40 times.
- The same in the second block but with different performances and number of funds.

Your decision for period 16

Which fund do you choose? (A or B) ○A ○B

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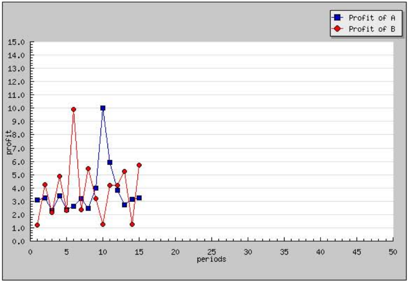

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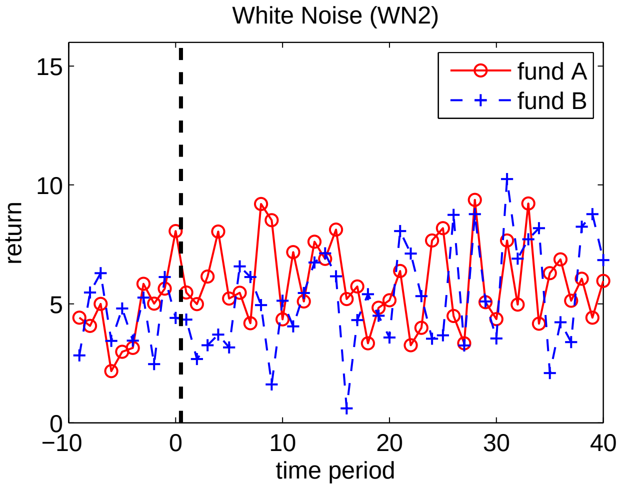
Treatments

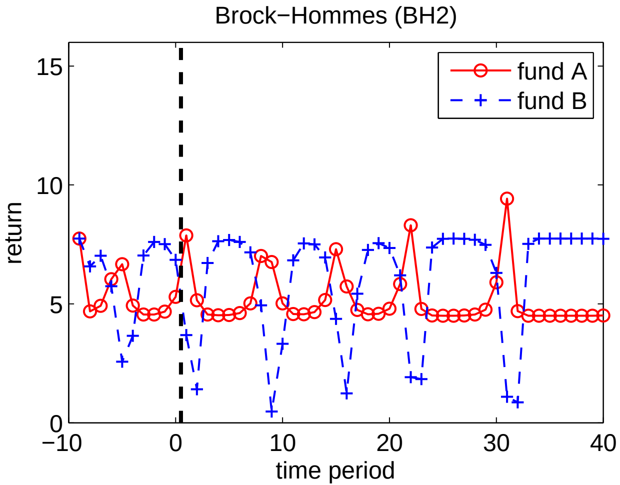
Treatment	Phase 1	Phase 2	Number of participants
T1	WN2	BH3	16
T2	BH2	SI4	15
T3	BH3	SI2	14
T4	SI2	BH4	14
T5	SI3	BH2	14
T6	SI4	WN2	13

WN2 - two i.i.d. white noise processes, from $N(0, 1)$
BH2, **BH3**, **BH4** - performances generated by Brock-Hommes (1997, 1998) model and augmented by noise
SI2, **SI3**, **SI4** - rotation based annual returns of 4 stock indices, the Austrian Trade Index (ATX), Belgium 20 Stock Index (BFX), Dow Jones Index (DJI) and FTSE 100 index (FTSE) from Oct. 2005 to Nov. 2009

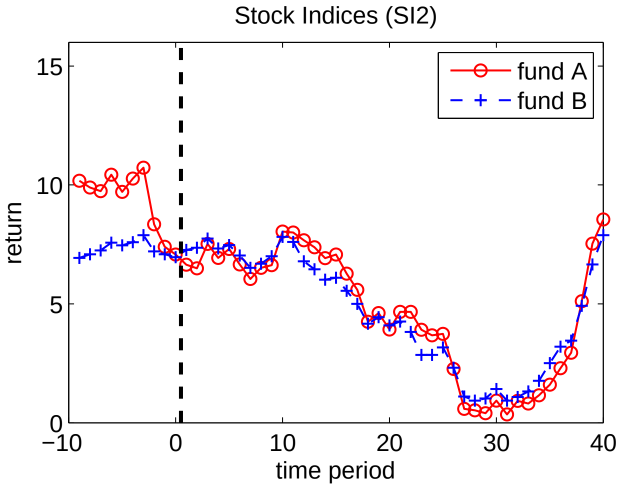
Time series: **WN2**



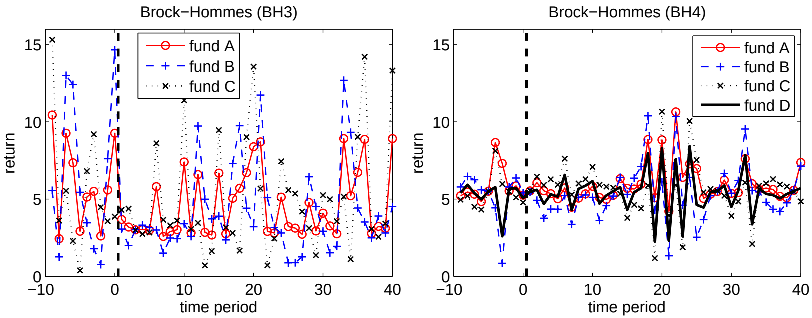
Time series: **BH2**



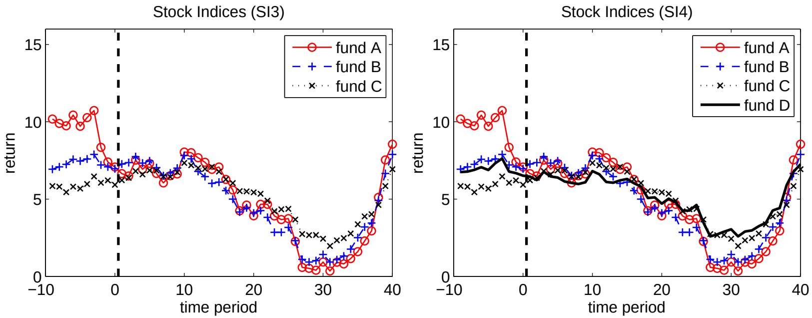
Time series: **SI2**



Time series: **BH3** and **BH4**



Time series: **SI3** and **SI4**



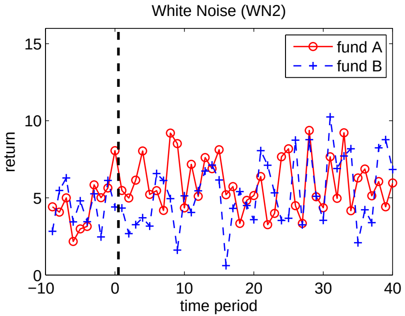
Descriptive Statistics of the time series

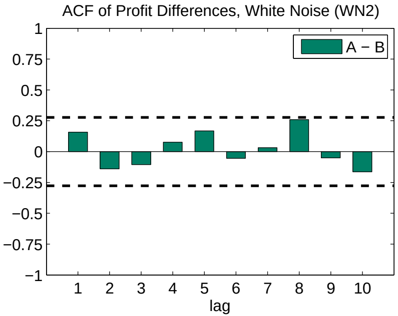
Time series	Fund	Min	Mean	Max	Variance
WN2	A	2.17	5.68	9.37	3.13
	B	0.60	5.16	10.25	4.48
	All	0.60	5.42	10.25	3.83
BH2	A	4.50	5.24	9.42	1.38
	B	0.47	6.01	7.75	5.42
	All	0.47	5.63	9.42	3.52
SI2	A	0.36	5.62	10.72	9.42
	B	0.93	5.18	7.89	5.73
	All	0.36	5.40	10.72	7.55

Characteristics of data

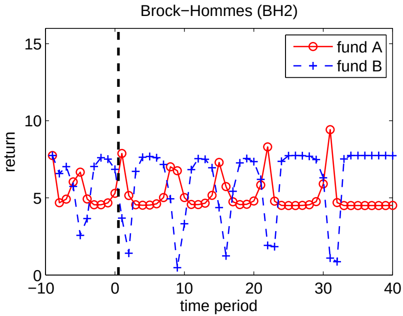
- WN2, BH3, BH4: noisy data with no (or little) structure;
- BH2: regular data with clearly recognizable, repeated, quasi-periodic patterns. The 'period' is unpredictable;
- SI2, SI3, SI4: highly correlated time series.

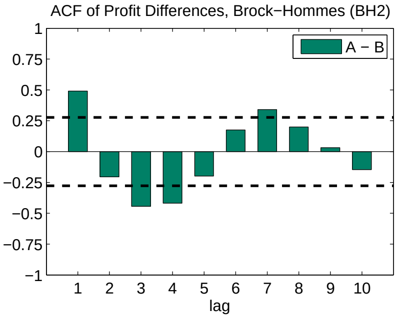
Time series: **WN2**



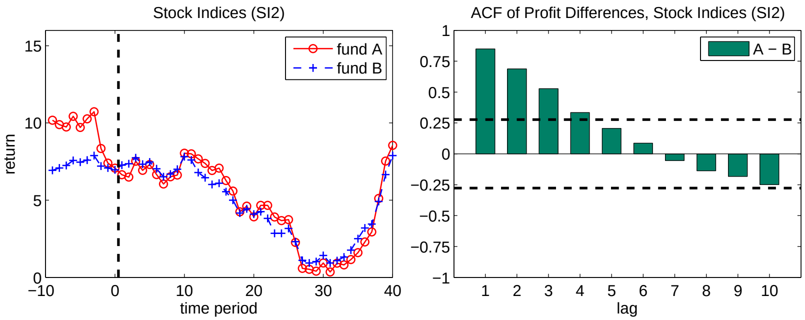


Time series: **BH2**





Time series: **SI2**



Testable Hypotheses

H1 The IoC parameter is significantly different from 0

H1' The simplest model

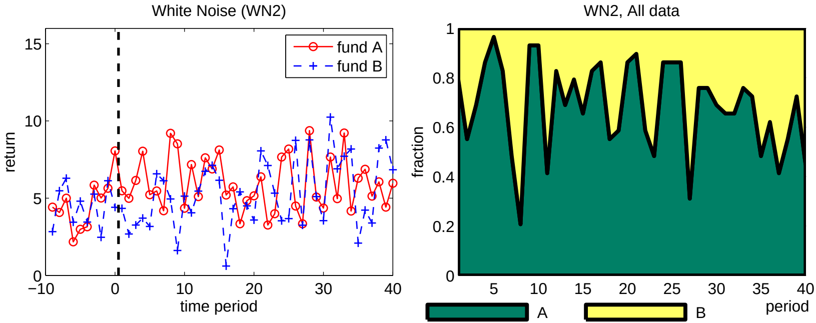
$$\Pr(c_{i,t} = A | \mathcal{I}_{t-1}) = \frac{\exp\left[\beta \pi^A_{t-1}\right]}{\exp\left[\beta \pi^A_{t-1}\right] + \exp\left[\beta \pi^B_{t-1}\right]}$$

or its small modification describes data quite well

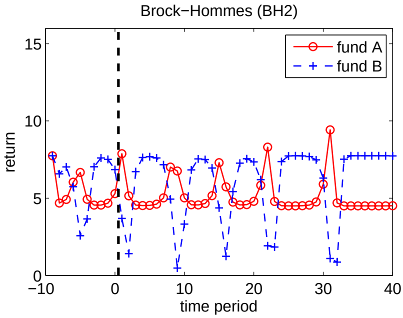
H2 There is no significant difference in IoC (or other parameters) between different blocks of data (WN2, BH2, SI2, ...)

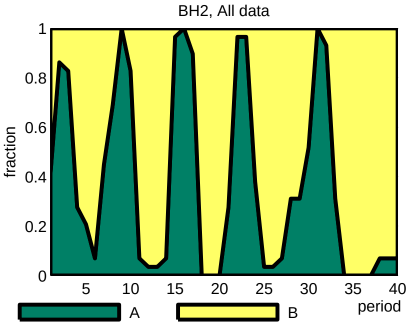
H3 A discrete choice model with more lags is not substantially better

Choices: WN2


White Noise (WN2)
fund A
fund B
return
time period
15
10
5
0
−10
0
10
20
30
40
WN2, All data
fraction
period
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
A
B

Choices: BH2


Brock−Hommes (BH2)
fund A
fund B
return
time period
15
10
5
0
−10
0
10
20
30
40


BH2, All data
fraction
period
A
B
1
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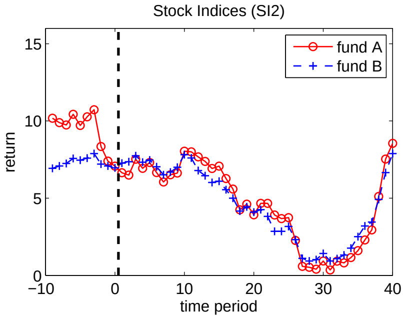
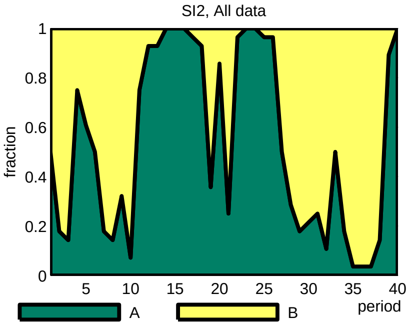
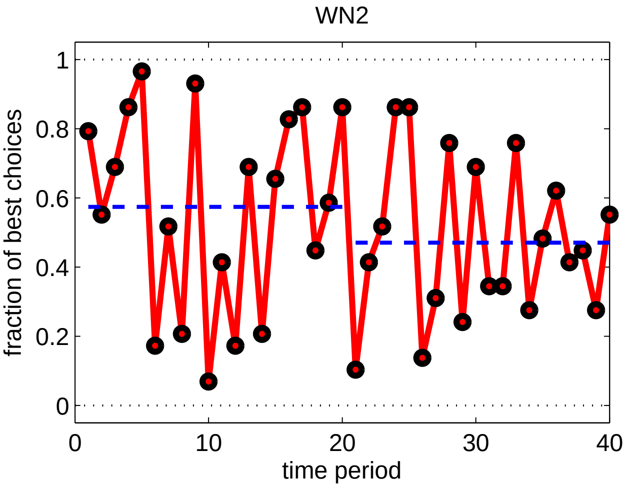
5
10
15
20
25
30
35
40

Choices: SI2


Stock Indices (SI2)
fund A
fund B
return
time period
15
10
5
0
−10
0
10
20
30
40


SI2, All data
fraction
period
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
A
B

How did subjects perform? Choice of the best.



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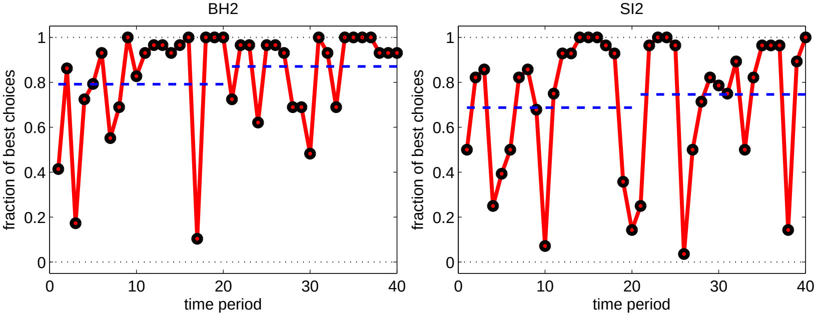


- learning within the block (where possible)
- almost no effect of 'experience' (i.e., when the time series is in the first block and when the same time series is in the second block)

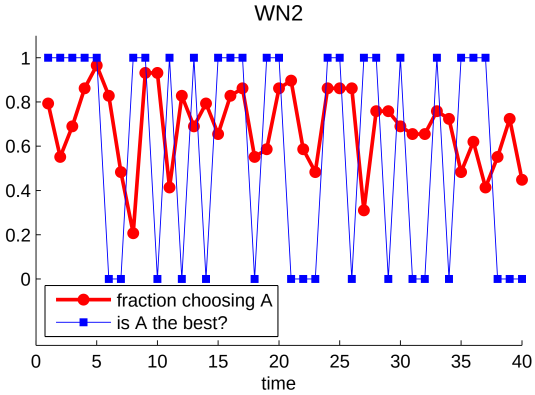
Efficiency

$$\frac{\text{Average Experimental Earnings} - \text{Earnings when Choosing Randomly}}{\text{Earnings when Choosing Optimally} - \text{Earnings when Choosing Randomly}}$$

Series	Max	Min	Rand	Experiment	Efficiency Total	Efficiency 1st half	Efficiency 2nd half
WN2	271.19	179.65	225.42	231.27	12.80%	32.19%	−5.33%
BH2	285.30	161.08	223.19	269.87	75.16%	66.87%	82.36%
BH3	258.71	105.16	181.94	200.10	23.65%	16.60%	28.64%
BH4	263.59	179.88	223.22	249.50	65.09%	71.31%	59.20%
SI2	197.22	175.81	186.51	193.32	63.55%	58.11%	68.08%
SI3	217.82	170.72	193.03	210.89	72.04%	56.39%	80.42%
SI4	228.81	166.25	195.49	216.38	76.46%	70.76%	80.15%

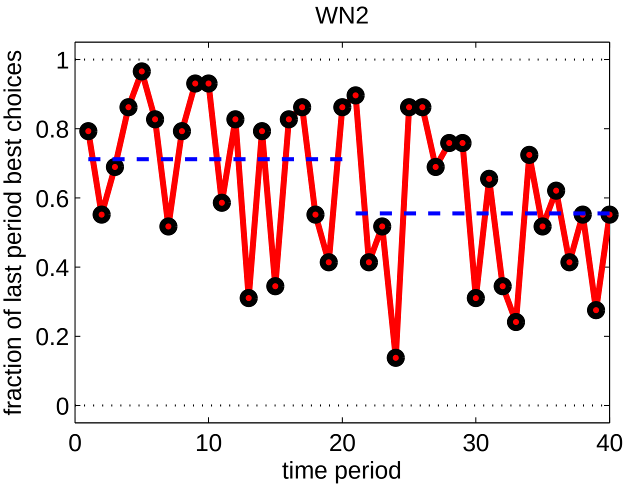
Payoffs under different scenarios / Average payoff / Efficiency

How did subjects choose the fund?



Observe: A certain inertia leading to "choose the best" heuristic.

How did subjects choose the fund? Choice of previous best.



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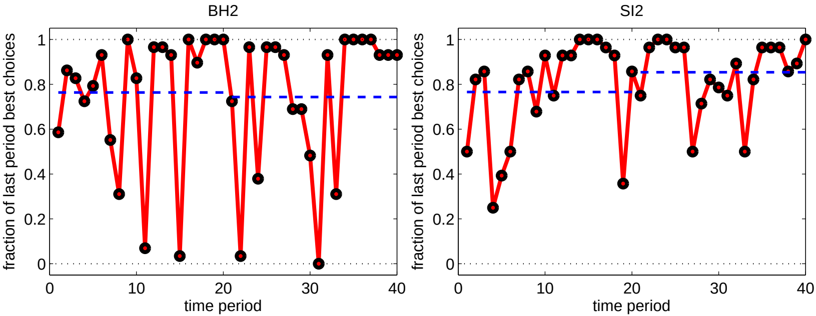

Binary choice estimation

At aggregate level we estimate **general logit model with one lag**

$$n_t^A = \frac{\exp\left[\alpha + \beta_A \pi_{A,t-1}\right]}{\exp\left[\alpha + \beta_A \pi_{A,t-1}\right] + \exp\left[\beta_B \pi_{B,t-1}\right]}.$$

using the method of maximum likelihood

Then we apply likelihood ratio test and information criteria to simplify the model

- **PreAsym1**
- **PreSym1**: if $\beta_A = \beta_B$
- **Sym1**: if $\beta_A = \beta_B$ and $\alpha = 0$ (classical BH model)

Binary choice estimation

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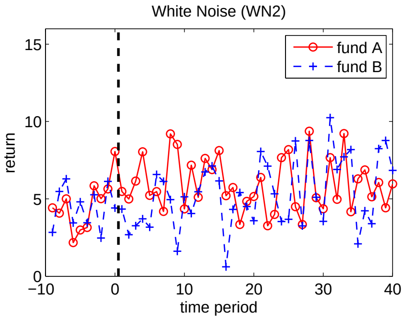
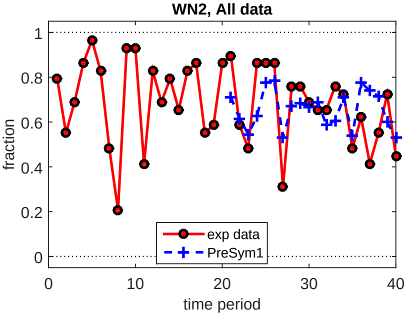
Aggregate Binary Choice Model with one lag

Model	Trtmnt	α	β_A	β_B	LLH	BIC	McFadden R-squared	LR test
Sym1	WN2	0.000	0.100 (0.030)	0.100	−396.432	799.226	−0.061	
	BH2	0.000	0.431 (0.034)	0.431	−285.560	577.484	0.210	
	SI2	0.000	3.747 (0.277)	3.747	−203.347	413.022	0.475	
PreSym1	WN2	0.693 (0.090)	0.133 (0.032)	0.133	−364.927	**742.580**	0.023	63.009 (0.000)
	BH2	−0.437 (0.114)	0.365 (0.035)	0.365	−278.606	569.938	0.230	13.908 (0.000)
	SI2	0.626 (0.162)	4.409 (0.370)	4.409	−194.622	**401.901**	0.498	17.449 (0.000)
PreAsym1	WN2	0.532 (0.350)	0.151 (0.050)	0.123 (0.038)	−364.813	748.715	0.024	0.228 (0.633)
	BH2	−12.973 (1.516)	2.609 (0.299)	0.095 (0.051)	−223.469	**466.027**	0.382	110.274 (0.000)
	SI2	0.925 (0.374)	4.652 (0.471)	4.754 (0.548)	−194.221	407.426	0.499	0.803 (0.370)

Last 20 periods of data are used (pooled over experiences).

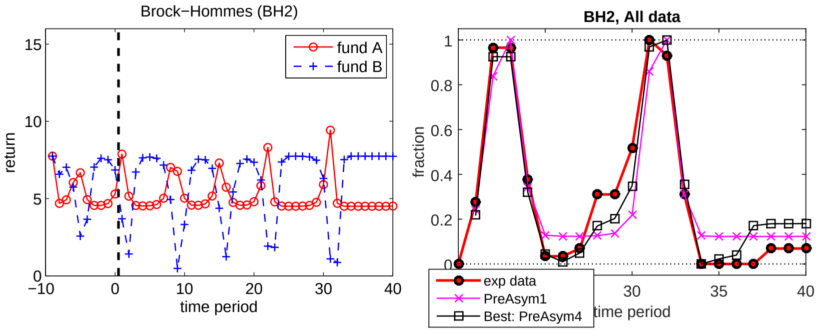
Results: **WN2**





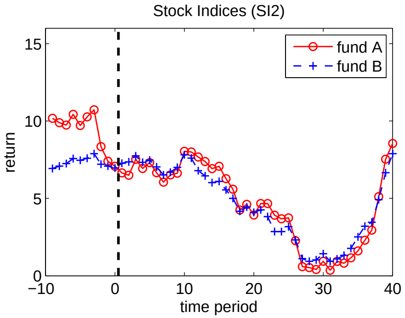
- **PreSym1**: $\alpha = 0.69, \beta = 0.13$
- significant predisposition effect towards fund A.
- Adding more lags do not improve significantly

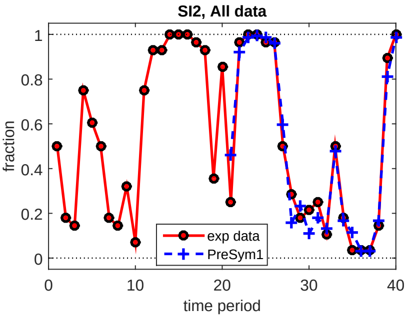
Results: **BH2**



- **PreAsym1**: $\alpha = -12.97, \beta_A = 2.61, \beta_B = 0.09.$
- strong pre-disposition effect towards B
- including more lags improve fit: **PreAsym4** is selected.

Results: **SI2**





- **PreSym1**: $\alpha = 0.63, \beta = 4.41$
- significant predisposition effect towards fund A.

Testable Hypotheses

- H1 YES the IoC parameter is significantly different from 0: people exhibit return chasing behavior in all treatments
- H1' predisposition effect is present in all treatments and model

$$\Pr(c_{i,t} = A | \mathcal{I}_{t-1}) = \frac{\exp\left[\alpha + \beta \pi^A_{t-1}\right]}{\exp\left[\alpha + \beta \pi^A_{t-1}\right] + \exp\left[\beta \pi^B_{t-1}\right]}$$

  describes data quite well (but not in BH)
- H2 There is significant difference in IoC (or other parameters) between different blocks of data (WN2, BH2, SI2, ...)
- H2' The IoC is higher in the series with high positive auto-correlations
- H3 A discrete choice model with more lags does not improve fitness, except for BH2

Overview of findings and Future work

- Human subjects switch a lot and are driven by past returns.
- They achieve higher level of efficiency when there is a structure in the data.
- One-lag, symmetric model with pre-disposition describes the data well
- Structure of the data matters both for the model of switching and for the parameters, with higher β in more structured data
- follow-up experiments
  - role of different information (e.g., other agents' choices)
  - role of payoff representation (tables vs. figures, cumulative vs. past payoffs)
  - role of feedback from individual choices to aggregate returns
  - role of switching fee

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THANK YOU!

Heterogeneous Agent Models

- macroeconomics: Marcet and Nicolini (2003), Branch and Evans (2007, 2011), Tuinstra and Wagener (2007), Lines and Westerhoff (2010), Branch and McGough (2010), Anufriev, Assenza, Hommes and Massaro (2013), ...
- financial markets: Chiarella (1992), Lux (1995), Brock and Hommes (1998), Chiarella and He (2001, 2002), DeGrauwe and Grimaldi (2006), Brock, Hommes and Wagener (2005, 2009), Anufriev and Panchenko (2009), ...
- behavioral game theory and IO: Erev and Roth (1998), Camerer and Ho (1999), Droste, Hommes and Tuinstra (2002), Anufriev, Kopányi and Tuinstra (2013), Bischi, Lamantia and Radi (2014), ...
- GA, IEL: Arifovic (1996), Arifovic and Ledyard (2007), ...
- Agent-based models: Dosi, Fagiolo, Napoletano and Roventini (2010, 2013), delli Gatti, Gaffeo and Gallegatti (2010), ...

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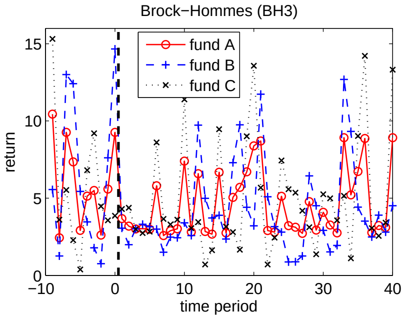
	B	0.47	6.01	7.75	5.42
	All	0.47	5.63	9.42	3.52
BH3	A	2.43	4.85	10.44	5.59
	B	0.76	4.64	14.66	12.34
	C	0.39	5.06	15.32	13.29
	All	0.39	4.85	15.32	10.29
BH4	A	4.20	5.93	10.64	1.52
	B	0.84	5.35	10.39	3.05
	C	1.17	5.56	10.66	2.62
	D	2.24	5.36	8.42	1.72
	All	0.84	5.55	10.66	2.25
SI2/SI3/SI4	A	0.36	5.62	10.72	9.42
	B	0.93	5.18	7.89	5.73
	C	1.96	5.31	7.34	2.44
	D	2.59	5.44	7.62	2.23
	All	0.36	5.39	10.72	4.91

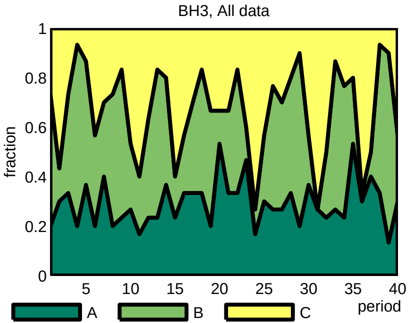
Descriptive statistics of the returns time series used in the experiment.

Available Experimental Data

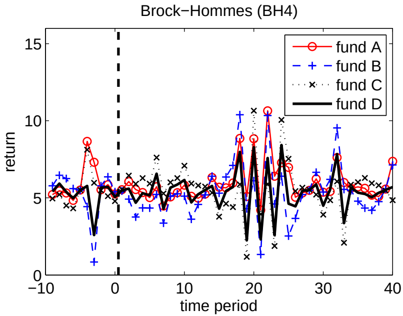
Time-series	Inexperienced	Experienced	Total
WN2 (T1 and T6)	16	13	29
BH2 (T2 and T5)	15	14	29
BH3 (T3 and T1)	14	16	30
BH4 (T4)	No	14	14
SI2 (T4 and T3)	14	14	28
SI3 (T5)	14	No	14
SI4 (T6 and T2)	13	15	28

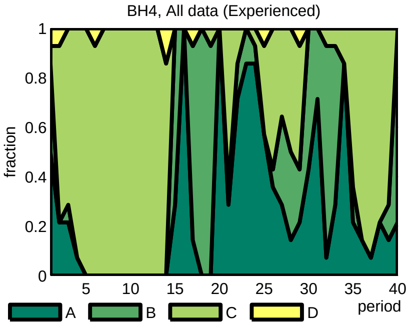
Choices: BH3


Brock−Hommes (BH3)
fund A
fund B
fund C
return
time period
15
10
5
0
−10
0
10
20
30
40

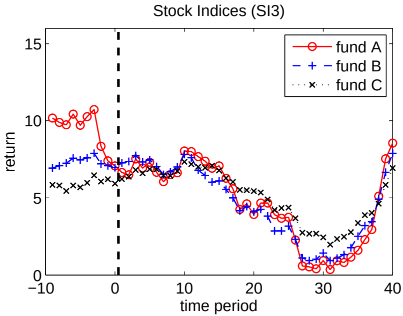

BH3, All data
fraction
period
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
A
B
C

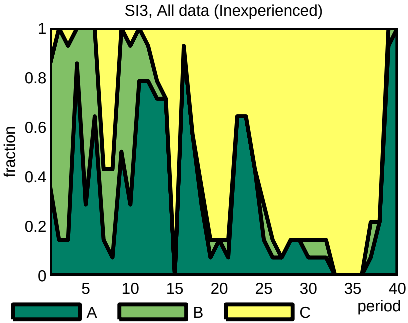
Choices: BH4


Brock−Hommes (BH4)
fund A
fund B
fund C
fund D
return
time period
15
10
5
0
−10
0
10
20
30
40

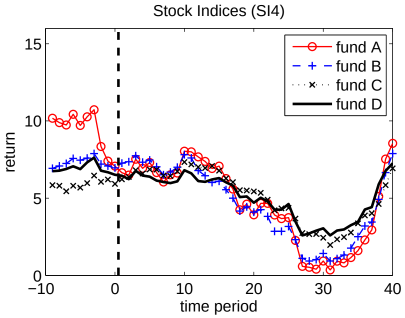

BH4, All data (Experienced)
fraction
period
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
A
B
C
D

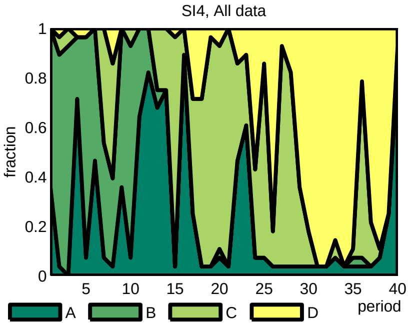
Choices: SI3


Stock Indices (SI3)
fund A
fund B
fund C
return
time period
15
10
5
0
−10
0
10
20
30
40


SI3, All data (Inexperienced)
fraction
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
period
A
B
C

Choices: SI4


Stock Indices (SI4)
fund A
fund B
fund C
fund D
return
time period
15
10
5
0
−10
0
10
20
30
40

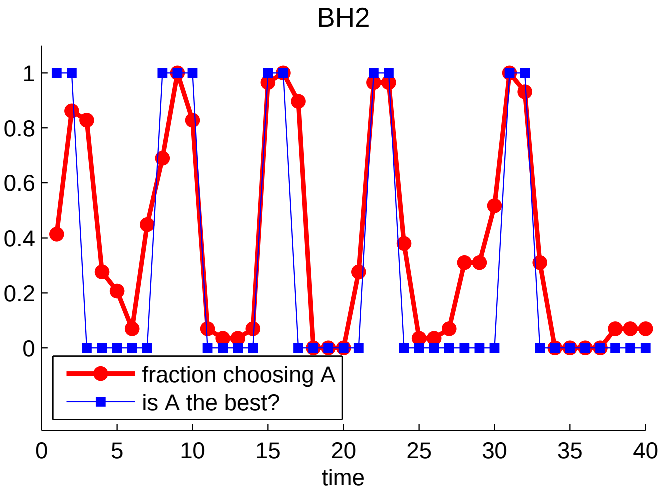

SI4, All data
fraction
period
1
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
A
B
C
D

How did subjects perform?

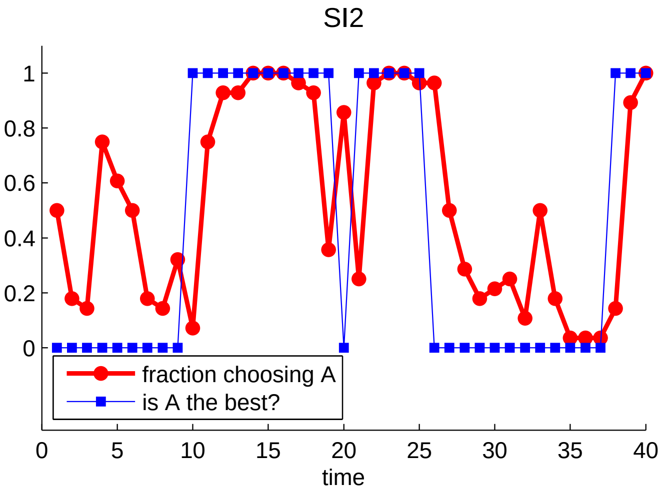
Time series	Treatments	Fraction of Best Choices		
		Inexperienced	Experienced	Total
WN2	T1 and T6	53.13%	51.15%	52.24%
BH2	T2 and T5	81.33%	85.00%	83.10%
BH3	T3 and T1	46.25%	43.13%	44.58%
BH4	T4	-	57.68%	57.68%
SI2	T4 and T3	72.50%	70.89%	71.70%
SI3	T5	65.18%	-	65.18%
SI4	T6 and T2	56.92%	59.67%	58.39%

Fraction of best choices in each block.

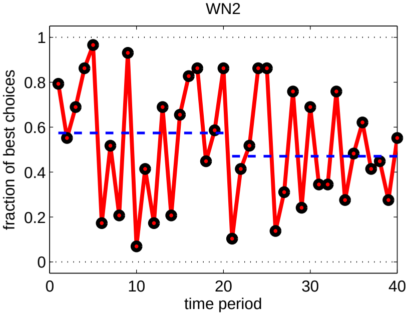
Aggregate data: 'ex post' efficiency

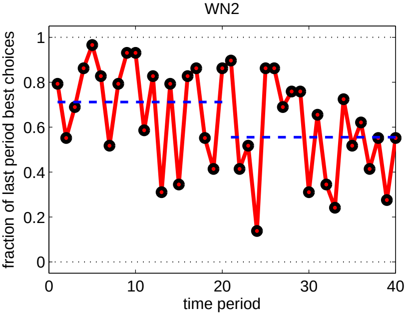


Aggregate data and efficiency



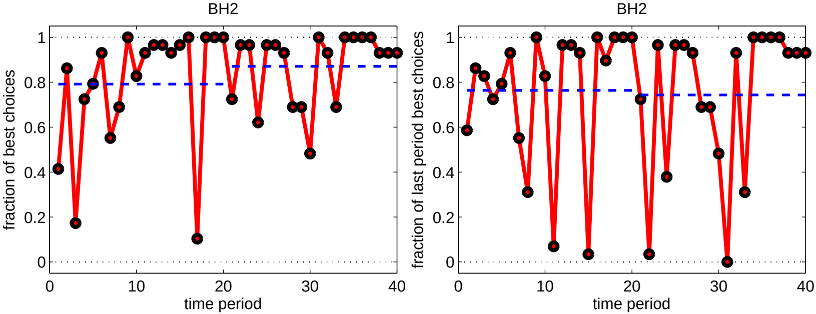
Best choice vs. Previous Best choice in **WN2**





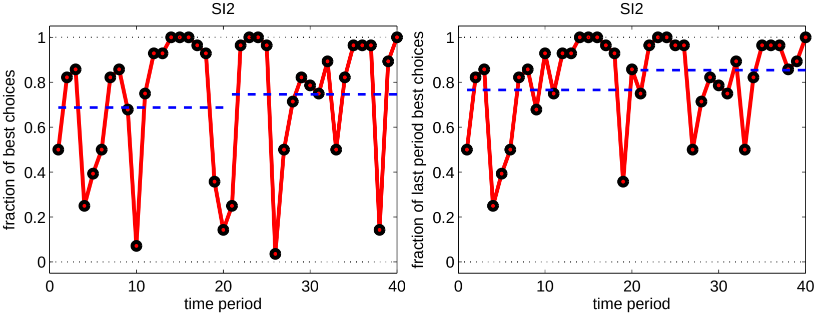
On average the previous best is chosen **more often** than the best.

Best choice vs. Previous Best choice in **BH2**



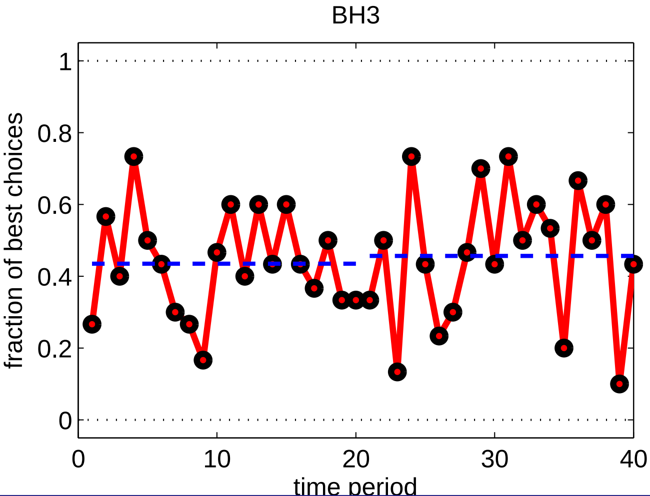
On average the previous best is chosen **less often** than the best.

Best choice vs. Previous Best choice in **SI2**

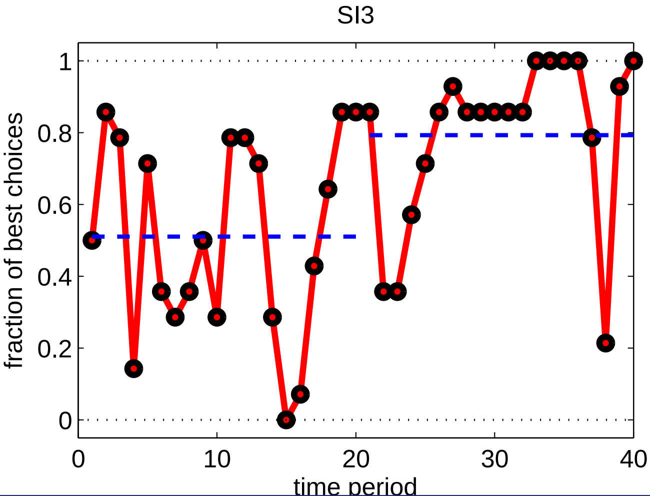


On average the previous best is chosen **more often** than the best.

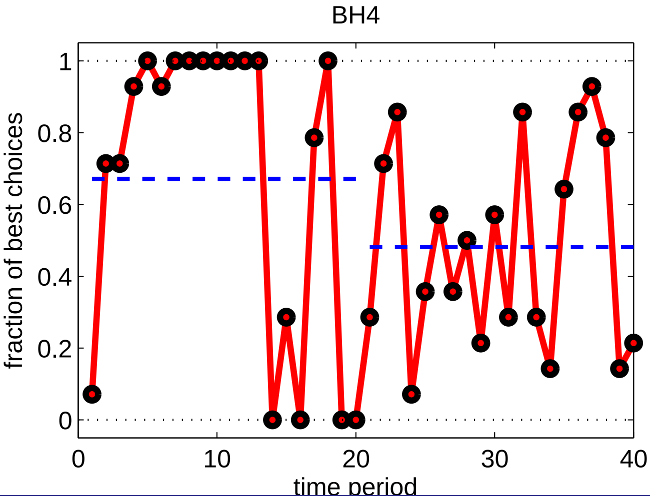
Best choice vs. Naive choice, BH3



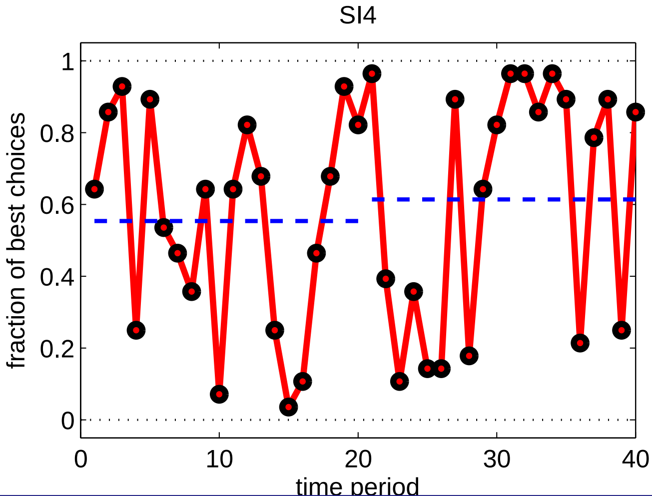
Best choice vs. Naive choice, SI3



Best choice vs. Naive choice, BH4



Best choice vs. Naive choice, SI4



BH(1)-model for **WN2**