Online Appendix to "Forecasting returns instead of prices exacerbates financial bubbles"

Nobuyuki Hanaki[*], Cars Hommes[†], Dávid Kopányi[‡], Anita Kopányi-Peuker[§] and Jan Tuinstra[¶]

A The asset pricing model

Let us first briefly summarize the market framework used in our learning to forecast experiment, following Heemeijer et al. (2009) and Bao et al. (2017). There are I agents in the market and they can invest in a risky asset and in a risk-free bond. The risky asset pays an uncertain dividend y_t in each period whereas the risk-free bond pays a gross return of $1 + r$.

Agent i's wealth W_i evolves according to

$$W_{i,t+1} = (1 + r)\left(W_{i,t} - p_t z_{i,t}\right) + z_{i,t}\left(p_{t+1} + y_t\right) = (1 + r)W_{i,t} + z_{i,t}\left(p_{t+1} + y_t - (1 + r)p_t\right), \tag{A.1}$$

where p_t is the price of the risky asset in period t (before the dividend is paid) and $z_{i,t}$ is the amount of risky asset agent i buys in period t.

Agents are assumed to have mean-variance preferences, that is they choose the amount of the risky asset in order to maximize

$$E_{i,t}\left(W_{i,t+1}\right) - \frac{1}{2} a Var_{i,t}\left(W_{i,t+1}\right),$$

where a is a parameter for risk aversion.

[*]Institute of Social and Economic Research, Osaka University, Osaka, Japan, email: nobuyuki.hanaki@iser.osaka-u.ac.jp, ORCID: 0000-0003-3127-690X

[†]University of Amsterdam and Tinbergen Institute, Amsterdam, The Netherlands, and Bank of Canada, Ottawa, Canada, email: c.h.hommes@uva.nl, ORCID: 0000-0002-2260-2665

[‡]The Netherlands Authority for Consumers and Markets, The Hague, The Netherlands, email: david.kopanyi@acm.nl, ORCID: 0000-0002-4613-5168

[§]Radboud University Nijmegen, Institute for Management Research, Nijmegen, The Netherlands, email: anita.kopanyi-peuker@ru.nl, ORCID: 0000-0002-3033-2597

[¶]Corresponding author, University of Amsterdam and Tinbergen Institute, Amsterdam, The Netherlands, email: j.tuinstra@uva.nl, ORCID: 0000-0001-6156-4940

This optimization problem leads to the following optimal demand for the risky asset:

$$z_{i,t}^{*} = \frac{p_{i,t+1}^{e} + y - (1+r)p_t}{aVar_{i,t}\left(p_{t+1} + y_t - (1+r)p_t\right)} = \frac{p_{i,t+1}^{e} + y - (1+r)p_t}{a\sigma^2}, \tag{A.2}$$

where $p_{i,t+1}^{e}$ is the price expectation of agent i for the next period and y is the (constant) expected dividend. Notice that we make the assumption that $Var_{i,t}\left(p_{t+1} + y_t - (1+r)p_t\right) = \sigma^2$ for each agent i. That is, we assume that agents can have heterogeneous price expectations but they all believe that the variance in question is equal to σ^2.

The price of the risky asset is governed by the aggregate demand (Z_t^D) and the exogenous aggregate supply (Z_t^S) of the asset according to the following price adjustment mechanism:

$$p_{t+1} = p_t + \lambda\left(Z_t^D - Z_t^S\right) + \varepsilon_t, \tag{A.3}$$

with $\varepsilon_t \sim N(0, 0.5^2)$ and λ is the speed of adjustment.

Assuming that the aggregate supply of the asset is 0 and combining (A.2) and (A.3), we get the following law of motion for prices:

$$p_{t+1} = p_t + \lambda \sum_{i=1}^{I} \frac{p_{i,t+1}^{e} + y - (1+r)p_t}{a\sigma^2} + \varepsilon_t \tag{A.4}$$

To further simplify the law of motion, we use the following assumptions about the parameters: $a\sigma^2 = I$ and $\lambda = \frac{1}{1+r}$. This yields

$$p_{t+1} = \frac{1}{1+r}\left(\bar{p}_{t+1}^{e} + y\right) + \varepsilon_t, \tag{A.5}$$

where $\bar{p}_{t+1}^{e}$ denotes the agents' average price expectation. An equivalent form of (A.5) is

$$p_{t+1} = p^f + \frac{1}{1+r}\left(\bar{p}_{t+1}^{e} - p^f\right) + \varepsilon_t, \tag{A.6}$$

where $p^f = \frac{y}{r}$ is the fundamental value of the risky asset.

Thus, in this asset market framework price dynamics is driven by the agents' average price expectations. Notice that agents form one-period-ahead forecasts as p_t depends on forecasts for the same period ($\bar{p}_t^e$).

B Instructions

B.1 Treatment PR

Welcome to this experiment on decision-making. Please read the following instructions carefully. If you have any questions, please raise your hand, and we will come to your table to answer your question in private.

General information

You are a financial advisor to a pension fund that wants to optimally invest a large amount of money. The pension fund has two investment options: a risk free investment (on a savings account) and a risky investment (on the stock market). As its financial advisor, you have to forecast the stock return for 50 subsequent time periods. The more accurate your forecasts are, the higher your total earnings are.

Your forecasting task

Your only task is to forecast the stock return in each time period as accurately as possible. The stock return is the relative price change compared to the previous period:

$$return_t = (price_t - price_{t-1})/price_{t-1}.$$

The return therefore measures how fast prices are increasing or decreasing. For example, if the price in period t-1 is 50 and the price in period t is 53, then the return in period t is (53-50)/50=0.06, or 6%. The stock return has to be forecasted one period ahead, that is at the beginning of each period you need to forecast what the return will be in that period. It is very likely that the stock return will be between -10% and 10% in the first period. After all participants have given their forecasts for the first period, the stock price for the first period will be revealed and, based upon your forecasting error, your earnings for period 1 will be given. After that you have to give your forecast for the stock return in the second period. After all participants have given their forecasts for period 2, the stock price in the second period will be revealed and, based upon your forecasting error, your earnings for period 2 will be given. This process continues for 50 time periods in total.

The available information for forecasting the stock return in period t consists of all past prices up to period t-1, your total earnings up to period t-1, and your past return forecasts up to period t-1. **Notice that the variable you need to forecast differs from the variable you receive information about: You need to forecast returns but you receive information about prices.**

In each period you have limited time to make your forecasting decision. If you do not submit a forecast during this time frame, your pension fund will be inactive, and you will not earn any points in that given period. A timer will show you the remaining time for each period (2 minutes for each of the first 10 periods, 1 minute for each of the later periods).

Information about the stock market

The stock price in period t depends on the aggregate demand for the stock and on the supply of stocks.

The supply of stocks is fixed during the experiment. The demand for stocks is mainly determined by the aggregate demand of the large pension funds active in the market. In addition, there are some small investors that are active on the stock market. The higher the aggregate demand for stocks is, the higher the realized market price will be. There are 6 large pension funds in the stock market. Each pension fund is advised by a participant of the experiment.

Earnings

Your earnings depend on the accuracy of your forecasts. Your payoff for your forecast in period t is given by

$$1300 * (1 - 625 * e_t^2),$$

where e_t is the forecast error, that is the absolute difference between your forecast of the return in period t and the realized return in that period. The maximum possible points you can earn in each period (if you make no forecast error) is 1300, and the larger your forecast error is, the fewer points you will make. Note, however, that you will never earn negative payoffs in a single period: If your forecast error in a particular period is very large, your payoffs for that period will be zero. There is a Payoff Table on your desk, which shows the points you can earn for different forecast errors.

We will pay you in cash at the end of the experiment based on the points you earned. You earn 0.5 euro for each 1300 points you make plus an additional 5 euros of participation fee.

Background information about the investment strategies of the funds

The precise investment strategy of the pension fund that you are advising and the investment strategies of the other pension funds and of the small investors are unknown. The savings account that pension funds can use for their risk free investment pays a fixed interest rate of 5% per time period. The stock pays an uncertain dividend in each time period. Economic experts have computed that the average dividend is 3.3 euros per period. The realized stock return per period is uncertain and depends upon the (unknown) dividend and upon stock price changes.

Based upon your stock return forecast, your pension fund will make an optimal investment decision. The higher your return forecast is, the more money will be invested in the stock market by the fund, so the larger will be the demand for stocks.

On the next screens you are asked to answer some questions in order to check if the experiment is clear to you.

B.2 Treatment ENDO

In this subsection we reproduce the instructions of the additional treatment. Text in italics is in the given order for half of the subjects (price first and return second), and in the opposite order for the other half of the subjects (return first and price second). Note that it was not shown in italics for subjects.

Welcome to this experiment on decision-making. Please read the following instructions carefully. If you have any questions, please raise your hand, and we will come to your table to answer your question in private.

General information

You are a financial advisor to a pension fund that wants to optimally invest a large amount of money. The pension fund has two investment options: a risk free investment (on a savings account) and a risky investment (on the stock market). As its financial advisor, you have to forecast the future development of the stock for 50 subsequent time periods, *either by forecasting its price or forecasting its return.*

The stock return is the relative price change compared to the previous period:

$$return_t = (price_t - price_{t-1})/price_{t-1}.$$

The return therefore measures how fast prices are increasing or decreasing. For example, if the price in period $t-1$ is 50 and the price in period t is 53, then the return in period t is (53-50)/50=0.06, or 6%.

The more accurate your forecasts are, the higher your total earnings are.

Your forecasting task

Your task in each period of this experiment is twofold. First, you have to decide whether - for that period - you want to predict the *future stock price or the future return* of the stock. Second, depending on your choice on what to forecast in that period, you have to submit your forecast of the stock *price or return* for that period. Your forecast should be as accurate as possible.

The *stock price or stock return* has to be forecasted one period ahead, that is at the beginning of each period you need to forecast what the *price or return* will be in that period. It is very likely that *the stock price will be between 0 and 100 in the first period and that the return will be between -10% and 10% in the first period.* After all participants have given their forecasts for the first period, the *stock price and* *stock return* for the first period will be determined and, based upon your forecasting error, your earnings for period 1 will be given. After that you have to select whether you want to predict *the stock price or the stock return* for the second period and submit your forecast. After all participants have given their forecasts for period 2, the *stock price and return* for the second period will be determined and, based upon your forecasting error, your earnings for period 2 will be given. This process continues for 50 time periods in total.

The available information for forecasting *the stock price or the stock return* in period t consists of all past *prices and returns* up to period $t-1$, your total earnings up to period $t-1$ and your past forecasts up to period $t-1$. Notice that you can decide for yourself whether you want to receive information *about past prices or about past returns*, and you can switch between *information about past prices and information about past returns* as often as you want while you make your decisions.

In each period you have limited time to make your two decisions. If you do not submit a forecast during this time frame, your pension fund will be inactive, and you will not earn any points in that given period. A timer will show you the remaining time for each period (2 minutes for each of the first 10 periods, 1 minute for each of the later periods).

Information about the stock market

The stock price in period t depend on the aggregate demand for the stock and on the supply of stocks. The supply of stocks is fixed during the experiment. The demand for stocks is mainly determined by the aggregate demand of the large pension funds active in the market. In addition, there are some small investors that are active on the stock market. The higher the aggregate demand for stocks is, the higher the realized market price will be. There are 6 large pension funds in the stock market. Each pension fund is advised by a participant of the experiment.

Earnings

Your earnings depend on the accuracy of your forecasts.

If you forecasted the price for period t your payoff for your forecast in that period is given by

$$1300 * (1 - 625 * e_t^2/p_{t-1}^2),$$

where p_{t-1} is the realized market price from the previous period $t-1$ and e_t is the price forecast error, that is the absolute difference between your forecast of the price in period t and the realized price in that *period.*

If for example the price in period $t-1$ was 50, the price in period t is 53, and you forecasted 54, then your error is 1. Applying the formula this results in a payoff of 975 for you in this period.

If you forecasted the return for period t your payoff for your forecast in that period is given by

$$1300 * (1 - 625 * f_t^2),$$

where f_t is the return forecast error, that is the absolute difference between your forecast of the return in period t and the realized return in that period.

For example assume that the price in period $t-1$ was 50, the price in period t is 53, which corresponds to a return of 6%, and you forecasted a return of 8% (corresponding to a price of 54 as in the previous example). In this case your error is 2 (f=0.02) which again gives you a payoff of 975 in this period.

The maximum possible points you can earn in each period (if you make no forecast error) is 1300, and the larger your forecast error is, the fewer points you will make. Note, however, that you will never earn negative payoffs in a single period: If your forecast error in a particular period is very large, your payoffs for that period will be zero. There are two Payoff Tables on your desk, which show the points you can earn for different forecast errors.

We will pay you in cash at the end of the experiment based on the points you earned. You earn 0.5 euro for each 1300 points you make plus an additional 5 euros of participation fee.

Background information about the investment strategies of the funds

The precise investment strategy of the pension fund that you are advising and the investment strategies of the other pension funds and of the small investors are unknown. The savings account that pension funds can use for their risk free investment pays a fixed interest rate of 5% per time period. The stock pays an uncertain dividend in each time period. Economic experts have computed that the average dividend is 3.3 euros per period. The realized stock return per period is uncertain and depends upon the (unknown) dividend and upon stock price changes.

Based upon your forecast, your pension fund will make an optimal investment decision. The higher your *price or return* forecast is, the more money will be invested in the stock market by the fund, so the larger will be the demand for stocks.

On the next screens you are asked to answer some questions in order to check if the experiment is clear to you.

C Time series of prices, returns and individual forecasts

C.1 Treatment PP

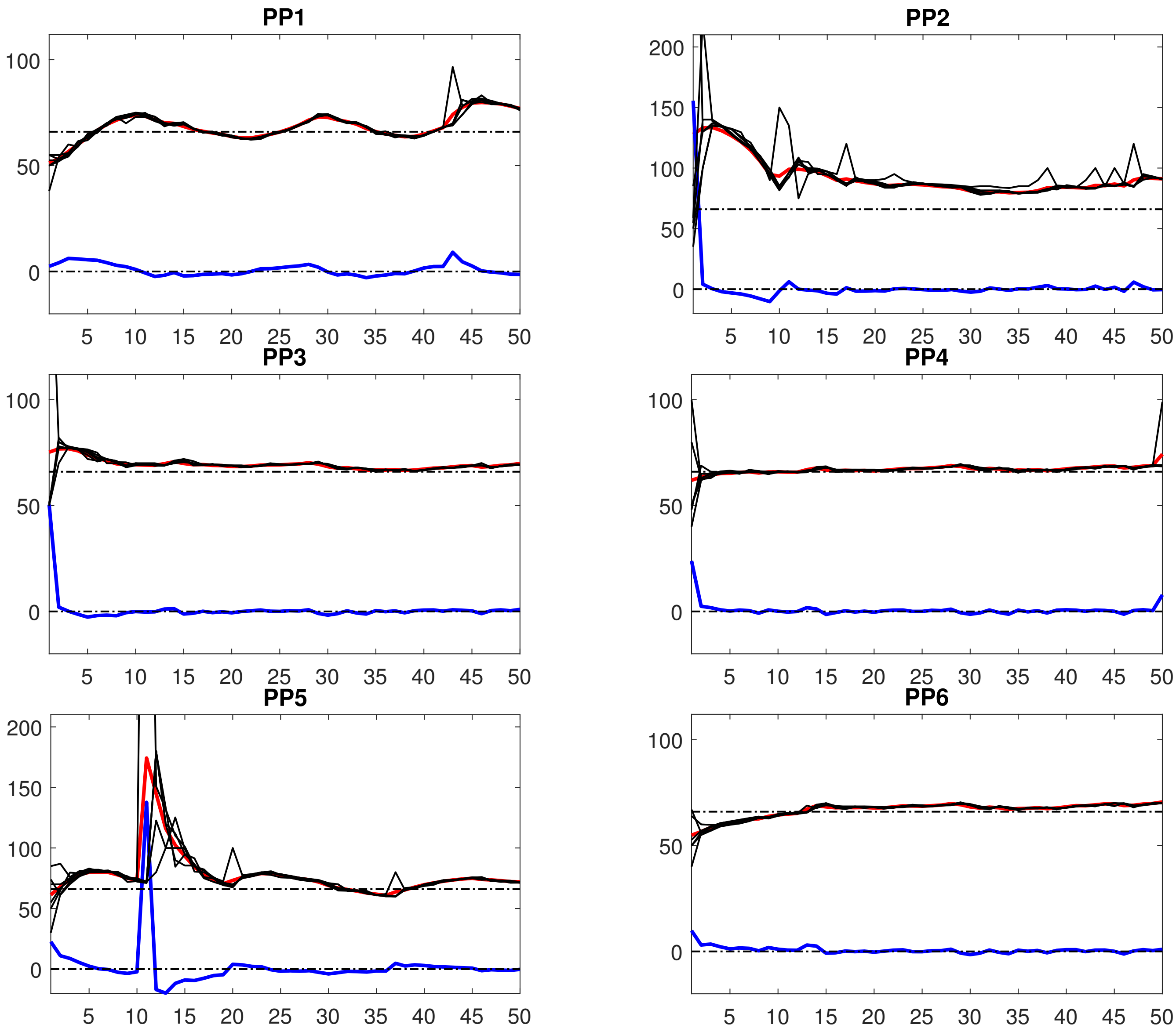

Figure C.1: Price forecasts (black), prices (red) and returns (blue) in treatment PP, markets 1 to 6. Note the different vertical scaling for the some market.

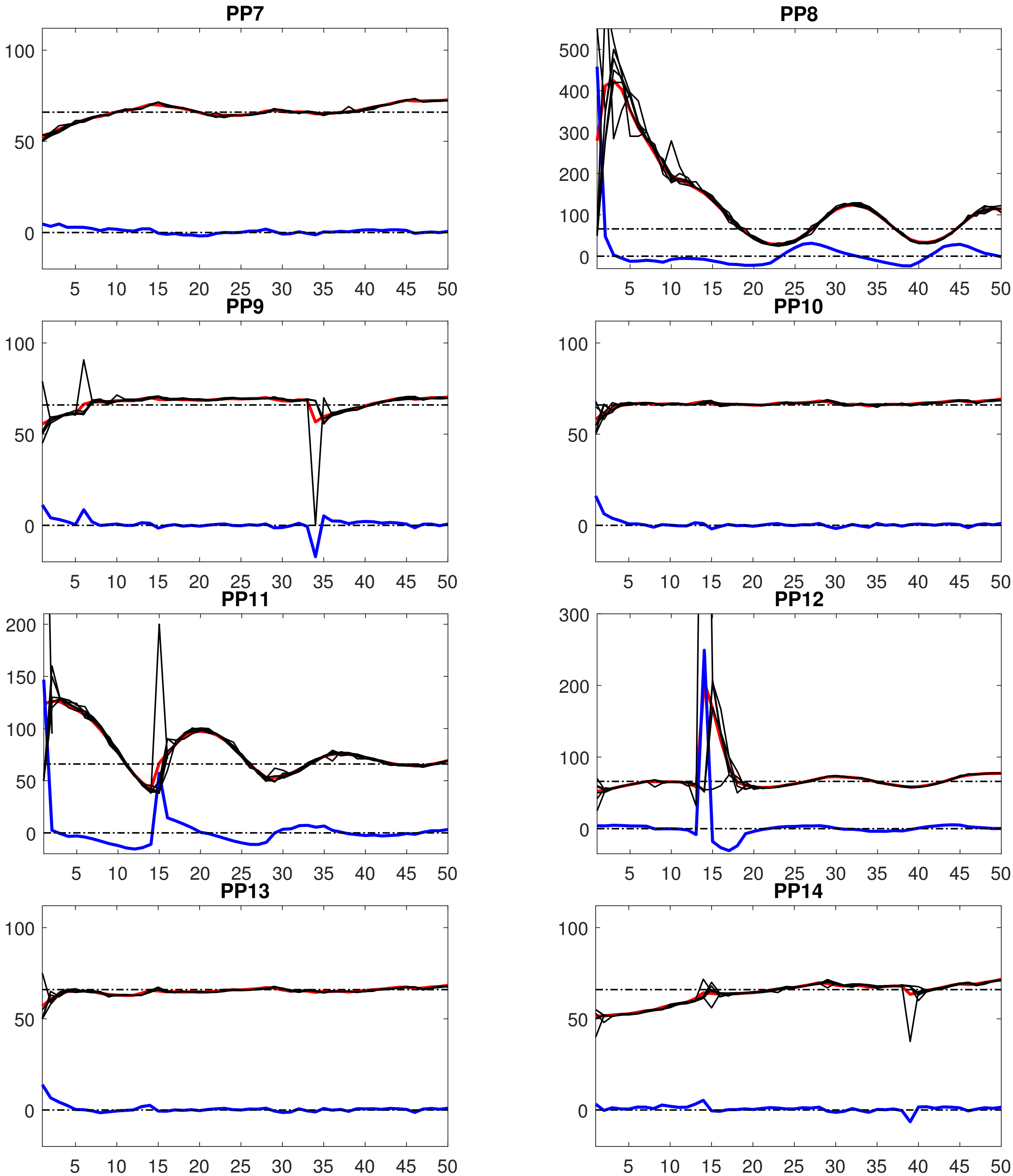

Figure C.2: Price forecasts (black), prices (red) and returns (blue) in treatment PP, markets 7 to 14. Note the different vertical scaling for some markets.

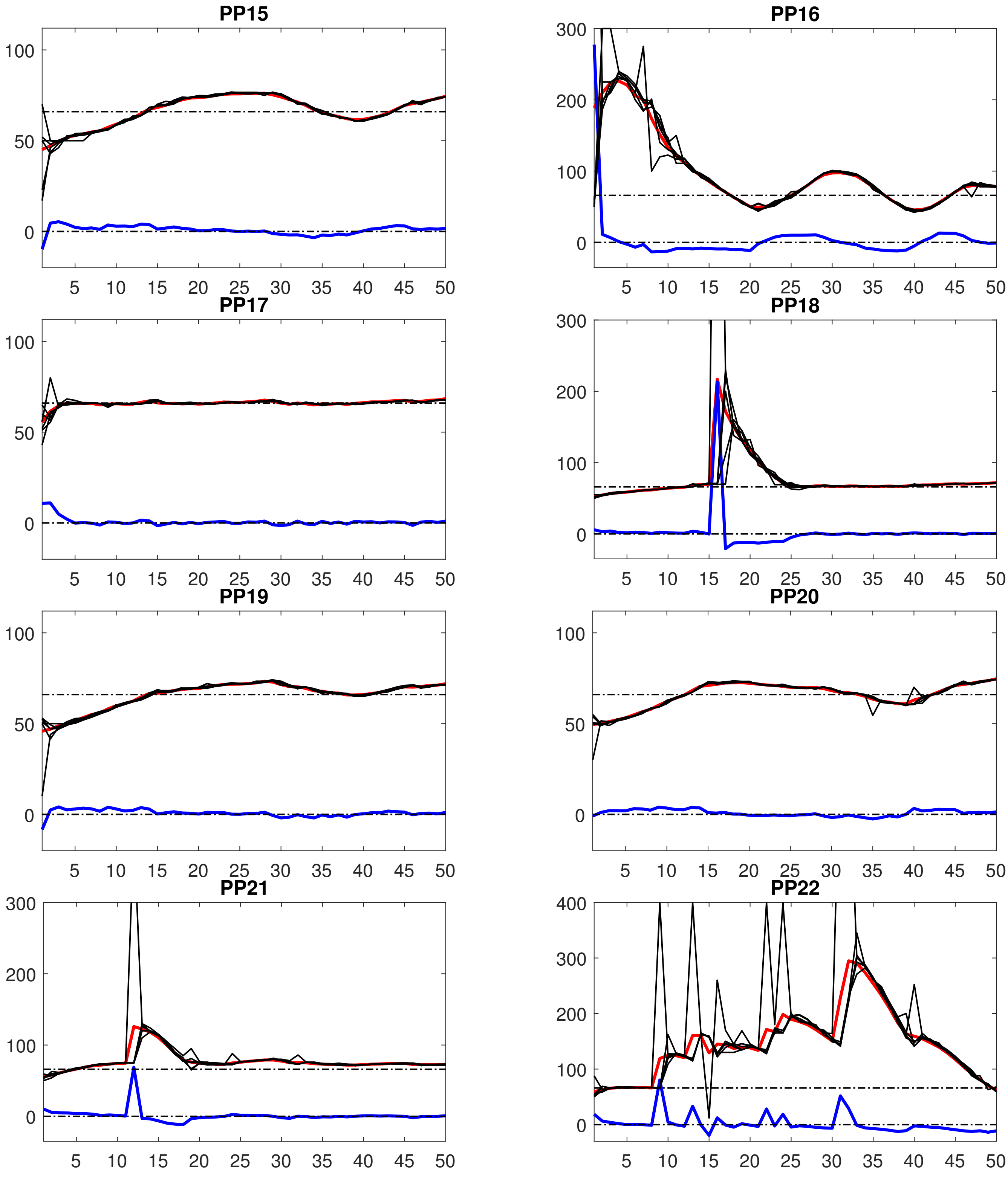

Figure C.3: Price forecasts (black), prices (red) and returns (blue) in treatment PP, markets 15 to 22. Note the different vertical scaling for some markets.

C.2 Treatment RP

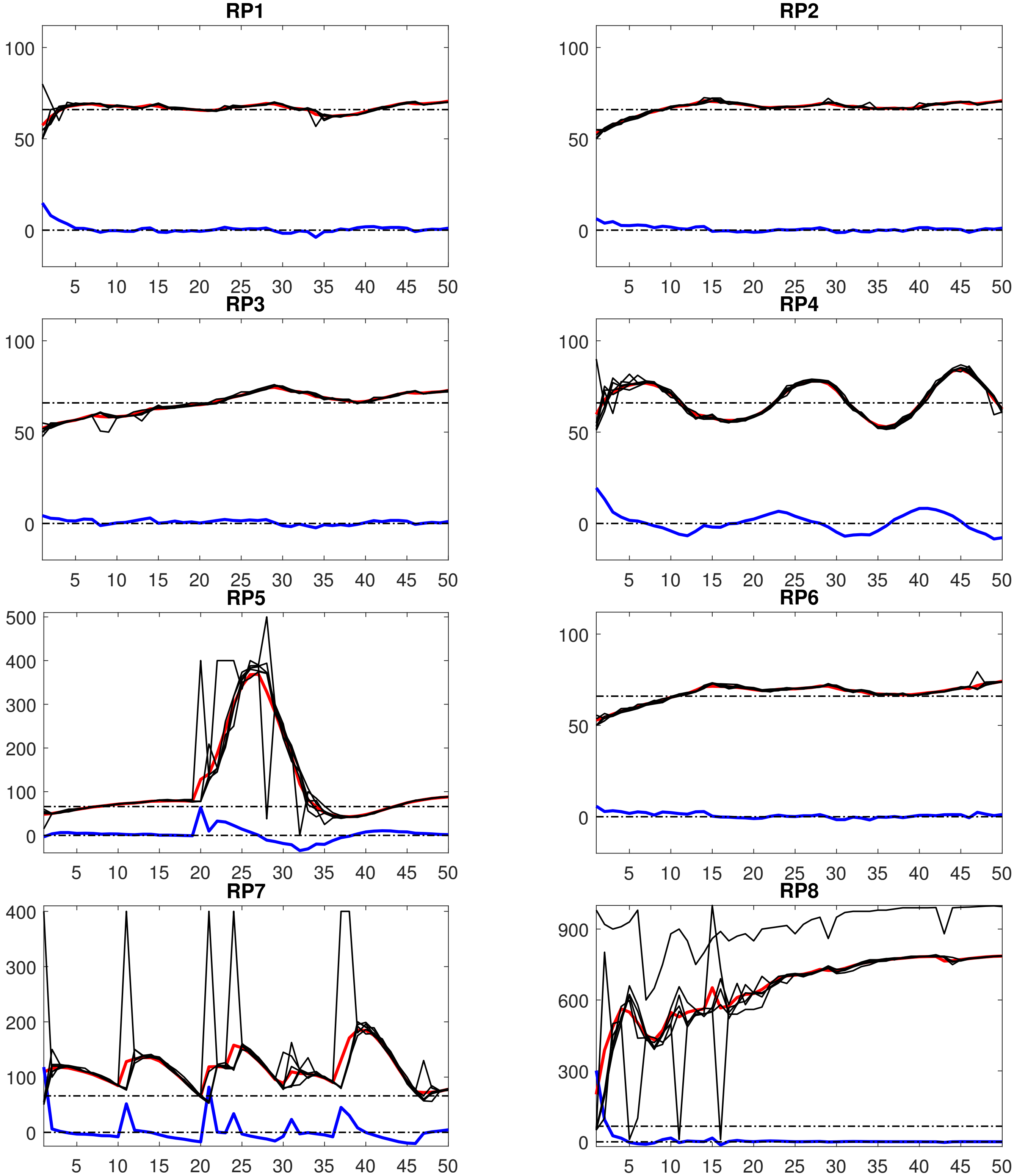

Figure C.4: Price forecasts (black), prices (red) and returns (blue) in treatment RP, markets 1 to 8. Note the different vertical scaling for the some market.

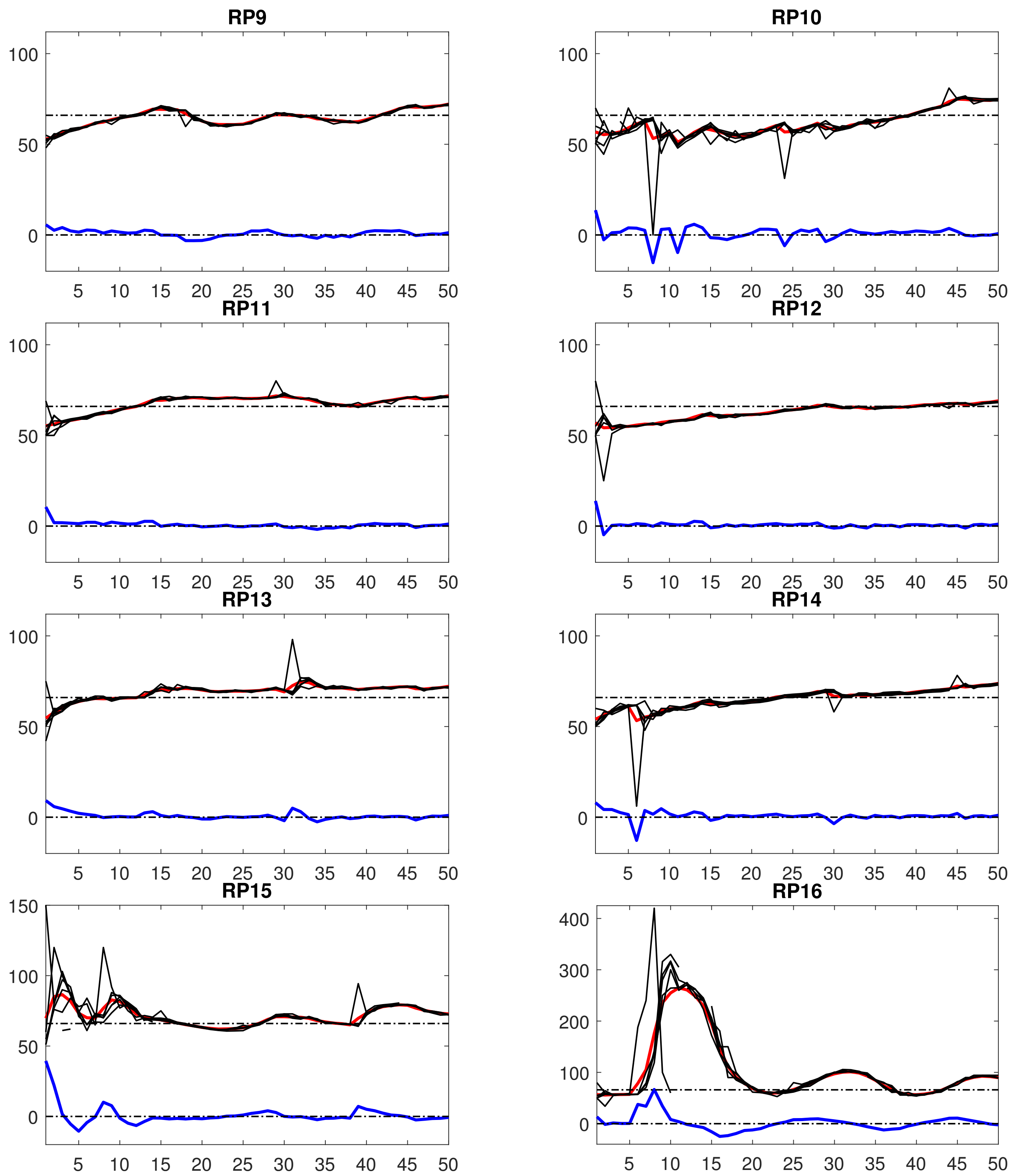

Figure C.5: Price forecasts (black), prices (red) and returns (blue) in treatment RP, markets 9 to 16. Note the different vertical scaling for some markets.

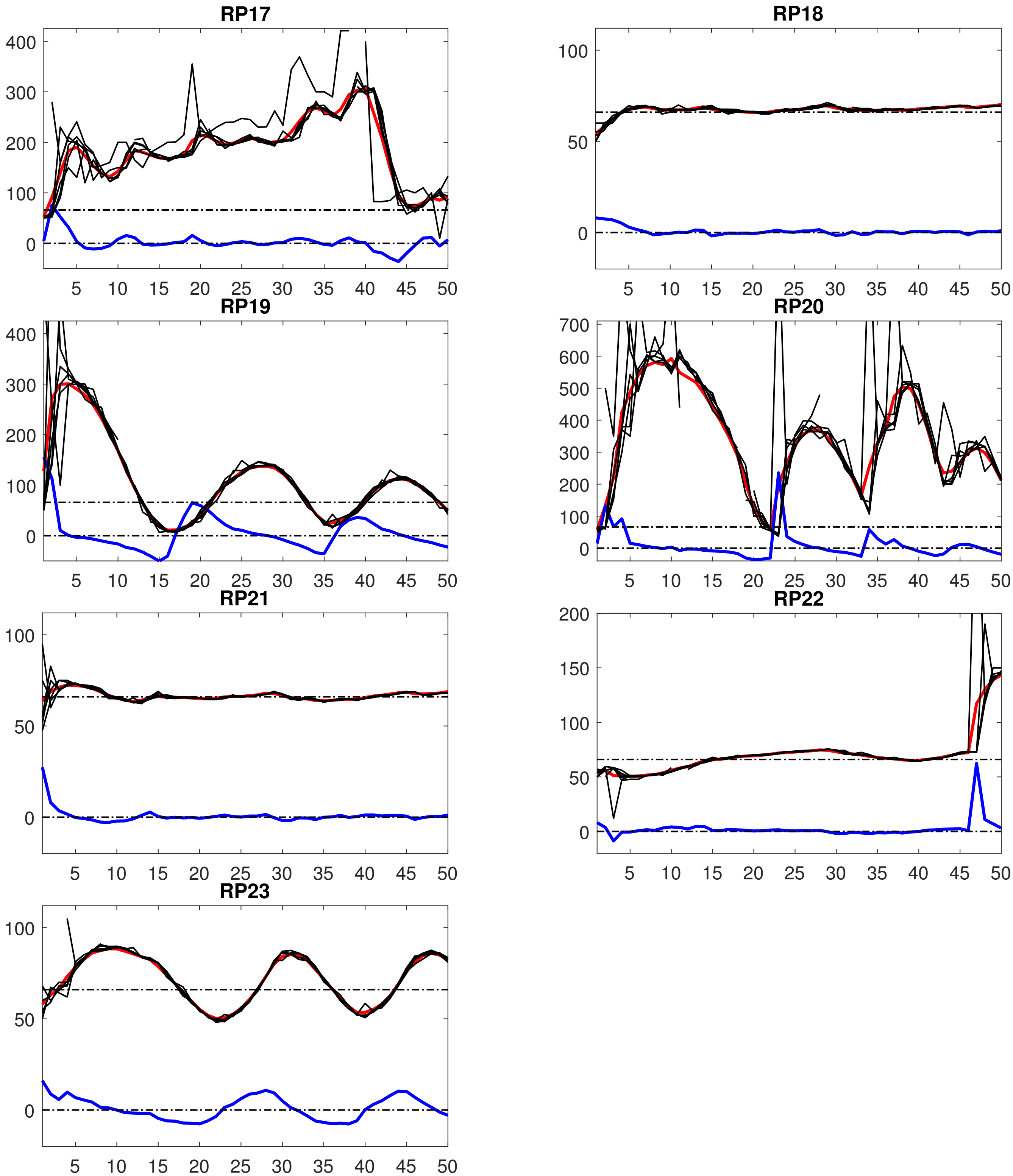

Figure C.6: Price forecasts (black), prices (red) and returns (blue) in treatment RP, markets 17 to 23. Note the different vertical scaling for some markets.

C.3 Treatment PR

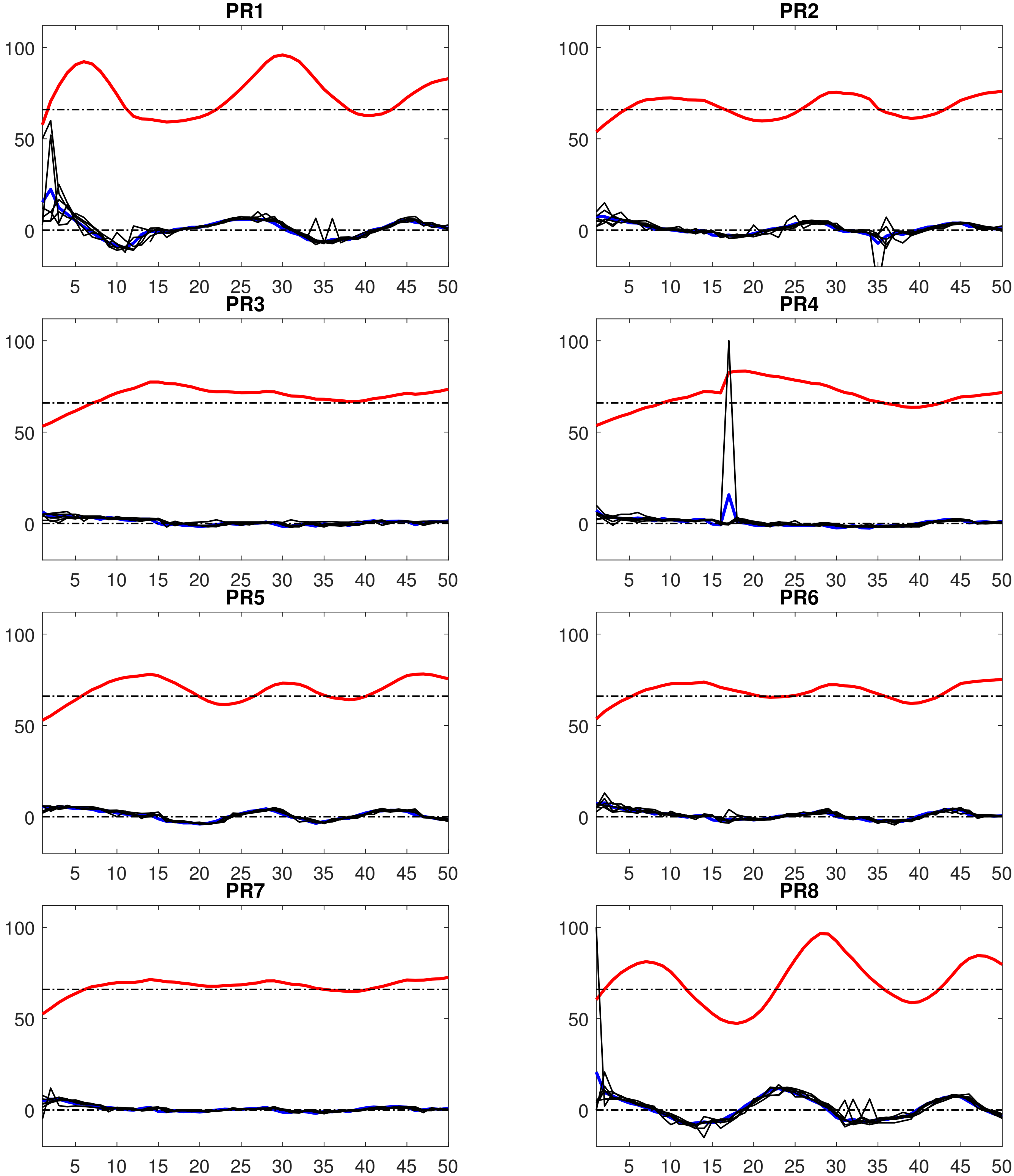

Figure C.7: Return forecasts (black), prices (red) and returns (blue) in treatment PR, markets 1 to 8

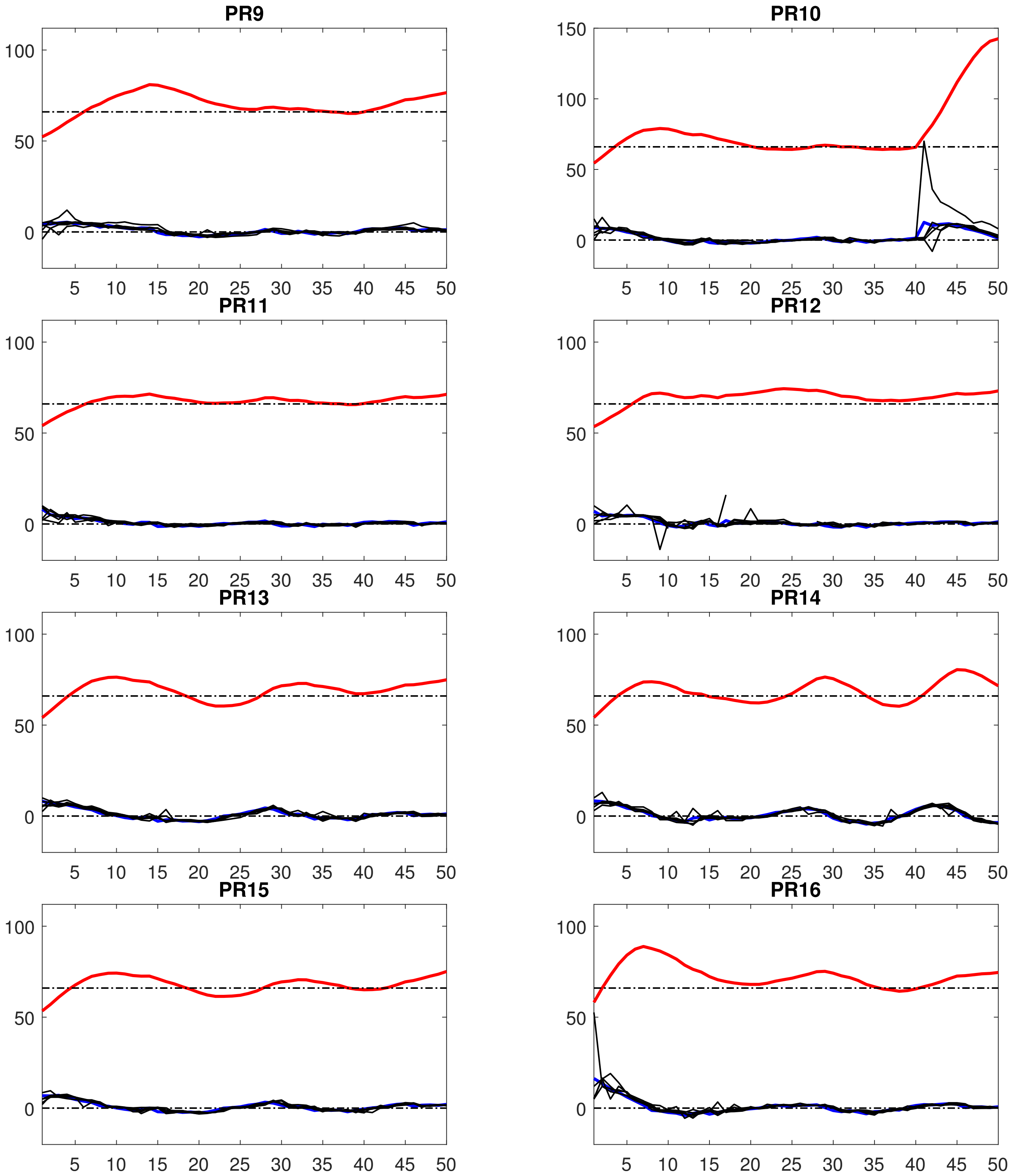

Figure C.8: Return forecasts (black), prices (red) and returns (blue) in treatment PR, markets 9 to 16. Note the different vertical scaling for some markets.

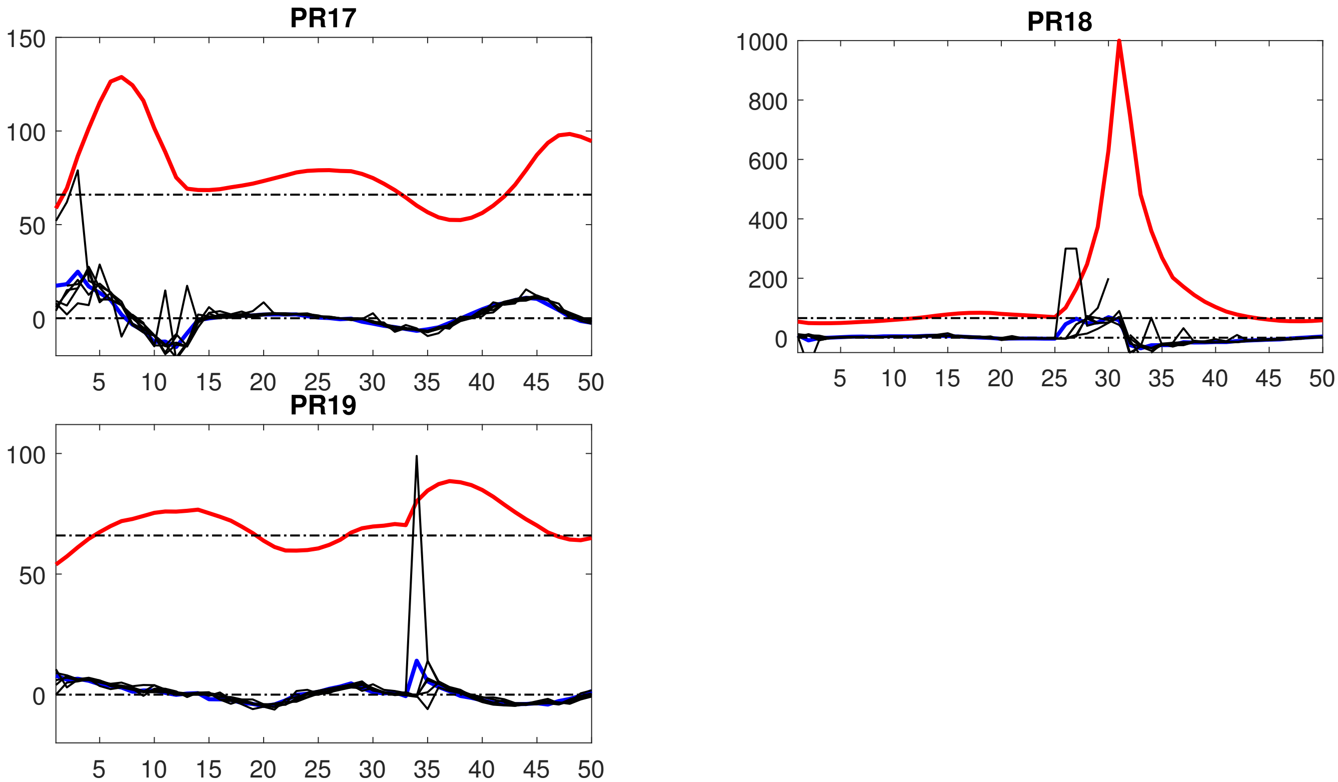

Figure C.9: Return forecasts (black), prices (red) and returns (blue) in treatment PR, markets 17 to 19. Note the different vertical scaling for some markets.

C.4 Treatment RR

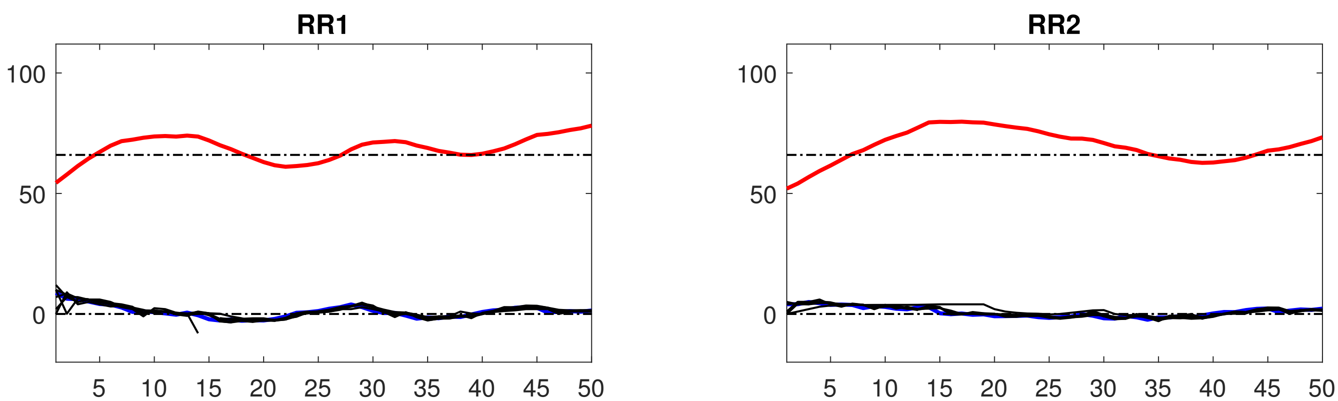

Figure C.10: Return forecasts (black), prices (red) and returns (blue) in treatment RR, markets 1 to 2.

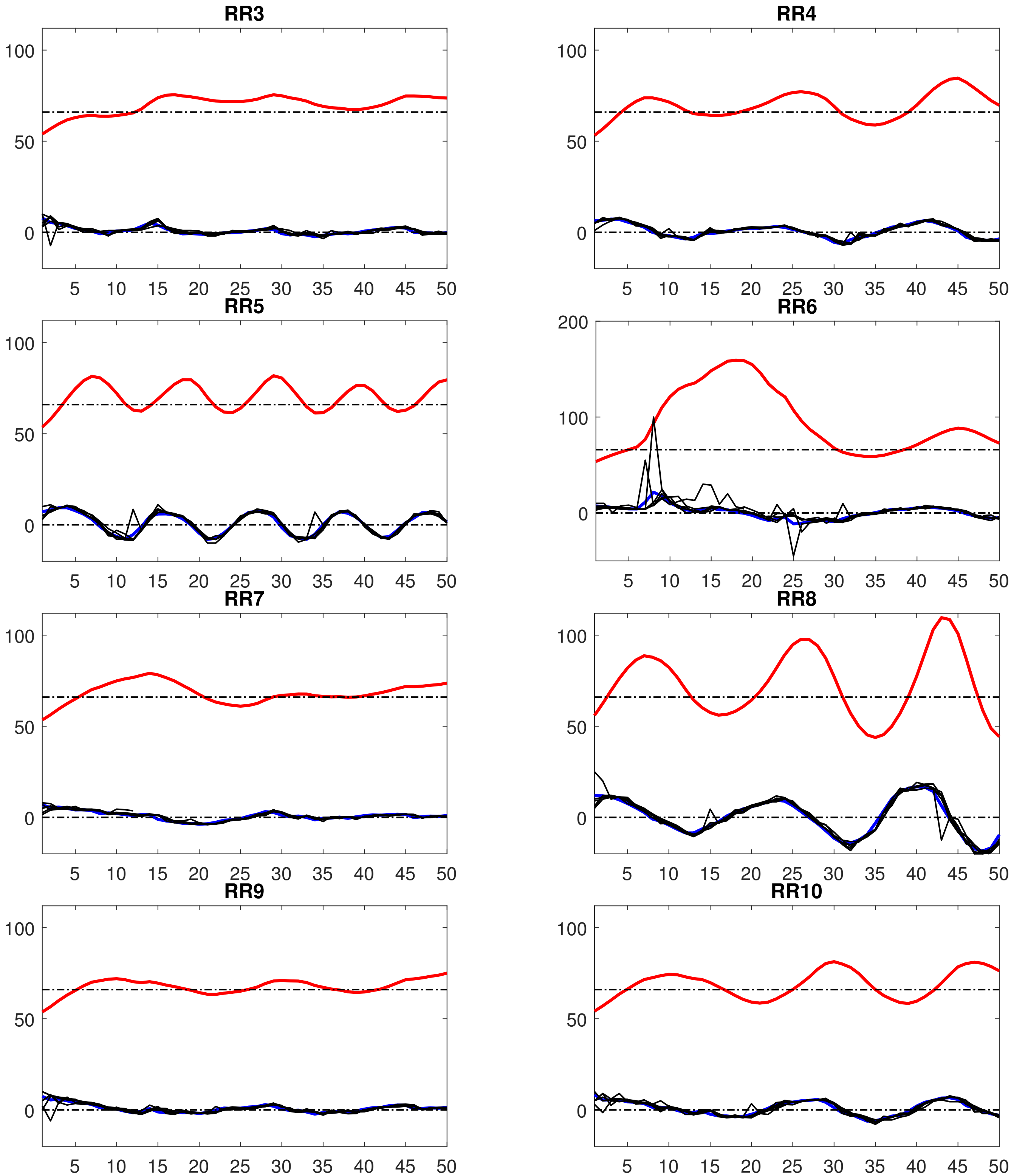

Figure C.11: Return forecasts (black), prices (red) and returns (blue) in treatment RR, markets 3 to 10. Note the different vertical scaling for some markets.

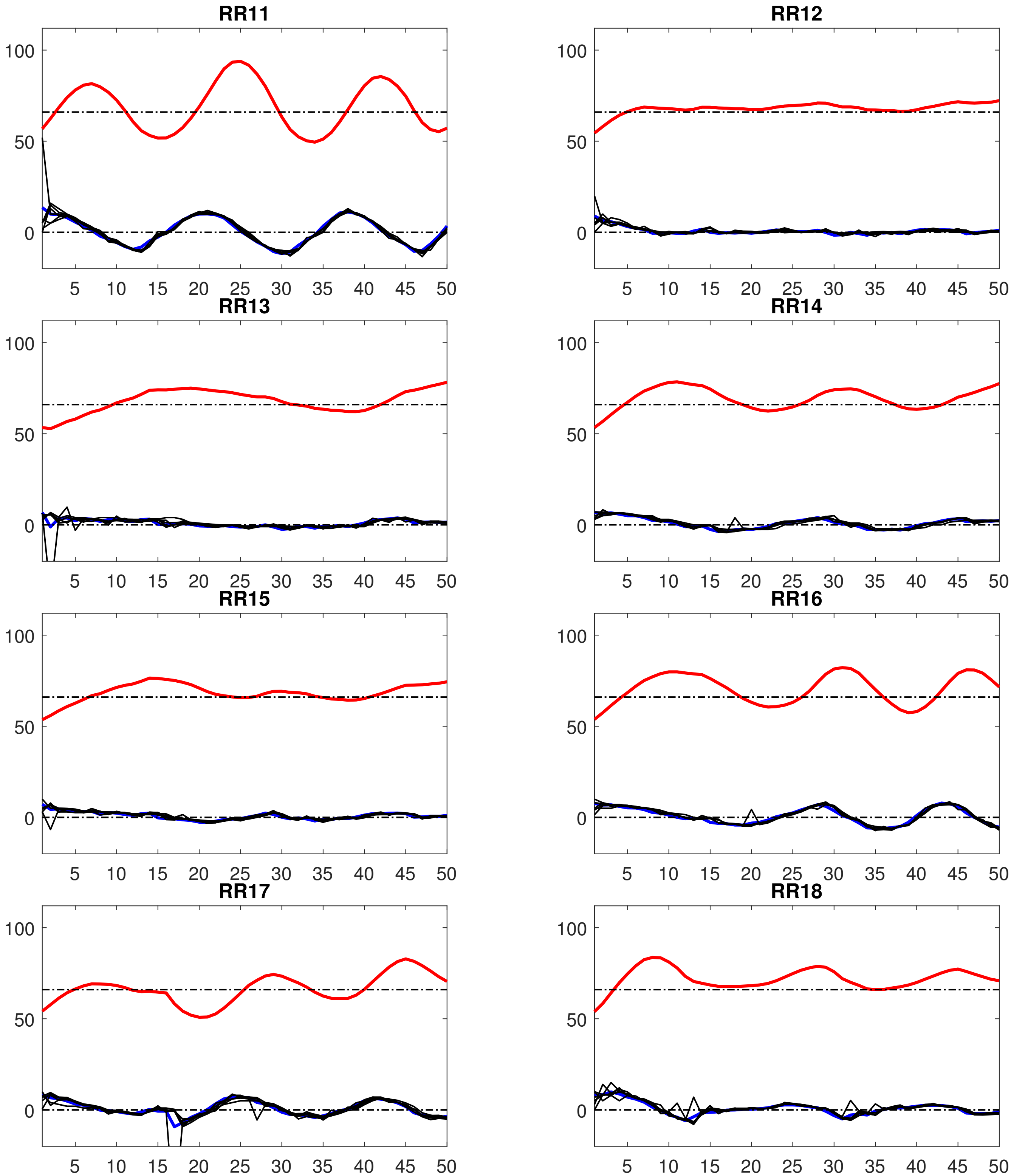

Figure C.12: Return forecasts (black), prices (red) and returns (blue) in treatment RR, markets 11 to 18.

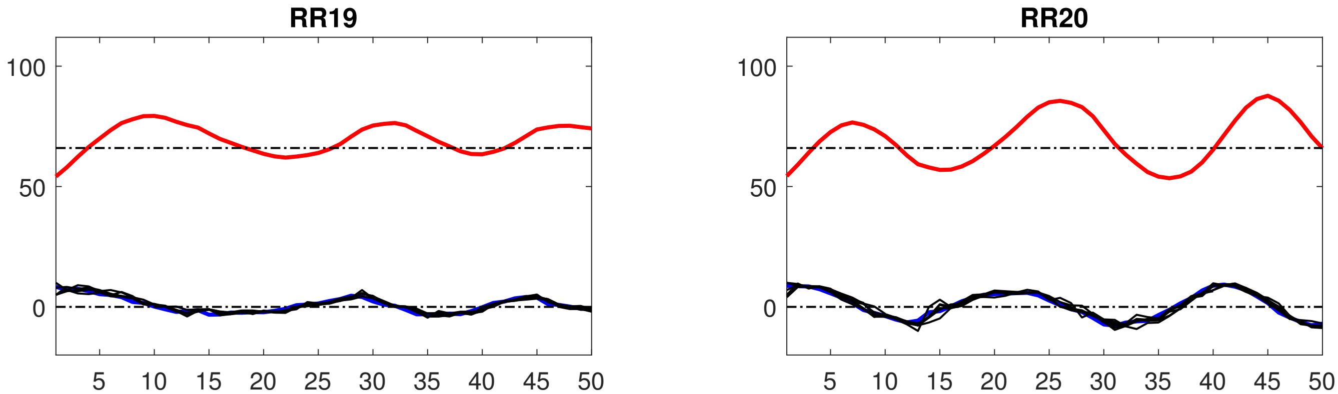

Figure C.13: Return forecasts (black), prices (red) and returns (blue) in treatment RR, markets 19 to 20.

C.5 Teatment ENDO

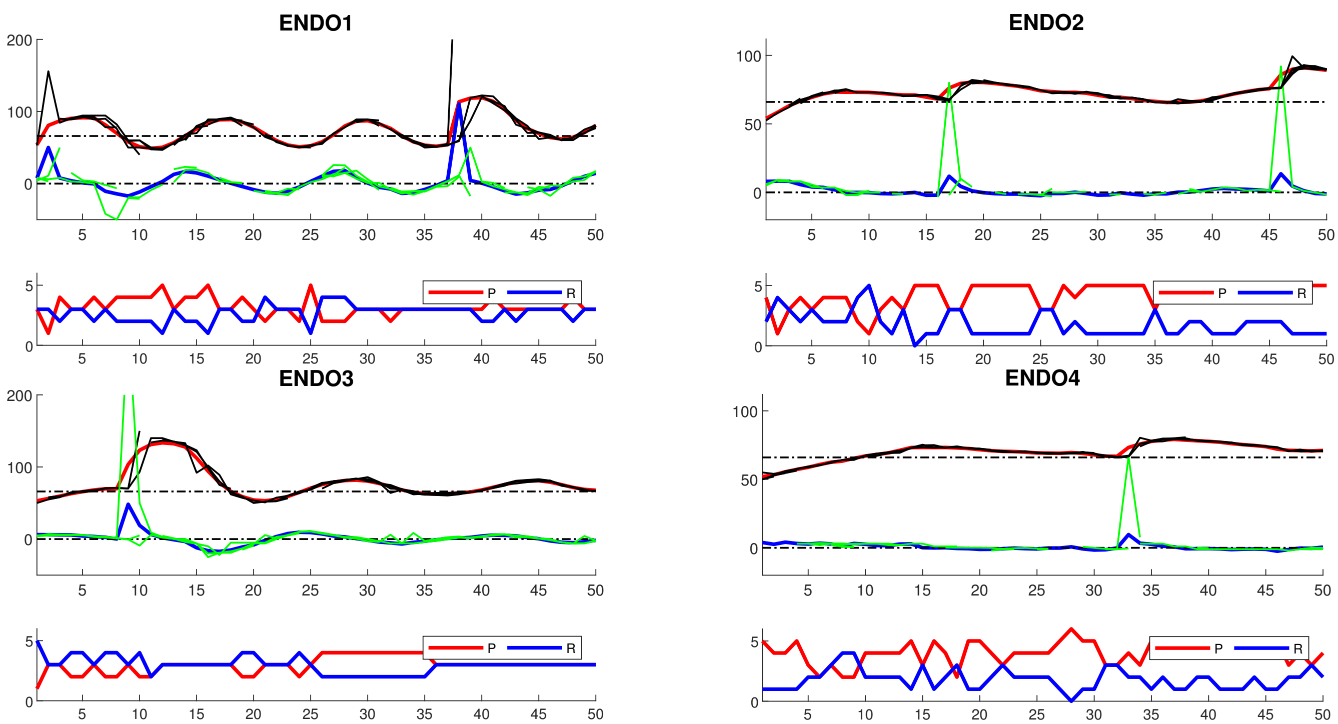

Figure C.14: Treatment ENDO, markets 1 to 4. Top panel: Price forecasts (black), return forecasts (green), prices (red), returns (blue). Bottom panel: number of subjects choosing to forecast the given variable. Note the different vertical scaling for some markets.

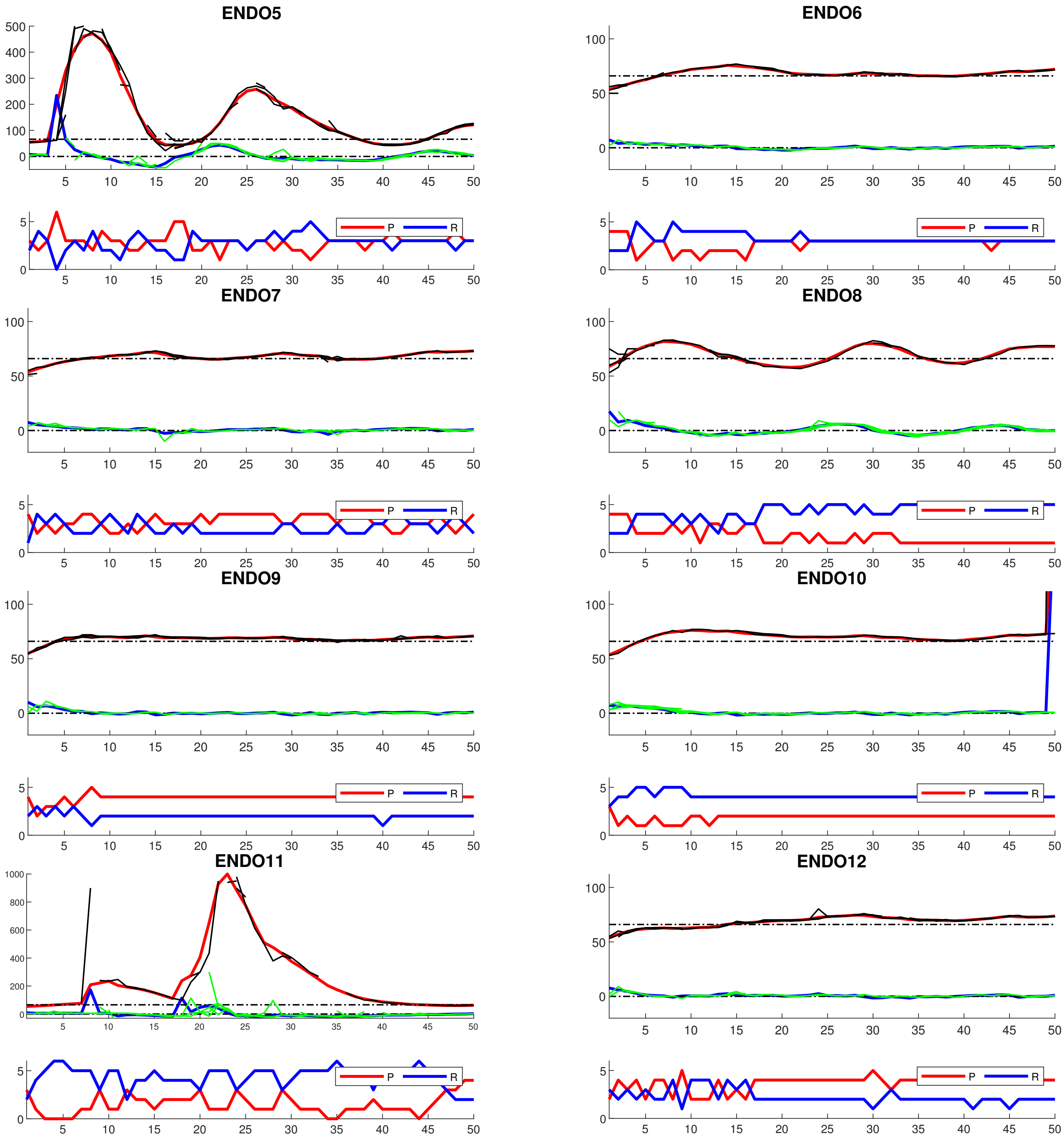

Figure C.15: Treatment ENDO, markets 5 to 12. Top panel: Price forecasts (black), return forecasts (green), prices (red), returns (blue). Bottom panel: number of subjects choosing to forecast the given variable. Note the different vertical scaling for some markets.

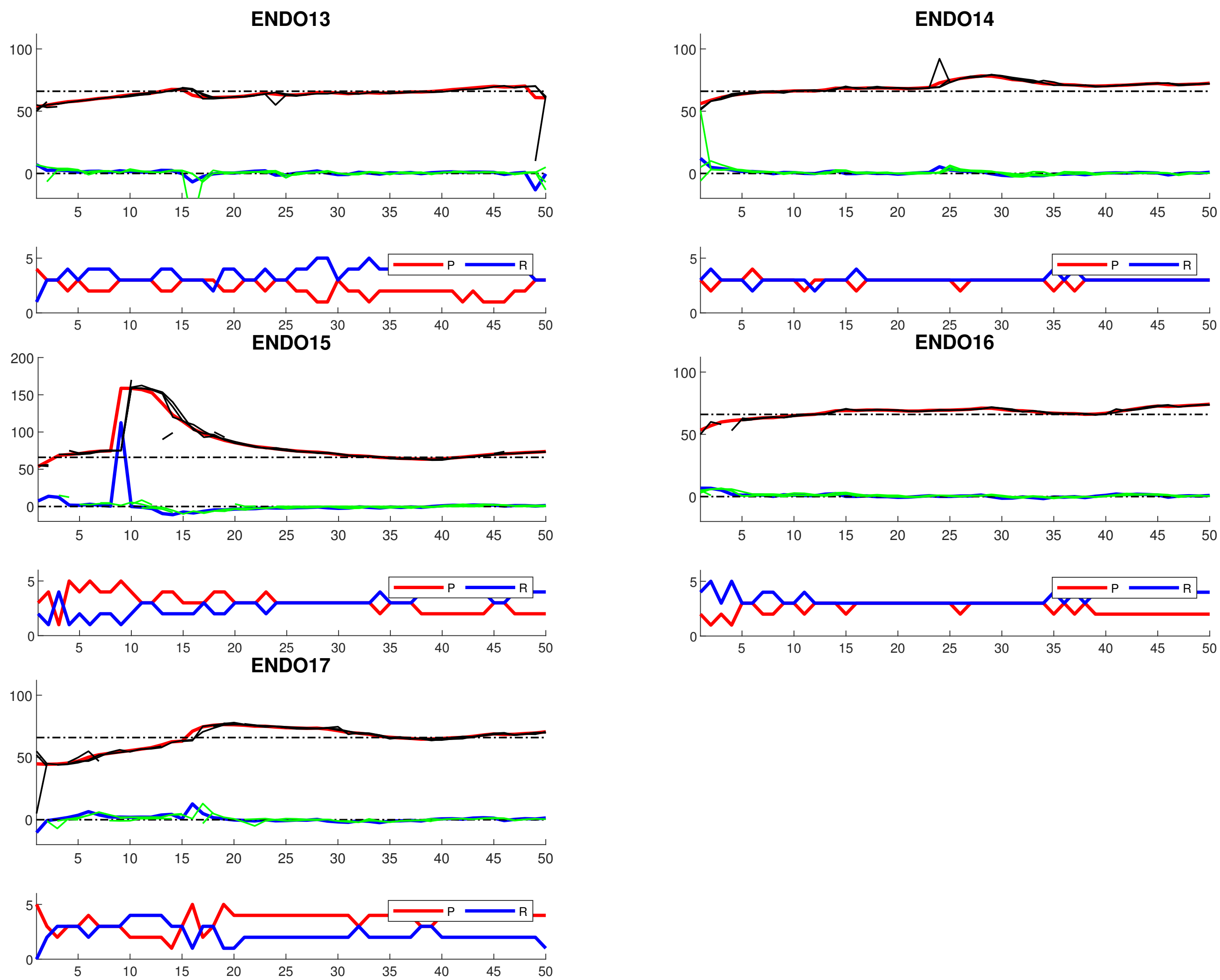

Figure C.16: Treatment ENDO, markets 13 to 17. Top panel: Price forecasts (black), return forecasts (green), prices (red), returns (blue). Bottom panel: number of subjects choosing to forecast the given variable. Note the different vertical scaling for some markets.

Table D.1: Average values, standard deviations (in parenthesis) and median values (second row) of the instability measures over the markets for each treatment, and combined treatments per information or task.

	std$_r$	**std**$_p$	**IQR**	**AR**	**RAD**	**RD**
PP	0.061 (0.069)	11.88 (15.02)	11.11 (17.50)	2.39 (3.46)	18.75 (31.50)	15.26 (30.68)
	0.019	4.35	4.52	0.93	6.56	4.89
RP	0.066 (0.084)	24.62 (34.92)	29.21 (41.10)	3.64 (4.89)	84.97 (212.08)	79.92 (213.44)
	0.025	5.15	6.33	1.17	7.57	5.49
PR	0.036 (0.047)	17.20 (45.89)	13.73 (21.31)	2.05 (1.57)	18.07 (36.04)	15.42 (35.51)
	0.024	5.35	9.54	1.43	8.18	7.40
RR	0.034 (0.024)	8.05 (7.47)	14.20 (13.77)	2.88 (2.17)	12.14 (10.66)	7.98 (10.05)
	0.023	5.34	10.26	2.09	9.21	5.74
***P**	0.063 (0.076)	18.39 (27.55)	20.36 (32.78)	3.03 (4.25)	52.59 (155.19)	48.31 (155.87)
	0.020	4.94	6.12	1.00	7.01	5.35
***R**	0.035 (0.037)	12.51 (32.35)	13.97 (17.61)	2.48 (1.92)	15.03 (26.10)	11.60 (25.73)
	0.024	5.35	9.78	1.81	8.53	6.23
P*	0.049 (0.061)	14.35 (32.76)	12.32 (19.16)	2.23 (2.72)	18.44 (33.25)	15.33 (32.58)
	0.020	4.94	6.37	1.32	7.92	6.50
R*	0.051 (0.065)	16.91 (27.09)	22.23 (32.06)	3.28 (3.84)	51.09 (157.99)	46.46 (158.83)
	0.024	5.15	9.45	1.38	8.94	5.62

D Measures of instability

In this appendix we report the values of the six measures of instability: standard deviation of logreturns, standard deviation of prices, interquartile range, median absolute returns, relative absolute deviation and relative deviation. We report both average and median values per treatment, as well as exact values for each market. These measures were introduced in Section 3.2 of the paper and we use these values in the statistical tests for comparing treatments. We also report detailed test results for comparing treatments in terms of instability. Table D.1 presents the average values per treatment, together with the standard deviations and the median values. Tables D.2 and D.3 summarize the instability measures for each individual market. The values of the measures *AR*, *RAD* and *RD* are reported in percentages.

Table D.4 presents the p-values of the Kolmogorov-Smirnov tests for comparing treatments based on the instability measures on the whole sample. In Table D.4 *same variable* corresponds to testing differences between observing and predicting the same variable (merging PP and RR) versus observing

Table D.2: Standard deviation of logreturns (std_r - left panel), standard deviation of prices (std_p - middle panel) and interquartile range of prices (IQR - right panel) over the last 40 periods. a denotes outlier markets. Last five rows are averages of the corresponding markets.

	$\mathbf{std}_r$				$\mathbf{std}_p$				**IQR**			
	PP	**RP**	**PR**	**RR**	**PP**	**RP**	**PR**	**RR**	**PP**	**RP**	**PR**	**RR**
1	0.02	0.01	0.04	0.02	5.19	2.11	11.41	4.58	7.96	2.66	19.23	7
2	0.02[a]	0.01	0.03	0.01	5.28[a]	1.29	5.35	5.66	6.37[a]	2.11	10.04	10.74
3	0.01	0.01	0.01	0.02	1.07	4.02	2.92	2.92	1.52	6.33	3.8	4.97
4	0.01	0.05	0.03[a]	0.03	1.36	9.36	6.03[a]	7.08	1.32	17.20	9.54[a]	11.07
5	0.15[a]	0.17[a]	0.02	0.05	21.39[a]	98.17[a]	5.42	6.46	7.95[a]	93.50[a]	10.54	12.03
6	0.01	0.01	0.02	0.05[a]	1.11	1.89	3.77	34.56[a]	1.16	2.94	6.82	64.36[a]
7	0.01	0.18[a]	0.01	0.02	2.68	31.75[a]	2.03	4.92	4.15	42.82[a]	2.8	6.34
8	0.17[a]	0.04[a]	0.06	0.1	42.55[a]	79.96[a]	14.19	19.1	68.94[a]	126.15[a]	22.91	31.04
9	0.03[a]	0.02	0.01	0.01	3.06[a]	3.27	4.77	3.08	1.32[a]	6.12	8.00	5.13
10	0.01	0.03[a]	0.04[a]	0.04	0.88	6.90[a]	23.21[a]	7.64	1.42	10.92[a]	11.56[a]	14.27
11	0.10[a]	0.01	0.01	0.07	13.19[a]	1.73	1.67	13.89	11.31[a]	2.38	3.01	24.87
12	0.22[a]	0.01[a]	0.01	0.01	28.33[a]	2.80[a]	1.94	1.6	12.08[a]	5.09[a]	2.95	2.63
13	0.01	0.01	0.02	0.02	1.2	1.7	4.38	4.66	1.7	1.8	5.46	8.11
14	0.02	0.01[a]	0.03	0.02	2.93	3.45[a]	5.88	4.9	4.18	5.29[a]	10.18	9.45
15	0.02	0.03[a]	0.02	0.01	4.94	5.15[a]	3.72	3.7	8.99	7.72[a]	5.33	6.55
16	0.08	0.10[a]	0.02	0.04	19.07	56.34[a]	3.87	7.91	30.74	32.42[a]	5.73	15.78
17	0.01	0.12[a]	0.06[a]	0.04[a]	0.8	62.56[a]	12.40[a]	8.47[a]	1.3	63.21[a]	12.15[a]	12.02[a]
18	0.19[a]	0.01	0.22[a]	0.02	32.10[a]	1.1	205.42[a]	3.84	4.16[a]	1.53	98.95[a]	6.73
19	0.01	0.28[a]	0.03[a]	0.02	2.77	39.51[a]	8.45[a]	5.03	4.18	69.80[a]	11.83[a]	9.78
20	0.02	0.28[a]		0.05	3.76	119.65[a]		11	5.98	138.05[a]		21.16
21	0.09[a]	0.01			14.11[a]	1.43			4.84[a]	2.41		
22	0.13[a]	0.08[a]			53.60[a]	19.72[a]			52.78[a]	6.23[a]		
23		0.06[a]				12.47[a]				25.06[a]		
average	0.06	0.07	0.04	0.03	11.88	24.62	17.2	8.05	11.11	29.21	13.73	14.2
outlier	0.123	0.105	0.076	0.047	23.74	41.42	51.1	21.51	18.86	48.17	28.8	38.19
non-outlier	0.018	0.015	0.022	0.032	3.67	2.79	5.09	6.55	5.74	4.55	8.34	11.54
stable	0.013	0.012	0.015	0.017	1.96	2.5	3.44	3.92	2.57	3.86	5.39	6.67
unstable	0.11	0.12	0.05	0.05	21.8	45.13	27.42	12.18	19.65	52.76	20.24	21.73

Table D.3: Median absolute returns (AR - left panel), relative absolute deviation (RAD - middle panel) and relative deviation (RD - right panel) over the last 40 periods (in percentages). a denotes outlier markets. Last five rows are averages of the corresponding markets.

	AR				**RAD**				**RD**			
	PP	**RP**	**PR**	**RR**	**PP**	**RP**	**PR**	**RR**	**PP**	**RP**	**PR**	**RR**
1	1.61	0.77	3.55	1.37	7.01	2.91	15.23	7.01	5.35	1.38	10.47	4.88
2	1.00[a]	0.63	1.94	1.33	31.38[a]	3.78	7.55	9.88	31.38[a]	3.78	2.93	8.41
3	0.56	1.17	0.94	1	3.89	6	8.37	8.94	3.89	3.39	8.37	8.81
4	0.58	4.24	1.12[a]	2.74	2.35	12.48	10.25[a]	9.75	2.32	0.82	9.44[a]	6.23
5	2.18[a]	7.92[a]	2.04	5.18	20.43[a]	103.09[a]	8.83	9.48	19.12[a]	92.12[a]	6.84	6.38
6	0.61	0.69	1.32	4.35[a]	3.67	5.49	6.19	52.73[a]	3.52	5.49	4.86	49.80[a]
7	0.78	8.15[a]	0.81	1.25	3.58	77.76[a]	4.7	6.63	2.61	77.69[a]	4.4	4.62
8	14.77[a]	0.81[a]	5.24	8.49	57.50[a]	971.57[a]	18.82	24.6	28.86[a]	971.57[a]	6.65	8.74
9	0.73[a]	1.08	1.27	1.2	4.93[a]	4.18	8.18	4.64	2.70[a]	-0.2	8.03	3.43
10	0.5	1.82[a]	1.42[a]	3.18	1.5	10.59[a]	20.87[a]	10.84	1.44	-5.20[a]	19.42[a]	5.38
11	3.71[a]	0.75	0.77	6.99	15.34[a]	5.36	3.48	18.4	6.50[a]	5.29	3.42	2.82
12	3.04[a]	0.75[a]	0.66	0.58	19.45[a]	3.60[a]	7.4	4.32	11.98[a]	-2.25[a]	7.4	4.32
13	0.6	0.45	1.32	1.03	1.55	6.95	7.28	8.07	-0.55	6.92	4.71	6.19
14	0.93	0.75[a]	2.41	2.05	3.76	4.69[a]	7.84	7.52	0.71	1.90[a]	4.29	5.61
15	1.55	1.36[a]	1.37	1.1	8.12	7.57[a]	5.27	6.23	5.57	5.62[a]	2.85	5.69
16	8.86	7.34[a]	1.48	3.4	25.67	56.20[a]	7.92	12.08	11.84	51.69[a]	7.52	7.46
17	0.55	3.82[a]	2.38[a]	3.26[a]	1.04	192.14[a]	17.57[a]	10.38[a]	0.51	192.14[a]	11.15[a]	1.04[a]
18	0.93[a]	0.63	6.69[a]	1.81	22.71[a]	2.69	165.53[a]	8.53	22.58[a]	2.65	161.19[a]	8.53
19	0.9	20.36[a]	2.28[a]	2.13	5.21	54.00[a]	12.15[a]	7.92	4.42	15.87[a]	8.98[a]	5.79
20	1.05	12.23[a]		5.16	6.11	388.39[a]		14.85	3.91	387.81[a]		5.5
21	0.93[a]	0.58			21.11[a]	1.82			21.11[a]	0		
22	6.20[a]	1.38[a]			146.15[a]	15.35[a]			145.86[a]	13.72[a]		
23		5.92[a]				17.65[a]				5.98[a]		
average	2.39	3.64	2.05	2.88	18.75	84.97	18.07	12.14	15.26	79.92	15.42	7.98
outlier	3.72	5.58	2.78	3.8	37.67	146.35	45.27	31.56	32.23	139.13	42.04	25.42
non-outlier	1.47	1.1	1.79	2.78	5.65	5.17	8.36	9.98	3.5	2.95	5.91	6.04
stable	0.71	0.8	1.19	1.35	3.42	4.59	6.63	6.98	2.32	2.83	5.45	5.79
unstable	4.07	6.28	2.78	4.41	34.08	158.9	26.6	17.3	28.2	150.82	22.63	10.17

Table D.4: Summary of p-values in the Kolmogorov-Smirnov tests for comparing treatments in terms of instability.

	std$_r$	**std$_p$**	**IQR**	**AR**	**RAD**	**RD**
PP vs RP	0.737	0.978	1.000	0.887	0.924	0.690
PR vs RR	0.893	0.779	0.947	0.952	0.770	0.117
PP vs PR	0.349	0.219	0.102	0.025*	0.083	0.127
RP vs RR	0.042*	0.150	0.052	0.042*	0.091	0.150
PP vs RR	0.199	0.109	0.006**	0.002**	0.049*	0.199
PR vs RP	0.351	0.351	0.243	0.104	0.203	0.081
*P vs *R	0.046*	0.053	0.024*	0.002**	0.008**	0.019*
P* vs R*	0.874	0.941	1.000	0.978	0.849	0.326
same variable	0.791	0.791	0.791	0.932	0.791	0.610

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. All tests are one-sided except for *PP vs RR* and *same variable*. Observations correspond to markets, the number of observations is $n_{PP} = 22$, $n_{RP} = 23$, $n_{PR} = 19$, $n_{RR} = 20$, $n_{*P} = 45$, $n_{*R} = 39$, $n_{P*} = 41$ and $n_{R*} = 43$.

and predicting different variables (merging RP and PR). The table shows that there are some significant differences between some of the treatments for some of the measures, but these results are not unequivocal across the measures. Finally, as we also discussed in the main text, the tests show a consistent significant difference between *P and *R. This means that forecasting prices leads to more stable markets than forecasting returns.

Table D.5 presents a summary of the instability measures for treatment ENDO as well as non-parametric test results comparing this additional treatment to the initial four treatments and to the merged treatments. Table D.6 lists the instability measures of the individual markets for the additional treatment, whereas Table D.7 presents the regression results investigating treatment differences in stability. These analyses do not reveal systematic treatment differences between the additional and the initial treatments.

Tables D.8 and D.9 repeat the main analysis for the sample splits considered in Section 3.3. Again, we do not find systematic treatment differences, except that RR seems to be more unstable and PP more stable for some instability measures than the additional treatment.

Finally, Table D.10 focuses only on treatment ENDO, and investigates how the number of subjects choosing to predict a given variable, choosing to observe a given variable, switching between tasks between periods and switching between history within a period influence market stability. Table D.10 shows the regression results on the market level of a multivariate multiple regression on the different instability

Table D.5: Summary of mean, standard deviation and median of the instability measures (Panel A) and p-values of the Kolmogorov-Smirnov tests for comparing the original treatments to treatment ENDO in terms of the instability measures (Panel B.)

	std$_r$	**std**$_p$	**IQR**	**AR**	**RAD**	**RD**
Panel A: descriptive statistics						
mean	0.060	26.956	31.905	2.962	34.457	31.637
standard deviation	0.072	62.230	75.460	4.041	78.467	77.903
median	0.027	4.995	5.340	0.885	9.603	8.144
Panel B: test results						
PP vs ENDO	0.852	0.680	0.385	0.680	0.266	0.070
RP vs ENDO	0.929	0.499	0.660	0.938	0.726	0.089
PR vs ENDO	0.581	0.470	0.436	0.051	0.581	0.292
RR vs ENDO	0.291	0.238	0.055	0.005**	0.708	0.055
*P vs ENDO	0.945	0.455	0.581	0.820	0.346	0.037*
*R vs ENDO	0.504	0.217	0.095	0.004**	0.545	0.095
P* vs ENDO	0.906	0.746	0.604	0.197	0.857	0.328
R* vs ENDO	0.908	0.683	0.229	0.107	0.993	0.308

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. All tests are two-sided. Observations correspond to markets, the number of observations is $n_{PP} = 22$, $n_{RP} = 23$, $n_{PR} = 19$, $n_{RR} = 20$, $n_{*P} = 45$, $n_{*R} = 39$, $n_{P*} = 41$, $n_{R*} = 43$, and $n_{ENDO} = 17$.

measures. We regress the instability measures on the task and history subjects choose, and on the switching rates between tasks and between information.[1] Consistent with our main finding for the original treatments, we find that predicting prices instead of returns result in a more stable market (first row of Table D.10). Note however, that the significantly negative coefficients for *price task* are the result of the outlier market ENDO11 (see Figure C.15 in Online Appendix C). That market has very large bubbles due to one subject inflating the bubble every now and then, and the market also has a high fraction of subjects submitting returns. Removing that market, and running the regression with the remaining 16 markets, results in insignificant, and substantially lower, coefficients for *price task*.

[1] We have substantial variation between markets with respect to these variables: *Price task* has 0.50 mean and 0.15 st. dev.; *switch task* has 2.94 mean and 2.38 st. dev.; *price history* has 0.50 mean and 0.15 st. dev; and *switch history* has 0.65 mean and 0.43 st. dev.

Table D.6: Instability measures for each market in treatment ENDO. a denotes outlier markets. Last five rows give averages of the corresponding markets.

	$\mathbf{std}_r$	$\mathbf{std}_p$	**IQR**	**AR**	**RAD**	**RD**
1^a	0.151	19.29	28.02	8.36	24.20	12.64
2^a	0.031	6.95	8.55	1.20	12.72	12.67
3^a	0.069	20.83	15.67	4.26	22.62	17.72
4^a	0.019	3.42	5.34	0.77	9.84	9.84
5^a	0.204	72.85	113.22	13.03	97.94	83.01
6	0.010	2.89	4.31	0.79	4.97	4.92
7	0.013	2.44	4.40	0.86	4.30	3.99
8	0.032	6.89	13.78	2.62	9.60	4.29
9	0.008	1.18	1.58	0.64	4.26	4.26
10^a	0.174	23.55	2.75	0.69	12.69	12.69
11^a	0.197	258.68	306.32	11.64	326.53	324.86
12	0.009	2.84	3.47	0.72	7.46	6.95
13^a	0.027	2.65	3.74	0.92	3.64	-1.54
14	0.013	3.13	4.00	0.55	8.14	8.14
15^a	0.033	23.52	16.77	1.81	24.54	23.68
16	0.009	2.15	2.56	0.61	5.06	5.03
17^a	0.024	4.99	7.91	0.88	7.27	4.67
average	0.060	26.956	31.905	2.962	34.457	31.637
outlier	0.093	43.673	50.829	4.356	54.198	50.025
non-outlier	0.013	3.074	4.872	0.97	6.256	5.369
stable	0.015	2.855	4.146	0.751	6.104	5.140
unstable	0.101	48.442	56.713	4.93	60.075	55.712

Table D.7: Multivariate multiple linear regressions

	Dependent variable:					
	$\mathbf{std}_r$	$\mathbf{std}_p$	**IQR**	**AR**	**RAD**	**RD**
PP	0.000 (0.021)	-15.08 (12.00)	-20.80 (12.61)	-0.57 (1.13)	-15.71 (35.10)	-16.38 (35.25)
RP	0.006 (0.020)	-2.33 (11.88)	-2.70 (12.49)	0.67 (1.12)	50.51 (34.77)	48.28 (34.91)
PR	-0.024 (0.021)	-9.75 (12.40)	-18.18 (13.04)	-0.91 (1.17)	-16.38 (36.29)	-16.22 (36.44)
RR	-0.027 (0.021)	-18.91 (12.26)	-17.70 (12.89)	-0.08 (1.15)	-22.32 (35.86)	-23.66 (36.01)
constant	0.060*** (0.015)	26.96** (9.01)	31.91** (9.47)	2.96** (0.85)	34.46 (26.36)	31.64 (26.47)
R^2	0.0463	0.0376	0.0488	0.0257	0.0652	0.0621

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. Standard errors are in brackets. The independent variables are dummy variables being 1 for the corresponding treatment, and 0 otherwise. The base treatment is the treatment ENDO. Observations correspond to markets, the number of observations is 101.

Table D.8: Summary of p-values of the Kolmogorov-Smirnov tests for comparing the original treatments to treatment ENDO for only non-outlier markets (Panel A), stable markets (Panel B) and unstable markets (Panel C).

	std$_r$	**std**$_p$	**IQR**	**AR**	**RAD**	**RD**
Panel A: non-outlier markets						
PP vs ENDO	0.641	0.641	0.432	0.641	0.046*	0.017*
RP vs ENDO	0.931	0.117	0.378	1.000	0.189	0.022*
PR vs ENDO	0.083	0.083	0.083	0.033*	0.341	0.981
RR vs ENDO	0.001**	0.008**	0.001**	0.001**	0.174	0.226
*P vs ENDO	0.818	0.227	0.489	0.818	0.040*	0.005**
*R vs ENDO	0.003**	0.010*	0.003**	0.001**	0.148	0.429
P* vs ENDO	0.159	0.333	0.333	0.104	0.481	0.173
R* vs ENDO	0.037*	0.098	0.037*	0.037*	0.556	0.556
Panel B: stable markets						
PP vs ENDO	0.504	0.242	0.070	0.242	0.028*	0.002**
RP vs ENDO	0.638	0.159	0.427	0.851	0.345	0.061
PR vs ENDO	0.787	0.135	0.343	0.007**	0.492	0.975
RR vs ENDO	0.075	0.045*	0.018*	0.000***	0.492	0.787
*P vs ENDO	0.714	0.096	0.164	0.764	0.054	0.003**
*R vs ENDO	0.172	0.035*	0.042*	0.000***	0.315	0.981
P* vs ENDO	0.800	0.467	0.605	0.151	0.467	0.055
R* vs ENDO	0.875	0.359	0.168	0.029*	0.953	0.528
Panel C: unstable markets						
PP vs ENDO	0.688	0.919	0.324	0.919	0.783	0.894
RP vs ENDO	0.729	0.427	0.268	0.851	0.427	0.729
PR vs ENDO	0.165	0.140	0.324	0.539	0.165	0.039*
RR vs ENDO	0.252	0.075	0.575	0.230	0.393	0.003**
*P vs ENDO	0.811	0.688	0.868	0.826	0.688	0.919
*R vs ENDO	0.184	0.043*	0.605	0.605	0.184	0.005**
P* vs ENDO	0.662	0.334	0.210	0.743	0.578	0.168
R* vs ENDO	0.472	0.690	0.690	0.395	0.940	0.076

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. All tests are two-sided. Observations correspond to markets, the number of observations is $n_{PP} = 13$, $n_{RP} = 10$, $n_{PR} = 14$, $n_{RR} = 18$, $n_{*P} = 23$, $n_{*R} = 32$, $n_{P*} = 27$, $n_{R*} = 28$, and $n_{ENDO} = 7$ in Panel A, $n_{PP} = 11$, $n_{RP} = 12$, $n_{PR} = 10$, $n_{RR} = 10$, $n_{*P} = 23$, $n_{*R} = 20$, $n_{P*} = 21$, $n_{R*} = 22$, and $n_{ENDO} = 9$ in Panel B and $n_{PP} = 11$, $n_{RP} = 12$, $n_{PR} = 11$, $n_{RR} = 10$, $n_{*P} = 23$, $n_{*R} = 22$, $n_{P*} = 22$, $n_{R*} = 24$, and $n_{ENDO} = 9$ in Panel C.

Table D.9: Multivariate multiple linear regressions for sample splits

	Dependent variable:					
	$\mathbf{std}_r$	$\mathbf{std}_p$	**IQR**	**AR**	**RAD**	**RD**
Panel A: non-outlier markets						
PP	0.004 (0.009)	0.599 (1.800)	0.866 (3.103)	0.497 (0.840)	-0.607 (2.184)	-1.866 (1.094)
RP	0.001 (0.009)	-0.283 (1.892)	-0.325 (3.262)	0.131 (0.883)	-1.090 (2.296)	-2.417* (1.150)
PR	0.008 (0.009)	2.020 (1.777)	3.470 (3.064)	0.825 (0.829)	2.105 (2.157)	0.541 (1.080)
RR	0.019* (0.008)	3.479* (1.710)	6.663* (2.948)	1.806* (0.798)	3.727 (2.075)	0.673 (1.039)
constant	0.013 (0.007)	3.074* (1.451)	4.872 (2.502)	0.970 (0.677)	6.256** (1.761)	5.369*** (0.882)
R^2	0.136	0.136	0.160	0.134	0.157	0.249
Panel B: stable markets						
PP	-0.002 (0.003)	-0.891 (0.520)	-1.580 (0.919)	-0.042 (0.144)	-2.688** (0.786)	-2.824* (1.060)
RP	-0.003 (0.003)	-0.359 (0.510)	-0.282 (0.901)	0.052 (0.141)	-1.518 (0.771)	-2.309* (1.040)
PR	0.000 (0.003)	0.586 (0.531)	1.247 (0.939)	0.438** (0.147)	0.529 (0.804)	0.308 (1.083)
RR	0.002 (0.003)	1.068 (0.531)	2.522* (0.939)	0.599*** (0.147)	0.878 (0.804)	0.646 (1.083)
constant	0.015*** (0.002)	2.855*** (0.385)	4.146*** (0.681)	0.751*** (0.107)	6.104*** (0.583)	5.140*** (0.786)
R^2	0.101	0.285	0.342	0.415	0.400	0.297
Panel C: unstable markets						
PP	0.008 (0.031)	-26.645 (21.303)	-37.063 (22.171)	-0.860 (1.830)	-25.996 (64.125)	-27.516 (64.913)
RP	0.015 (0.030)	-3.314 (20.900)	-3.956 (21.751)	1.348 (1.795)	98.824 (62.911)	95.108 (63.684)
PR	-0.049 (0.031)	-21.020 (21.303)	-36.473 (22.171)	-2.153 (1.830)	-33.478 (64.125)	-33.085 (64.913)
RR	-0.051 (0.032)	-36.266 (21.777)	-34.979 (22.664)	-0.523 (1.870)	-42.775 (65.552)	-45.537 (66.357)
constant	0.101*** (0.023)	48.442** (15.799)	56.713** (16.442)	4.930** (1.357)	60.075 (47.556)	55.712 (48.141)
R^2	0.162	0.083	0.112	0.086	0.137	0.130

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. Standard errors are in brackets. The independent variables are dummy variables being 1 for the corresponding treatment, and 0 otherwise. The base treatment is treatment ENDO. Observations correspond to markets, the number of observations is 62 in Panel A, 52 in Panel B and 53 in Panel C.

Table D.10: Multivariate multiple linear regressions on task and information choices

	Dependent variable:					
	$\mathbf{std}_r$	$\mathbf{std}_p$	**IQR**	**AR**	**RAD**	**RD**
price task	-0.24 (0.12)	-259.06* (98.95)	-310.20* (118.22)	-13.84* (5.96)	-315.17* (125.80)	-303.47* (128.44)
switch task	0.01 (0.01)	7.11 (7.31)	7.48 (8.47)	0.37 (0.43)	7.67 (9.01)	7.55 (9.20)
price history	-0.08 (0.14)	39.36 (111.11)	81.96 (132.59)	4.20 (6.69)	73.07 (141.10)	63.84 (144.06)
switch history	0.05 (0.04)	53.78 (32.21)	70.30 (38.58)	5.07* (1.95)	71.44 (41.06)	67.93 (41.92)
constant	0.16 (0.07)	81.51 (58.61)	77.88 (69.67)	3.37 (3.51)	86.09 (74.14)	84.72 (75.70)
R^2	0.39	0.48	0.50	0.55	0.48	0.45

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. Standard errors are in brackets. *Price task* denotes the average fraction of subjects choosing to predict price throughout the experiment. *Switch task* is the average number of switching between the two prediction variables per subject in the group throughout the experiment. *Price history* is the average fraction of subjects for whom price is the last observed history in a given period. *Switch history* is the average number of switches per subject between the two different histories within a given period. Observations correspond to markets, the number of observations is 17.

Table E.1: Reactions to price changes: treatment comparison with linear regression

Dependent variable: $p^f_{h,t+1} - p_t$							
$(p_t - p_{t-1})$	$(p_t - p_{t-1})$ ·PP	$(p_t - p_{t-1})$ ·RP	$(p_t - p_{t-1})$ ·PR	PP	RP	PR	constant
0.967***	-0.864***	-0.339***	-0.500***	0.165	2.193	0.282	0.155***
(0.013)	(0.114)	(0.085)	(0.014)	(0.178)	(1.444)	(0.227)	(0.055)

Notes: ***: significant at 0.1% level, **: significant at 1% level, *: significant at 5% level. Linear regression with individual decisions as observations: $n = 20,066$, $R^2 = 0.077$. PP, PR and RP are treatment dummies, the base treatment is RR. Standard errors are in parentheses, and clustered on the market level.

E Trend extrapolation

In this appendix we start by investigating how subjects respond to price changes in the different treatments. Figure E.1 shows a scatter plot of $p^f_{h,t+1} - p_t$ against $p_t - p_{t-1}$ for the four treatments.[2] Obviously, there is a strong positive relation between the expected change in the price and the last observed price change. That is, in each of the four treatments subjects have a tendency to extrapolate trends: If they observe a price increase (decrease) in the previous period they expect that the price will again increase (decrease) in the current period.

[2]Return forecasts in treatments PR and RR are transformed to price forecasts by $p^f_{h,t} = \left(1 + r^f_{h,t}\right) p_{t-1}$. As before, we use the data of the last 40 periods only.

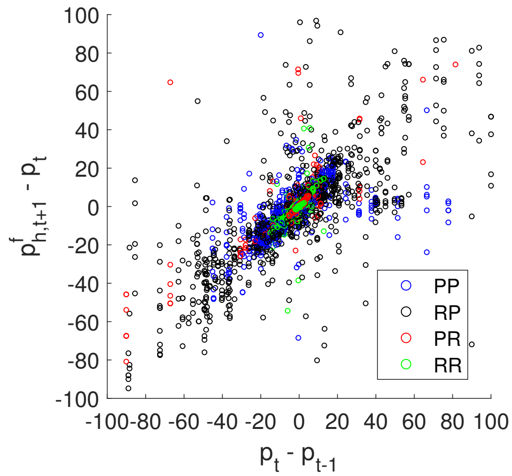

Figure E.1: A scatter plot of $p^f_{h,t+1} - p_t$ vs. $p_t - p_{t-1}$

We investigate the relation between the past price change and the adjustment in forecast with a linear regression with the expected price change as dependent variable. The independent variables include a constant, the last observed price change, treatment dummies and interaction between the last observed price change and the treatment dummies. The corresponding coefficients are reported in Table E.1. The slopes are almost always significantly different from each other (the only exception is PR and RP), and all but PP are significantly higher than 0.[3] Notice that the slopes are higher in treatments *R than in treatments *P once we fix the information subjects can observe. Also, the slopes are higher in treatments R* than in treatments P*.[4] We therefore find that, although trend extrapolation plays a role in almost all treatments, it is clearly stronger in treatments where returns need to be forecasted than in treatments where prices need to be forecasted. Subjects tend to extrapolate trends in past price changes more strongly when they need to forecast returns than when they need to forecast prices. In the treatments where prices need to be forecasted, in particular in treatment PP, there is a stronger tendency for subjects to believe that, although the change in price will continue, the price change will decrease in size. The stronger trend following in the *R treatments can result in more unstable dynamics. This is consistent with Glaser et al. (2007), who also explain their results by stronger trend extrapolation (in prices) when subjects have to

[3] We tested all six pairwise comparisons, almost all resulting in a p-value of 0.000. The difference between PP and PR results in a p-value of 0.002, and the difference between PR and RP in a p-value of 0.059. Furthermore, for PP, RP and PR we also tested whether the slopes are significantly different from zero (i.e. whether subjects react to the price changes at all in those treatments). The p-values are 0.37 for PP, and $<$0.001 for the other two treatments.

[4] With another regression we tested the differences between the merged treatment by including *P and P* dummies instead of the three separate treatments, and the interaction terms of these two with the previous price change. The results confirm our findings here.

Table F.1: Percentage of subjects with significant coefficient

	C_h	p_t	p_{t-1}	p_{t-2}	p_{t-3}	$p^f_{h,t}$	$p^f_{h,t-1}$	$p^f_{h,t-2}$	$p^f_{h,t-3}$
PP	34.8%	92.4%	59.8%	31.1%	22.7%	34.1%	30.3%	19.7%	15.9%
RP	31.2%	95.7%	60.1%	31.9%	21.0%	37.0%	19.6%	13.8%	13.0%
PR	24.6%	96.5%	82.5%	37.7%	28.9%	35.1%	19.3%	14.0%	18.4%
RR	24.2%	100%	92.5%	53.3%	30.0%	30.8%	16.7%	10.8%	11.7%

forecast returns. Furthermore, subjects tend to extrapolate trends in past price changes more strongly when they observe past returns than when they observe past prices. Note however, that even though here we observed treatment differences for the information seen, it does not translate into differences in market stability.

F Individual forecasting behavior

Figure E.1 and Table E.1 in Appendix E present individual behavior in an aggregate form, namely looking at how subjects react on price changes on average. However, we can also investigate forecasting behavior at the individual level. To that end we estimate the following forecasting rule for each individual subject

$$p^f_{h,t+1} = C_h + \sum_{l=0}^{3} \beta_{hl} p_{t-l} + \sum_{l=0}^{3} \gamma_{hl} p^f_{h,t-l} + \varepsilon_{h,t+1}, \tag{F.1}$$

on data from the last 40 periods of the experiment.[5] Tables F.1 and F.2 summarize the results on treatment level (individual estimations are available in the replication package).

Table F.1 presents, for each variable in Equation (F.1), the share of subjects in each treatment for which the coefficient on that variable is significantly different from zero at the 5% level. Variables p_t and p_{t-1} appear most often: The coefficient on p_t is significantly different from zero for almost all subjects, and p_{t-1} is significant for a vast majority of the subjects as well. In addition, variables p_{t-2} (in particular for treatment RR) and $p^f_{h,t}$ feature regularly, but the coefficient of none of the other variables is significantly different from zero for more than around 30% of the subjects.

To better understand the impact that p_t and p_{t-1} (as well as the other variables) have on the forecasts of the subjects, Table F.2 presents for each variable the average value of the estimated coefficients on that

[5]Hommes et al. (2005) and Bao et al. (2020) investigate a similar individual forecasting rule in a two-period ahead learning to forecast experiment. This is a more general version of the forecasting rule we estimated in Appendix E.

Table F.2: Average coefficients over all subjects

	C_h	p_t	p_{t-1}	p_{t-2}	p_{t-3}	$p^f_{h,t}$	$p^f_{h,t-1}$	$p^f_{h,t-2}$	$p^f_{h,t-3}$
PP	5.99	1.38	-0.39	-0.03	-0.01	0.03	-0.03	-0.01	0.00
RP	18.00	1.54	-0.57	0.04	0.02	0.00	-0.05	-0.03	0.00
PR	2.30	1.95	-1.14	0.20	-0.04	0.03	0.02	-0.03	-0.02
RR	0.22	2.16	-1.55	0.34	0.02	0.09	-0.04	-0.02	-0.01

variable for the different treatments.[6] Some features stand out from this table. First, with the exception of the average coefficient of p_{t-2} in treatment PR and RR, the average estimated values of the coefficients of p_t and p_{t-1} (and of the constant) are substantially larger (in absolute value) than those of the other variables. Second, the average estimated forecasting rule in treatments PP, and RP is close to the trend extrapolation rule

$$p^f_{t+1} = p_t + \theta_0 \left(p_t - p_{t-1}\right),$$

with values of θ_0 of around 0.39, and 0.57 for treatments PP, and RP, respectively. For treatments PR and RR the average estimated forecasting rule is close to the more general trend extrapolation rule

$$p^f_{t+1} = p_t + \theta_0 \left(p_t - p_{t-1}\right) + \theta_1 \left(p_{t-1} - p_{t-2}\right),$$

with about $\theta_0 = 0.95$ and $\theta_1 = -0.2$ for PR and $\theta_0 = 1.2$ and $\theta_1 = -0.34$ for RR. Note that the main trend extrapolation parameter θ_0 is much higher for treatments PR and RR than for treatments PP and RP.[7] This is consistent with our finding that the tendency to extrapolate trends is stronger when subjects have to forecast returns.

[6]The average is calculated over all subjects in the given treatment. If a variable is insignificant in the regression for a given subject, then its coefficient is considered as 0 when calculating the average over all subjects.

[7]Running a linear regression with θ_0 defined as the coefficient of p_t minus one from the individual regressions confirms the treatment effect. Here θ_0 is the dependent variable, and *P and P* are the independent variables. Observations are individuals. The regression shows a highly significant negative coefficient for *P, and an insignificant coefficient for P*. Restricting our analysis to those that have a significant coefficient both for p_t and p_{t-1}, so those potentially chasing the trend, does not change our conclusion with respect to the effect of predicting prices.

References

Bao, T., Hennequin, M., Hommes, C., and Massaro, D. (2020). Coordination on bubbles in large-group asset pricing experiments. *Journal of Economic Dynamics and Control*, 110:103702.

Bao, T., Hommes, C., and Makarewicz, T. (2017). Bubble formation and (in) efficient markets in learning-to-forecast and optimise experiments. *The Economic Journal*, 127(605):F581–F609.

Glaser, M., Langer, T., Reynders, J., and Weber, M. (2007). Framing effects in stock market forecasts: The difference between asking for prices and asking for returns. *Review of Finance*, 11(2):325–357.

Heemeijer, P., Hommes, C., Sonnemans, J., and Tuinstra, J. (2009). Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. *Journal of Economic Dynamics and Control*, 33(5):1052–1072.

Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2005). Coordination of expectations in asset pricing experiments. *The Review of Financial Studies*, 18(3):955–980.