Online Appendix for “Managing Self-organization of Expectations through Monetary Policy: a Macro Experiment”

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This online appendix contains material in addition to the manuscript and to the printed appendix. Figure numbers build on the numbers in the article, therefore starting with Figure B.7 in this online appendix.

Supplementary material (for online publication)

Appendix A. Instructions for participants

Instructions

Welcome to this experiment! The experiment is anonymous, the data from your choices will only be linked to your station ID, not to your name. You will be paid privately at the end, after all participants have finished the experiment. After the main part of the experiment and before the payment you will be asked to fill out a short questionnaire. On your desk you will find a calculator and scratch paper, which you can use during the experiment.

During the experiment you are not allowed to use your mobile phone. You are also not allowed to communicate with other participants. If you have a question at any time, please raise your hand and someone will come to your desk.

General information and experimental economy

All participants will be randomly divided into groups of six people. The group composition will not change during the experiment. You and all other participants will take the roles of statistical research bureaus making predictions of inflation and the so-called ”output gap”. The experiment consists of 50 periods in total. In each period you will be asked to predict inflation and output gap for the next period.

The economy you are participating in is described by three variables: inflation π_t, output gap y_t and interest rate i_t. The subscript t indicates the period the experiment is in. In total there are 50 periods, so t increases during the experiment from 1 to 50.

Inflation

Inflation measures the percentage change in the price level of the economy. In each period, inflation depends on inflation predictions and output gap predictions of the statistical research bureaus in the economy (a group of six participants in this experiment) and on a random term. There is a positive relation between the actual inflation and both inflation predictions and actual output gap. This means for example that if the inflation predictions of the research bureaus increase, then actual inflation will also increase (everything else equal). In economies similar to this one, inflation has historically been between −5% and 15%.

Output gap

The output gap measures the percentage difference between the Gross Domestic Product (GDP) and the natural GDP. The GDP is the value of all goods produced during a period in the economy. The natural GDP is the value the total production would have if prices in the economy were fully flexible. If the output gap is positive (negative), the economy therefore produces more (less) than the natural GDP. In each period the output gap depends on inflation predictions and output gap predictions of the statistical bureaus, on the interest rate and on a random term. There is a positive relation between the output gap and inflation predictions and also between the output gap and output gap predictions. There is a negative relation between the output gap and the interest rate. In economies similar to this one, the output gap has historically been between -5% and 5%.

Interest Rate

The interest rate measures the price of borrowing money and is determined by the central bank. If the central bank wants to increase inflation or output gap it decreases the interest rate, if it wants to decrease inflation or output gap it increases the interest rate.

Prediction task

Your task in each period of the experiment is to predict inflation and output gap in the next period. When the experiment starts, you have to predict inflation and output gap for the first two periods, i.e. π_1^e and π_2^e, and y_1^e and y_2^e. The superscript e indicates that these are predictions. When all participants have made their predictions for the first two periods, the actual inflation (π_1), the actual output gap (y_1) and the interest rate (i_1) for period 1 are announced. Then period 2 of the experiment begins. In period 2 you make inflation and output gap predictions for period 3 (π_3^e and y_3^e). When all participants have made their predictions for period 3, inflation (π_2), output gap (y_2), and interest rate (i_2) for period 2 are announced. This process repeats itself for 50 periods.

Thus, in a certain period *t* when you make predictions of inflation and output gap in period *t + 1*, the following information is available to you:

- Values of actual inflation, output gap and interest rate up to period *t – 1*;
- Your predictions up to period *t*;
- Your prediction scores up to period *t – 1*.

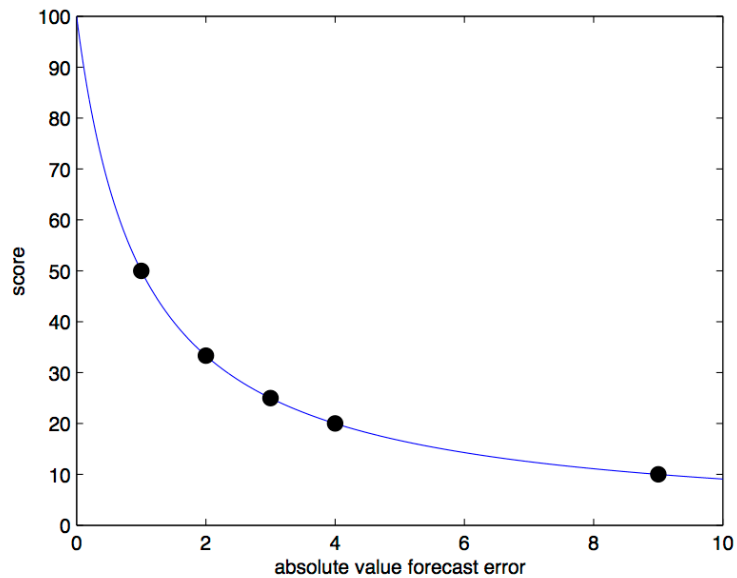
Payments

Your payment will depend on the accuracy of your predictions. You will be paid either for predicting inflation or for predicting the output gap. The accuracy of your predictions is measured by the absolute distance between your prediction and the actual values (this distance is the prediction error). For each period the prediction error is calculated as soon as the actual values are known; you subsequently get a prediction score that decreases as the prediction error increases. The table below gives the relation between the prediction error and the prediction score. The prediction error is calculated in the same way for inflation and output gap.

Prediction error	0	1	2	3	4	9
Score	100	50	33.33	25	20	10

Example: If (for a certain period) you predict an inflation of 2%, and the actual inflation turns out to be 3%, then you make an absolute error of 3% – 2% = 1%. Therefore you get a prediction score of 50. If you predict an inflation of 1%, and the actual inflation turns out to be negative 2% (i.e. -2%), you make a prediction error of 1% – (−2%) = 3%. Then you get a prediction score of 25. For a perfect prediction, with a prediction error of zero, you get a prediction score of 100.

The figure below shows the relation between your prediction score (vertical axis) and your prediction error (horizontal axis). Points in the graph correspond to the prediction scores in the previous table.



At the end of the experiment, you will have two total scores, one for inflation predictions and one for output gap predictions. These total scores simply consist of the sum of all prediction scores you got during the experiment, separately for inflation and output gap predictions. **When the experiment has ended, one of the two total scores will be randomly selected for payment.**

Your final payment will consist of 0.75 euro for each 100 points in the selected total score (200 points therefore equals 1.50 euro). This will be the only payment from this experiment, i.e. you will not receive a show-up fee on top of it.

Computer interface

The computer interface will be mainly self-explanatory. The top right part of the screen will show you all of the information available up to the period that you are in (in period *t*, i.e. when you are asked to make your prediction for period *t + 1*, this will be actual inflation, output gap, and interest rate until period *t – 1*, your predictions until period *t*, and the prediction scores arising from your predictions until period *t – 1* for both inflation (I) and output gap (O)). The top left part of the screen will show you the information on inflation and output gap in graphs. The axis of a graph shows values in percentage points (i.e. 3 corresponds to 3%). **Note that the values on the vertical axes may change during the experiment and that they are different between the two graphs – the values will be such that it is comfortable for you to read the graphs.**

Next to each graph, you will find an input box for your predictions.

On top of the **inflation** graph you are asked to enter your prediction for **inflation**.

At the bottom of the **output gap** graph you are asked to enter your prediction for the **output gap**.

In the bottom left part of the screen you will find a **Submit** button, to submit your predictions. **When submitting your prediction, use a decimal point if necessary (not a comma). For example, if you want to submit a prediction of 2.5% type ”2.5”; for a prediction of –1.75% type ” –1.75”.** The sum of the prediction scores over the different periods are shown in the bottom right of the screen, separately for your inflation and output gap predictions.

At the bottom of the screen there is a status bar telling you when you can enter your predictions and when you have to wait for other participants.

Appendix B. Computer interface

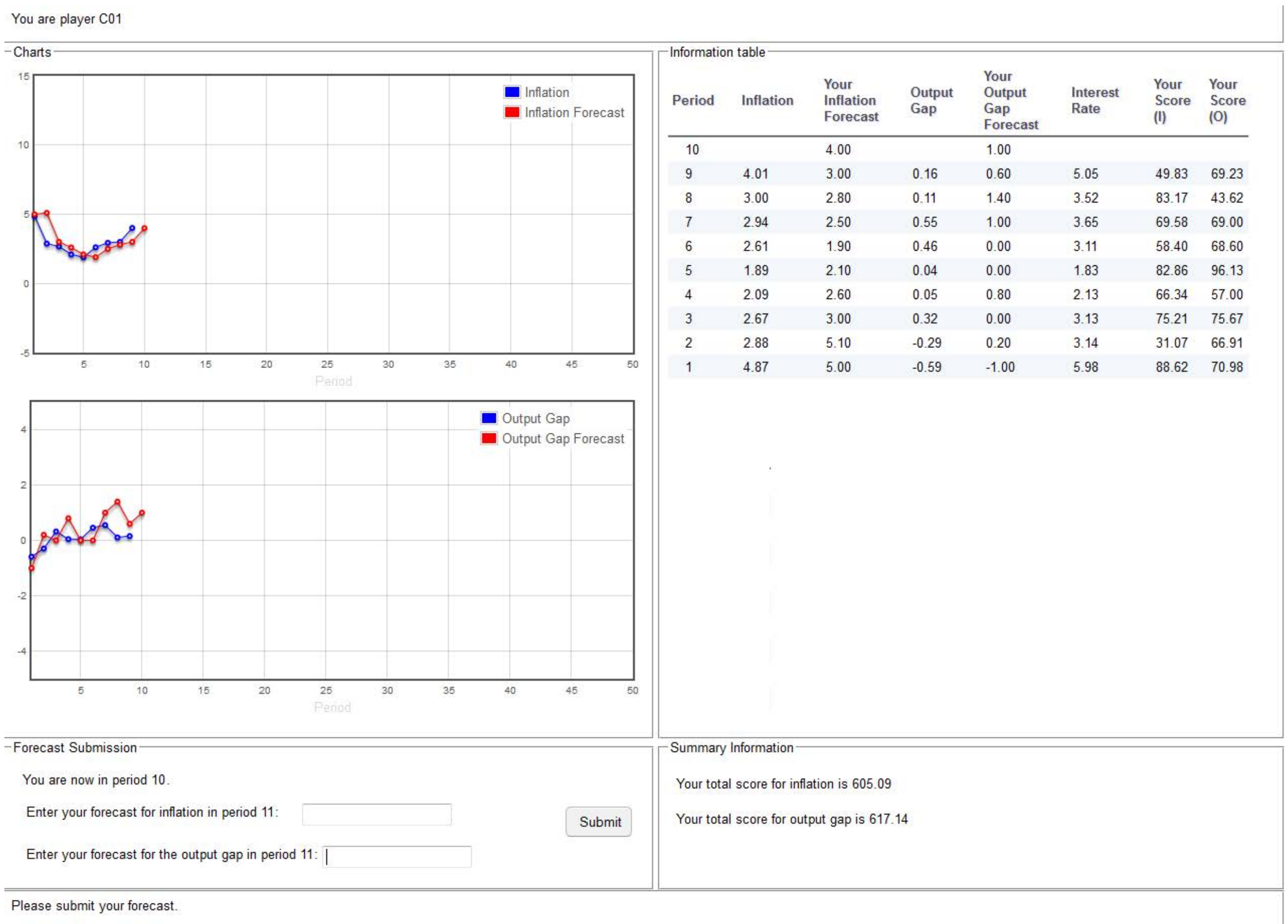


Figure B.7: Screenshot of computer interface.

Appendix C. Summary of all experimental data by group

Figs. C.8–C.15 show the realizations and forecasts of inflation and output gap. Each graph corresponds to one group of six people. The solid black line shows the realization of inflation (left panels) and the output gap (right panels), while the different markers show the forecasts of the six individuals in the group. For some experimental economies, for which dynamics were not very visible in the plot range $(-100, +100)$, we report a zoom over a smaller interval in the inset graphs.

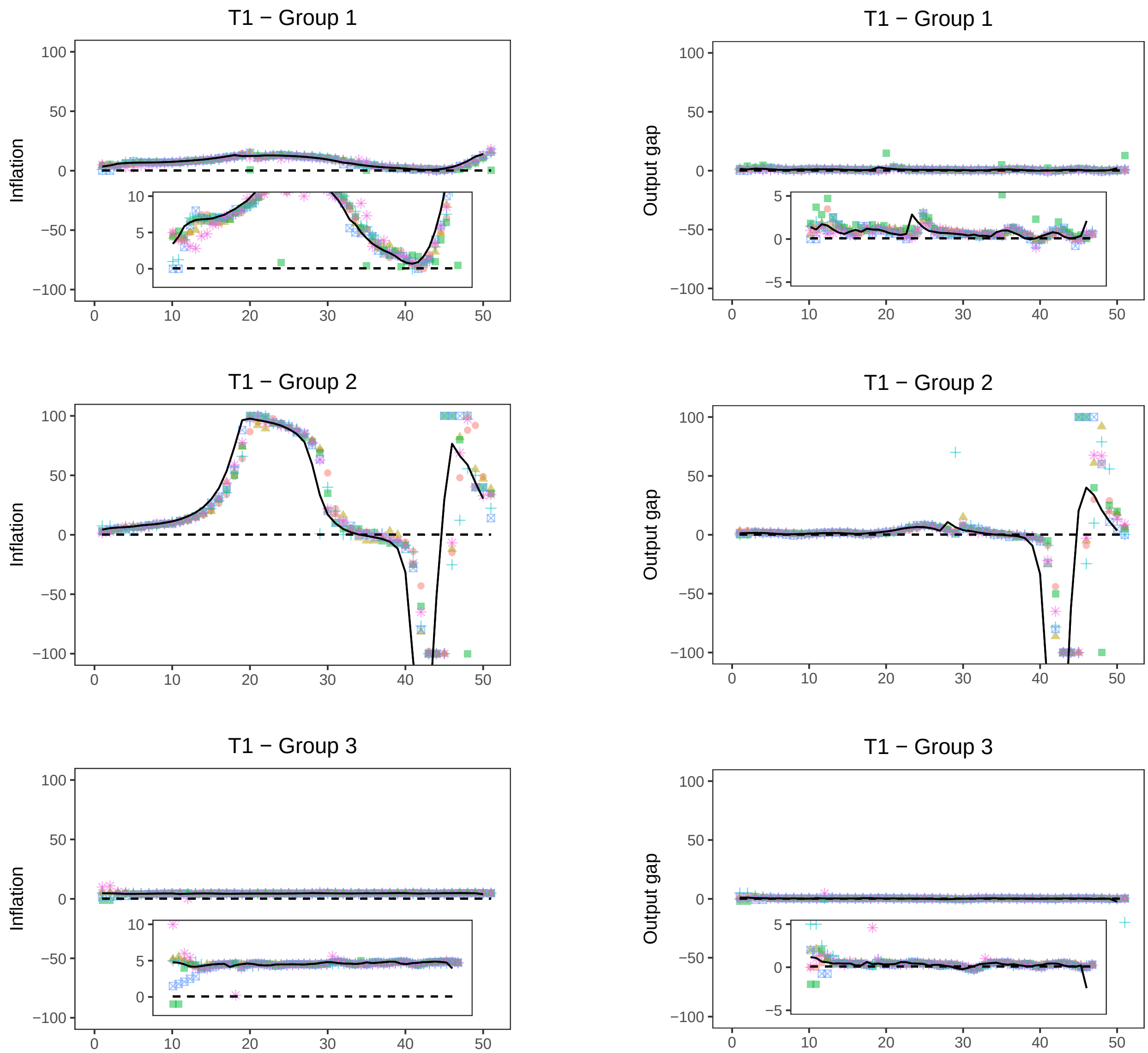


Figure C.8: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T1$ (groups 1–3).

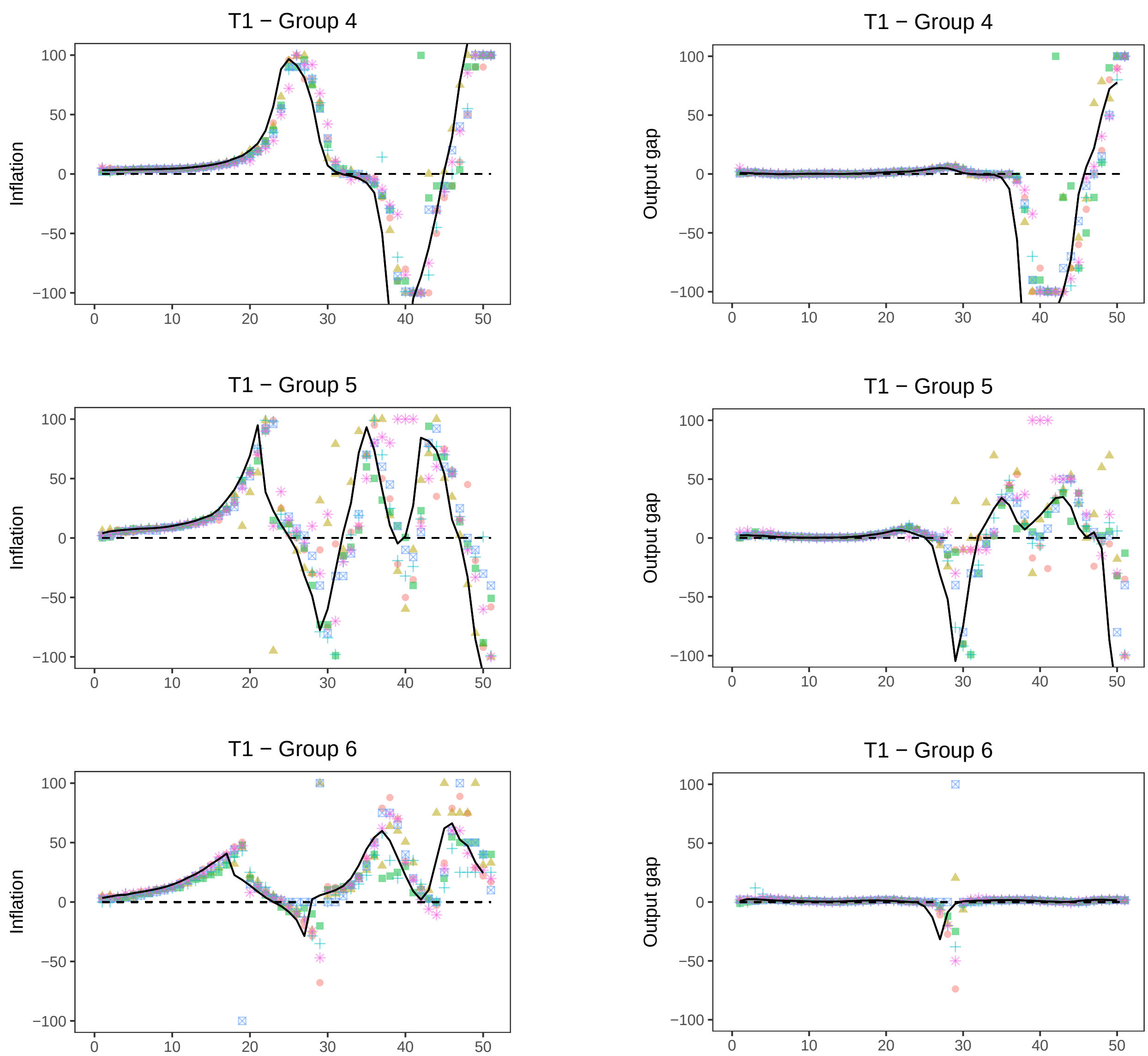


Figure C.9: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T1$ (groups 4–6).

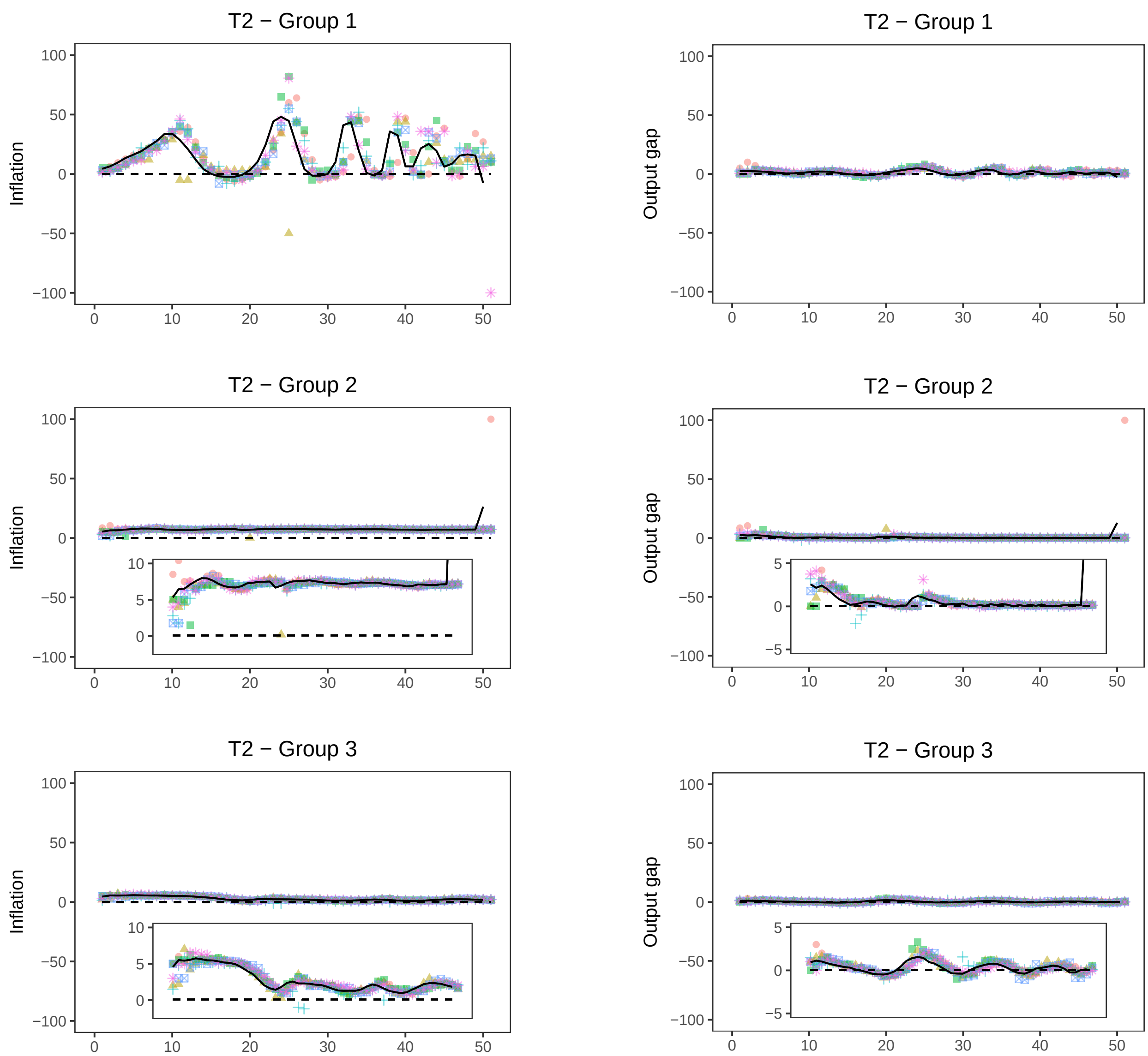


Figure C.10: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T2$ (groups 1–3).

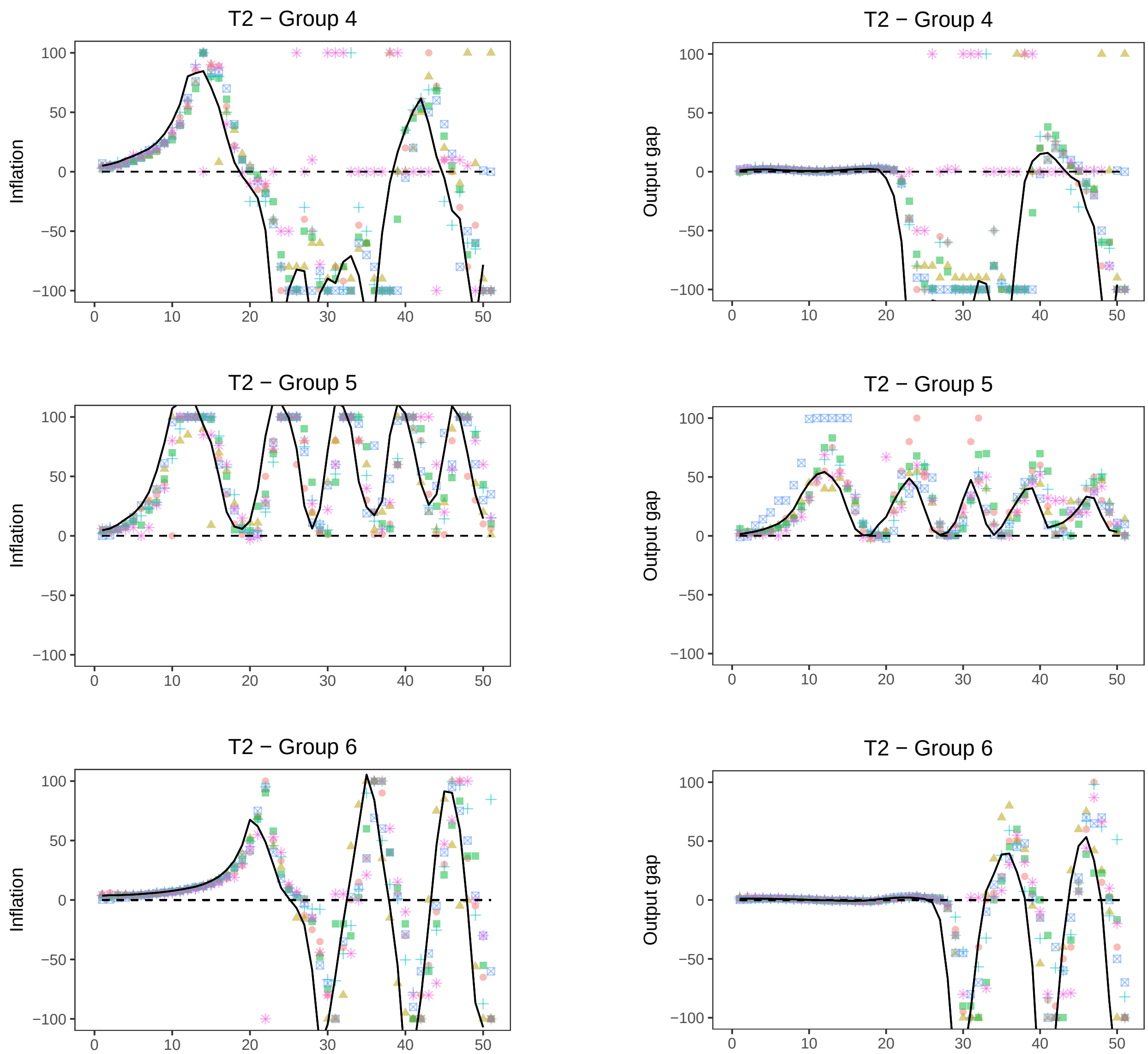


Figure C.11: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T2$ (groups 4–6).

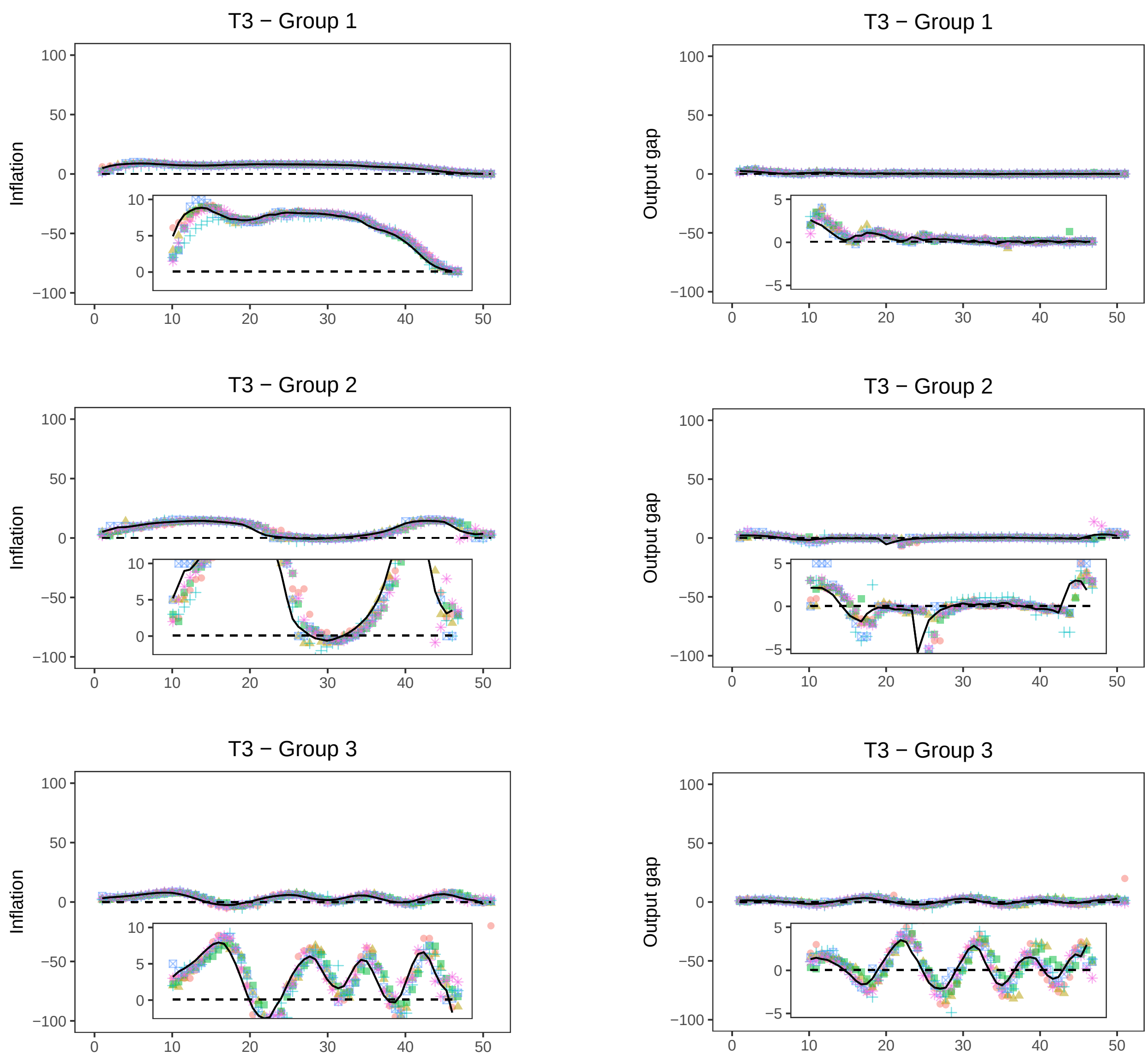


Figure C.12: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T3$ (groups 1–3).

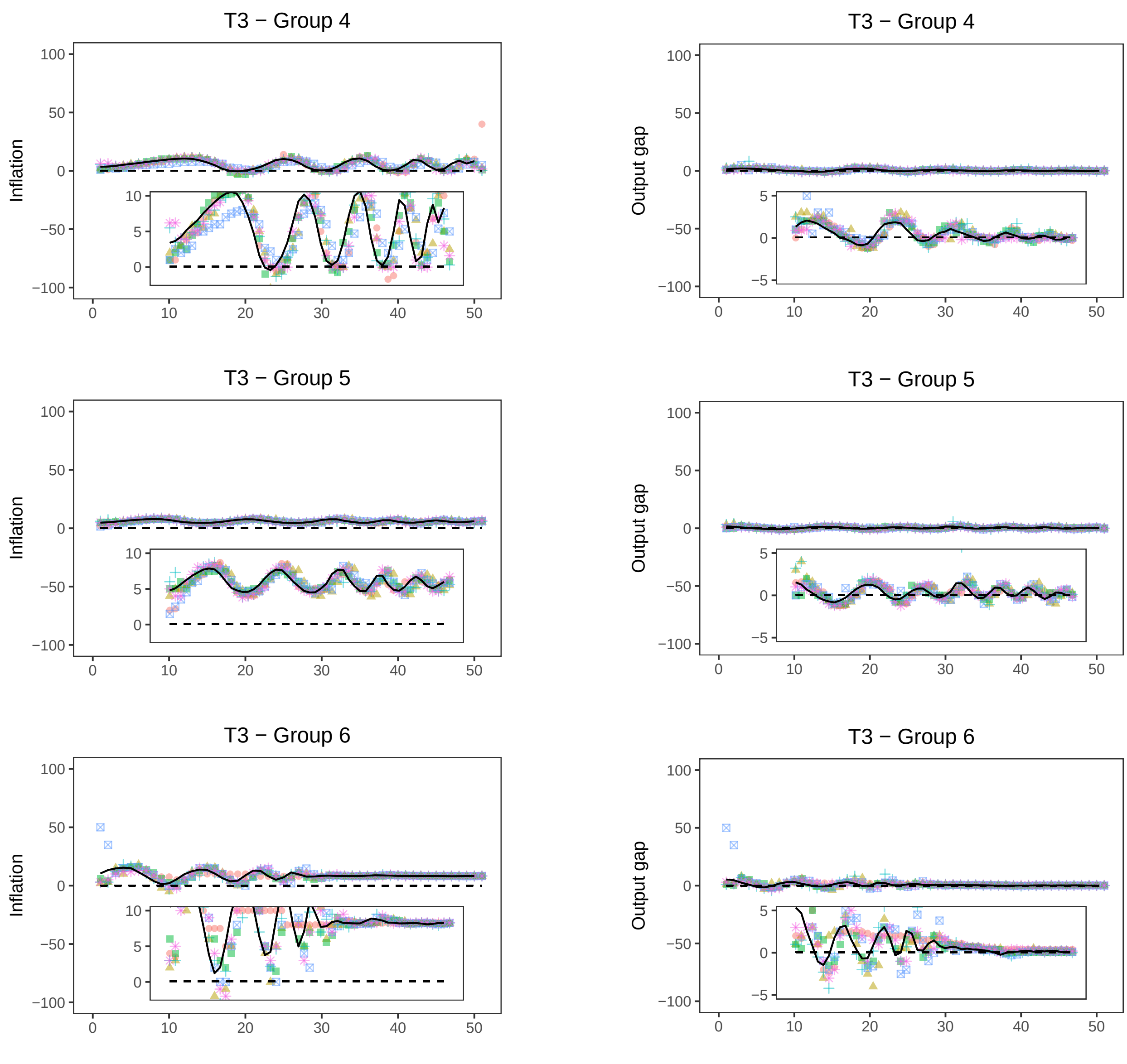


Figure C.13: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T3$ (groups 4–6).

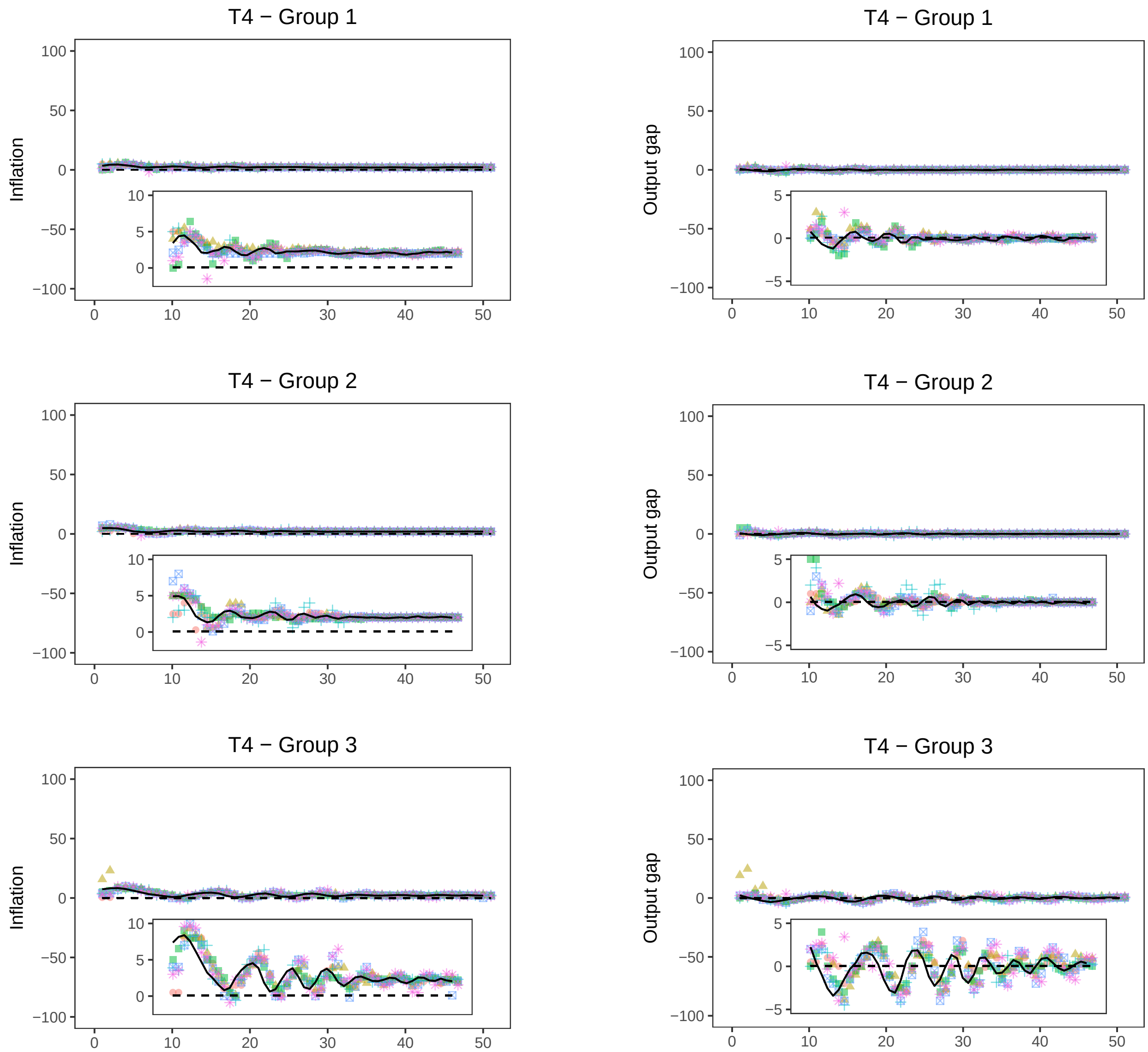


Figure C.14: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T4$ (groups 1–3).

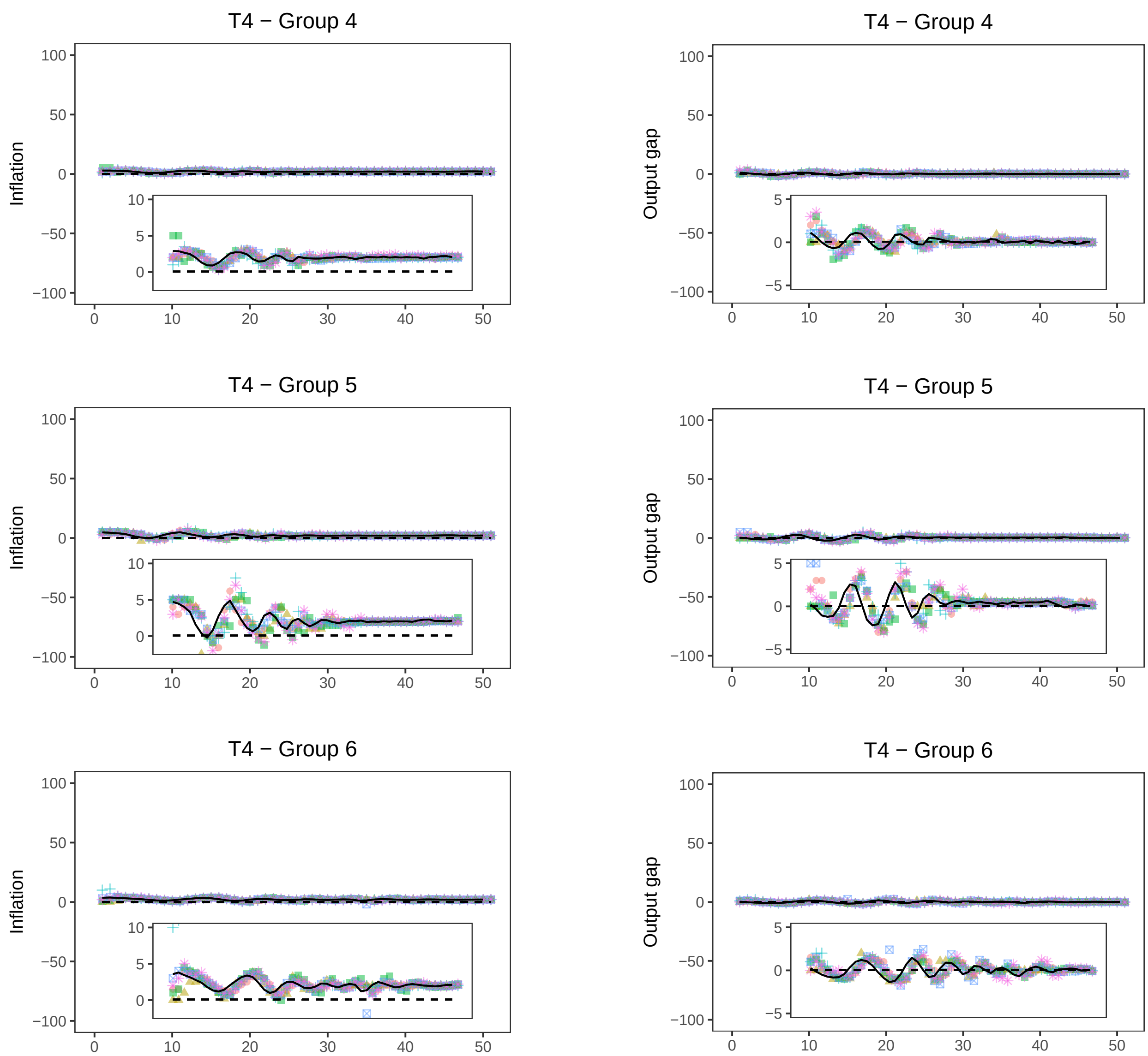


Figure C.15: Realizations and forecasts of inflation (left panels) and the output gap (right panels) for $T4$ (groups 4–6).

Figs. C.8–C.15 show that subjects tend to coordinate on a common prediction strategy, although participants in different groups may coordinate on different strategies. In order to quantify coordination on a common prediction strategy we consider, for each group, the average individual quadratic forecast error

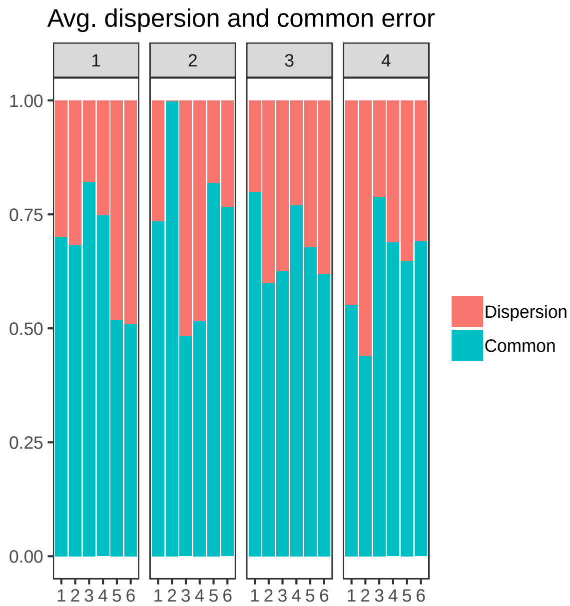
$$\frac{1}{6 \times 36} \sum_{i=1}^{6} \sum_{t=15}^{50} (x^e_{i,t} - x_t)^2 \ ,$$

defined as the individual quadratic forecast error averaged over time and over participants within a group. Note that we consider observations from period 15 on to allow for an initial learning phase. In the context of the NK model, x refers to either inflation or the output gap. Defining $\bar{x}^e_{i,t} = \sum_{i=1}^{6} x^e_{i,t}$ as the average prediction in a group, we can decompose the average individual quadratic forecast error as follows

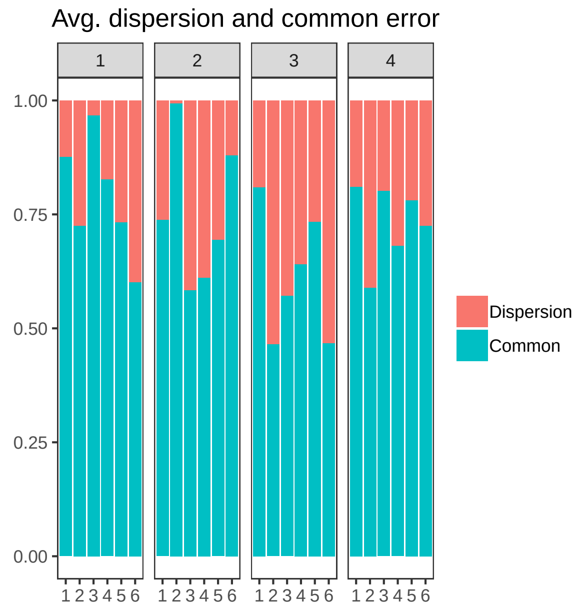
$$\frac{1}{6 \times 36} \sum_{i=1}^{6} \sum_{t=15}^{50} (x^e_{i,t} - x_t)^2 \ = \frac{1}{6 \times 36} \sum_{i=1}^{6} \sum_{t=15}^{50} (x^e_{i,t} - \bar{x}^e_t)^2 + \frac{1}{36} \sum_{t=15}^{50} (\bar{x}^e_t - x_t)^2 \ . \tag{C.1}$$

The first term on the RHS of Eq. (C.1) measures the dispersion among individual predictions as the quadratic distance between individual and average prediction within each group, averaged over time and participants. This term equals 0 when all participants in a group use exactly the same forecasting strategy. Therefore this term measures deviation from coordination on a common prediction strategy. The second term on the RHS of Eq. (C.1) measures instead the average distance between average forecast $\bar{x}^e_t$ and realization x_t. Fig. C.16 reports, for each of the 6 groups in the 4 treatments, the decomposition of the average quadratic forecast error into average dispersion and average common error.[1] From inspection of Fig. C.16 it is clear that only a relatively small part of the average quadratic forecasting error can be explained by the dispersion in expectations. In fact, on average respectively 68% and 72% of the average quadratic forecast error in inflation and output gap can be attributed to the average common error. Overall, the decomposition of the average quadratic forecast

[1] In order to avoid the big impact that outliers have on the measure of dispersion in individual forecasts, e.g. when bounds on individual predictions were reached or subjects tried to strategically reverse explosive trends, we remove them using linear interpolation of neighboring, non-outlier values. Outliers are defined as observations more than three MAD from the local median defined over a window of 4 observations.



(a) Inflation



(b) Output gap

Figure C.16: Decomposition of average quadratic forecast error of individual prediction strategies into average dispersion error and average common error for each of the 6 groups in the 4 treatments.

error suggests that there is coordination on a common prediction strategy, although some heterogeneity in individual forecasts persists.

Appendix D. Switching behavior

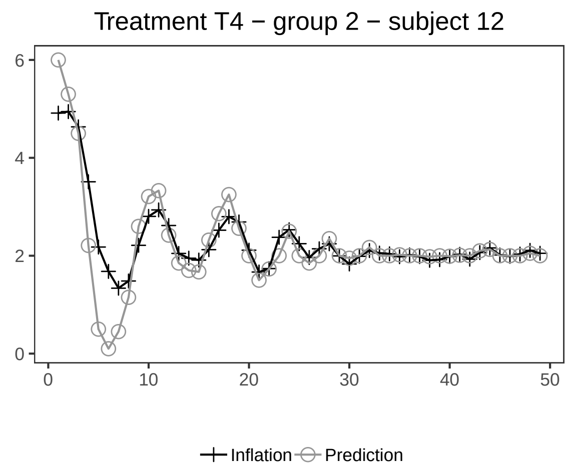
Evidence of switching behavior can be found by inspecting the time series of individual forecasts. Fig. D.17 reports some graphical evidence of individual switching behavior. For every period t we plot realized inflation or output gap in that period, together with the prediction submitted by subjects in period $t+1$. In this way we can graphically infer how individual predictions use past available observations of the variable being forecasted. For example, if the time series coincide, the participant is submitting predictions identical to the last observation.

In Fig. D.17(a) (treatment $T4$, group 2), subject 12 extrapolates the direction of change in inflation in the early stage of the experiment. Starting from about period 20 the participant switches to a much weaker form of trend extrapolation, to later on adopt an adaptive forecasting strategy in which individual forecasts are somewhere in between the last available observation and the previous prediction.

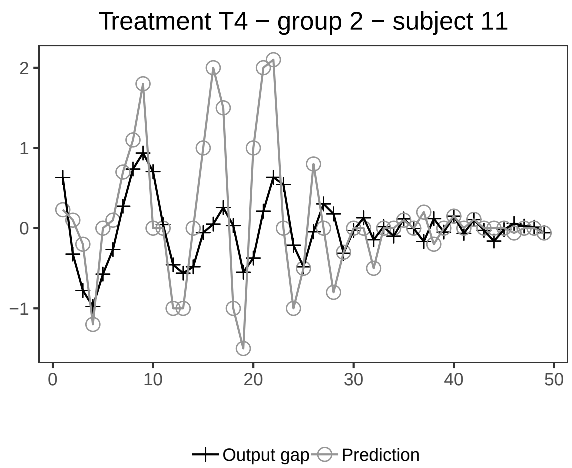
In Fig. D.17(b) (treatment $T4$, group 2), we observe a somewhat similar forecasting behavior as subject 11 strongly extrapolates past changes in the output gap in the first half of the experiment. In the second half the participant switches to an adaptive forecasting heuristic.

In Fig. D.17(c) (treatment $T3$, group 6), subject 7 switches between various constant predictors for inflation in the first 20 periods of the experimental session. Later on the participant converges to a predictor of about 8%, which represents an almost self-fulfilling equilibrium for the experimental economy.

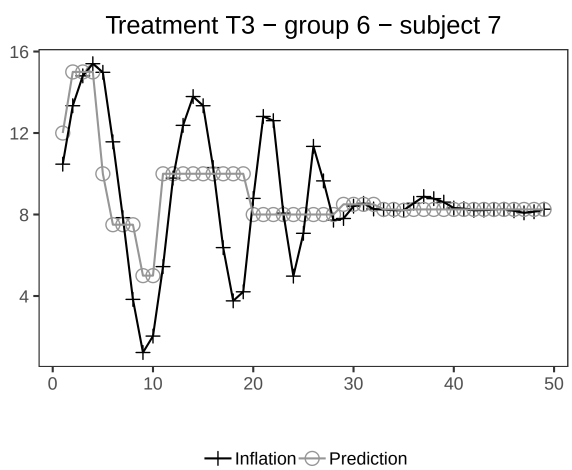
In Fig. D.17(d) (treatment $T3$, group 6), subject 12 starts out with a trend extrapolating strategy and later on switches to a "naive" forecasting rule that basically uses the last available observation to predict future output gap.



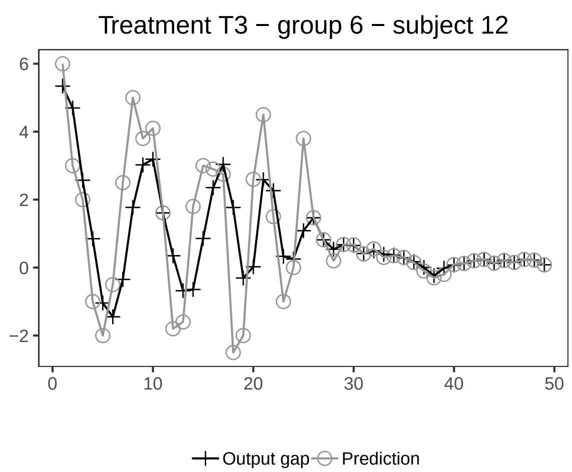
(a)



(b)



(c)



(d)

Figure D.17: Individual learning as switching between heuristics. For every period t, subject i's prediction $x^e_{i,t+2}$ and the last available observation of the variable x_t being forecasted (with x being either inflation or the output gap) are reported.

Appendix E. Estimation of forecasting rules

In what follows we only consider experimental economies in which expectations did not reach the artificial bounds on admissible forecasts. Accordingly, we exclude from the sample groups 2, 4, 5 and 6 in $T1$ and groups 4, 5, and 6 in $T2$. In all analyses performed below, we consider a significance level of 0.05. For each of the 102 participants in the considered subsample we estimated linear prediction rules of the form

$$\pi^e_{j,t+1} = c + \sum_{i=0}^{2} \alpha^e_i \pi^e_{j,t-i} + \sum_{i=1}^{3} \alpha^\pi_i \pi_{t-i} + \sum_{i=1}^{3} \alpha^y_i y_{t-i} + \xi_t \tag{E.1}$$

$$y^e_{j,t+1} = c + \sum_{i=0}^{2} \alpha^e_i y^e_{j,t-i} + \sum_{i=1}^{3} \alpha^y_i y_{t-i} + \sum_{i=1}^{3} \alpha^\pi_i \pi_{t-i} + \epsilon_t \ , \tag{E.2}$$

where $\pi^e_{j,t+1}$ and $y^e_{j,t+1}$ refer to inflation or output gap forecast of participant j for period $t+1$ (submitted in period t). We allow for an initial learning phase, in which subjects may have not yet converged to a prediction rule and still be experimenting with different strategies, by considering observations starting from period 15.[2] Overall, for about 65% of the estimated rules we do not detect any first-order autocorrelation in the residuals according to a Breusch-Godfrey test. Moreover, in about 75% of the cases an $F-$test indicates that we can restrict rules (E.1)–(E.2) to simpler rules in which predictions depend only on past forecasts and past observations of the forecasting objective. Averaging over participants of all treatments, the number of significant regressors in the estimated prediction rules is about 2. The most popular significant regressor is the last available observation of the forecasting objective (π_{t-1} or y_{t-1}), followed by the second last available observation π_{t-2} for Eq. (E.1) and by the most recent own prediction y^e_t for Eq. (E.2). Looking at the estimated coefficients, a remarkable property is that 100% of the significant coefficients associated to the last observed forecasting objective and about 90% of the significant coefficients associated to the most recent own prediction are positive. In contrast, about 92% of the significant coefficients associated to the second last observed forecasting objective are negative.

[2]We remove outliers in individual forecasts using linear interpolation of neighboring, non-outlier values. Outliers are defined as observations more than three MAD from the local median defined over a window of 4 observations.

Overall, the estimation results indicate that most participants use a linear prediction rule, at least after an initial learning phase. What is more, the fact that the two latest observations of the forecasting objective and the latest own prediction are generally the most used prediction rule components, implies that these variables are of particular importance in the prediction rule specification. The relatively low average number of significant regressors in Eqs. (E.1)–(E.2) means that the other variables are used very little as input to form predictions. It is therefore worthwhile to restrict specifications (E.1)–(E.2) by leaving out these infrequently used regressors. The fact that the estimated non-zero coefficients for the most recent values of the forecasting objective and the own prediction are almost all positive, while the non-zero coefficients of the other variables tend to be negative, similarly suggests that the specifications (E.1)–(E.2) are too flexible and could be restricted without losing much explanatory power. Restricting (E.1)–(E.2) along the lines of these regularities could increase the efficiency of the estimates, as well as make the estimated rules easier to interpret from a behavioral viewpoint.

In particular, we perform an $F-$test to check whether we could restrict the general forecasting rules in Eqs. (E.1)–(E.2) to simpler prediction rules of the form

$$\pi^e_{j,t+1} = \alpha_1\pi_{t-1} + \alpha_2\pi^e_{j,t} + (1-\alpha_1-\alpha_2)\frac{1}{35}\sum_{t=15}^{50}\pi_t + \alpha_3(\pi_{t-1}-\pi_{t-2}) + \xi_t \tag{E.3}$$

$$y^e_{j,t+1} = \alpha_1 y_{t-1} + \alpha_2 y^e_{j,t} + (1-\alpha_1-\alpha_2)\frac{1}{35}\sum_{t=15}^{50} y_t + \alpha_3(y_{t-1}-y_{t-2}) + \epsilon_t\,. \tag{E.4}$$

Forecasting rules (E.3)–(E.4) are referred to as *First-Order Heuristics* (FOH) and can be interpreted as anchoring-and-adjustment heuristics *à la* Tversky and Kahneman. The first three terms in (E.3) and (E.4) are a weighted average of the latest realization of the forecasting objective, the latest own prediction and the forecasting objective's sample mean (excluding a learning phase).[3] This weighted average is the (time varying) "anchor" of the prediction, which is a zeroth-order extrapolation from the available data at period t. The

[3]In the estimation of (E.3) and (E.4) we include the sample mean of inflation and the output gap, which is of course not available to the subjects at the moment of the prediction, but acts as a proxy of the equilibrium level. In the HSM of Section 4.1, the LAA rule uses sample average up to $t-1$, which is observable to subjects when the forecast is made and generally converges quickly to the full sample mean.

fourth term in (E.3) and (E.4) is a simple first-order extrapolation from the two most recent realizations of the forecasting objective; this term is the "adjustment" or trend extrapolation part of the heuristic. An advantage of FOH is that it simplifies to well-known forecasting rules for different boundary values of the parameter space. For example, Eqs. (E.3)–(E.4) reduce to Naive Expectations if $\alpha_1 = 1$, $\alpha_2 = \alpha_3 = 0$; they reduce to Adaptive Expectations if $\alpha_1 + \alpha_2 = 1$ (with $\alpha_1, \alpha_2 \in (0, 1)$) and $\alpha_3 = 0$ (ADA rule considered in Section 4.1); they reduce to the simplest Trend-Following rule if $\alpha_1 = 1$, $\alpha_2 = 0$ and $\alpha_3 > 0$ (WTR and STR rules considered in Section 4.1). When $0 < \alpha_1 < 1$, $\alpha_2 = 0$ and $\alpha_3 = 1$, with the sample average computed using observations up to period $t - 1$, we obtain an Anchoring and Adjustment rule with a time-varying anchor (LAA rule considered in Section 4.1). Overall, about 66% of the general forecasting rules (E.1)–(E.2) could be restricted to FOH rules (E.3)–(E.4) according to an $F-$test. In about 54% of the cases we do not detect any first-order autocorrelation in the residuals according to a Breusch-Godfrey test. Moreover, about 53% of the estimated rules could be exactly restricted to one of the types considered in Section 4.1, while the others present different anchor–adjustment combinations within the classes defined in Eqs. (E.3)–(E.4). Fig. E.18 reports estimates of the FOH coefficients in Eqs. (E.3)–(E.4).

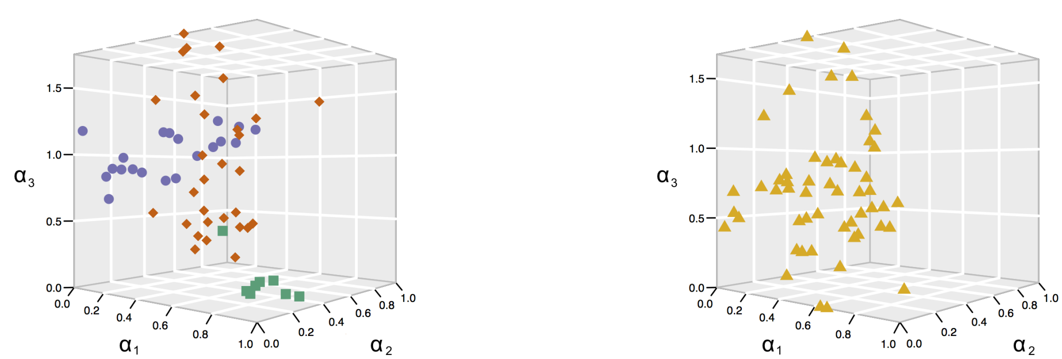


Figure E.18: Left panel: estimated coefficients of rules classified as Adaptive (squares), Trend-Following (diamonds) and Anchoring and Adjustment (circles). Right panel: estimated coefficients of rules with different anchor–adjustment combinations.

Appendix F. Homogeneous expectations models

In this section we analyze the stability properties of the NK model in Eq. (4) under homogeneous expectations, i.e. when all participants in the economy use the same forecasting heuristic. In particular, we study the deterministic skeleton of model (4), i.e. setting the noise term ϵ_t to zero, under the homogeneous expectations presented in Table 2 in different policy regimes.

Adaptive heuristics

Under adaptive expectations for both inflation and the output gap we can write the vector of expected future aggregate variables $z^e = (y^e, \pi^e)'$ as

$$z^e_{t+1} = \chi z_{t-1} + (1-\chi) z^e_t \ , \tag{F.1}$$

where scalar $0 < \chi < 1$ denotes the relative weight of past observations. Rewriting the NK model in Eq. (4) as

$$z^e_{t+1} = -\mathrm{M}^{-1}\mathrm{A} + \mathrm{M}^{-1} z_t \ . \tag{F.2}$$

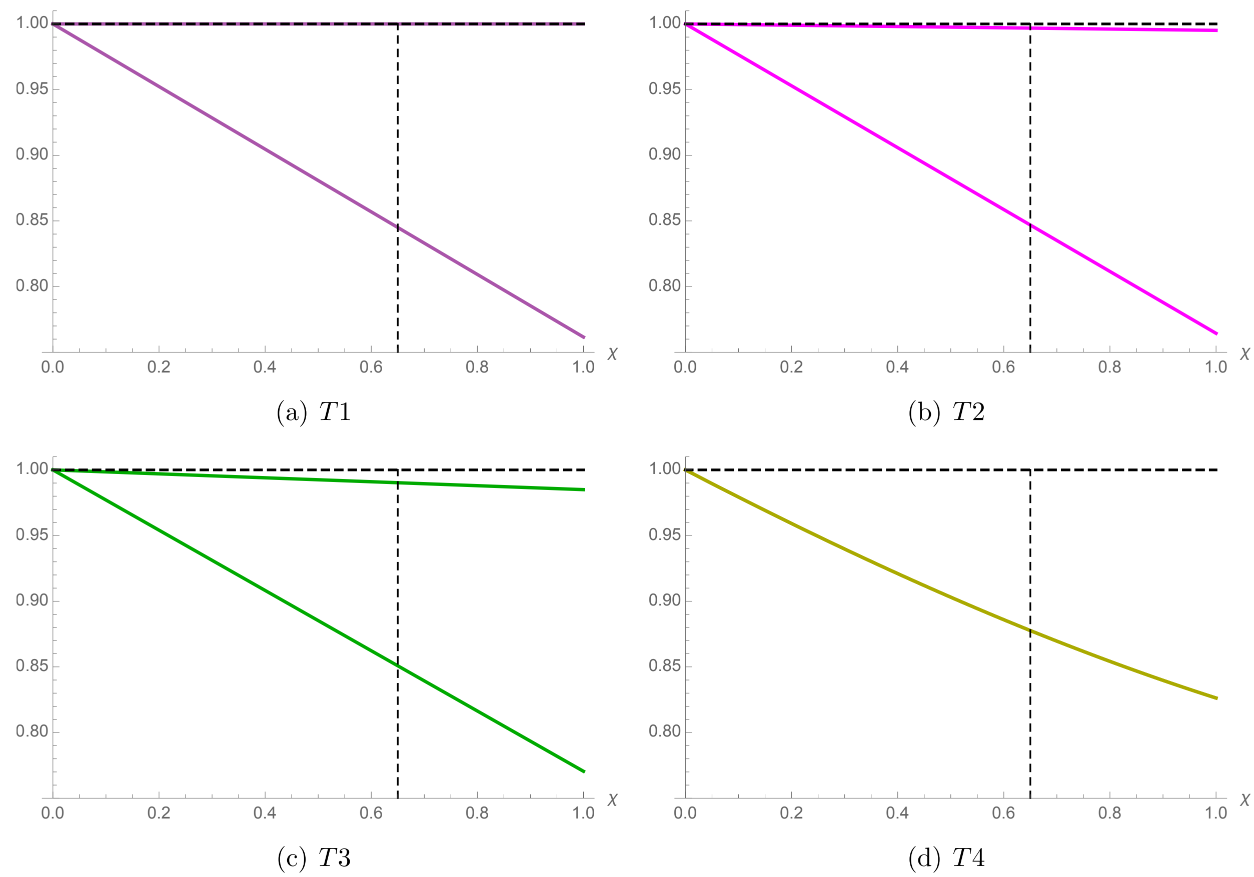
Substituting Eq. (F.2) lagged one period in Eq. (F.1) we can write z^e_{t+1} as function of z_{t-1}

$$z^e_{t+1} = -(1-\chi)\,\mathrm{M}^{-1}\mathrm{A} + (\chi\, I + (1-\chi)\,\mathrm{M}^{-1}) z_{t-1} \ , \tag{F.3}$$

where I denotes the identity matrix. Substituting Eq. (F.3) in the NK model (4) we obtain

$$z_t = \chi\,\mathrm{A} + (\chi\,\mathrm{M} + (1-\chi)\,I) z_{t-1} \ . \tag{F.4}$$

The dynamic properties of the NK model under homogeneous adaptive expectations are described by Eq. (F.4). Simple calculations show that the unique steady state of system (F.4) is the FS-RE equilibrium $\bar{z} = (I-\mathrm{M})^{-1}\mathrm{A}$, provided that matrix $(I-\mathrm{M})$ is invertible, i.e. $\phi_\pi > 1$. Stability of the FS-RE equilibrium under adaptive expectations depends on the eigenvalues of matrix $\chi\,\mathrm{M} + (1-\chi)\,I$. Fig. F.19 displays the absolute value of the eigenvalues of matrix $\chi\,\mathrm{M} + (1-\chi)\,I$ as function of parameter χ under policy regimes implemented in different treatments. In treatment $T1$ one eigenvalue is always on the unit circle so that



(a) $T1$ (b) $T2$

(c) $T3$ (d) $T4$

Figure F.19: Absolute value of eigenvalues of matrix $\chi\,\mathrm{M} + (1-\chi)\,I$ as function of χ. Dashed vertical lines refer to ADA rule ($\chi = 0.65$).

the steady state of Eq. (F.4) is indeterminate and there is a continuum of stable steady states. In treatments $T2$, $T3$ and $T4$ the FS-RE steady state is stable for all values of χ. Convergence under homogeneous adaptive expectations is monotonic in $T2$ and $T3$ due to real eigenvalues and oscillatory in $T4$ due to complex eigenvalues. Finally, local stability of the FS-RE steady state under the ADA rule considered in Table 2 is obtained when $\phi_\pi > 1$.

Trend-following heuristics

Under trend-following heuristics for both inflation and the output gap we can write the vector of expected future aggregate variables $z^e = (y^e, \pi^e)'$ as

$$z^e_{t+1} = z_{t-1} + \xi(z_{t-1} - z_{t-2}) \;, \tag{F.5}$$

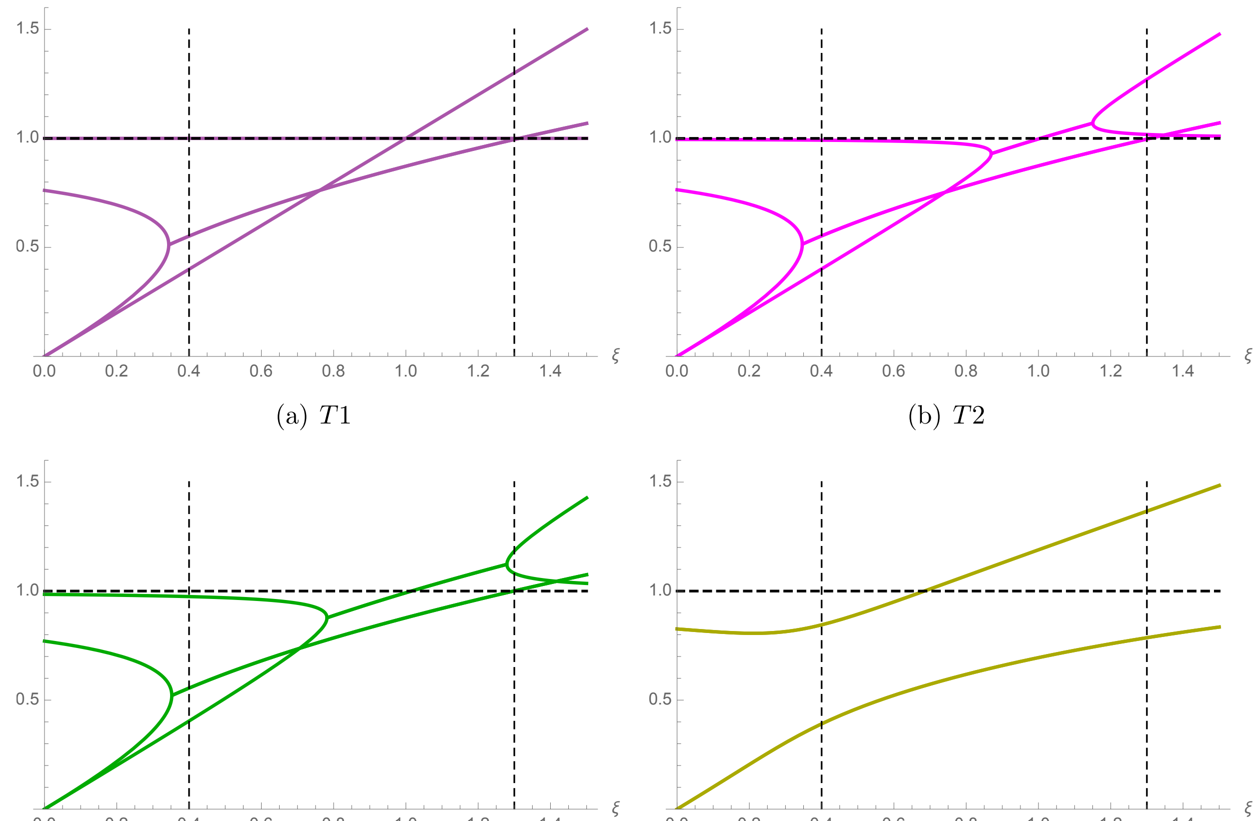
where scalar $\xi > 0$ denotes the degree of trend-extrapolation. Under expectations defined in Eq. (F.5) the NK model can be rewritten as

$$z_t = \mathrm{A} + \mathrm{M}\,(1+\xi)z_{t-1} - \xi\, z_{t-2} \;. \tag{F.6}$$

Defining $w_t = z_{t-1}$ we can rewrite Eq. (F.6) as a first-order system defined by

$$\begin{aligned} \begin{pmatrix} z_t \\ w_t \end{pmatrix} &= \begin{pmatrix} \mathrm{A} \\ 0 \end{pmatrix} + \begin{pmatrix} (1+\xi)\,\mathrm{M} & -\xi\,\mathrm{M} \\ I & 0 \end{pmatrix} \begin{pmatrix} z_{t-1} \\ w_{t-1} \end{pmatrix} \\ s_t &= \mathrm{B} + \mathrm{N}\, s_{t-1} \;, \end{aligned} \tag{F.7}$$

where $s = (z, w)'$. The dynamic properties of the NK model under homogeneous trend-following expectations are described by the 4-dimensional system in Eq. (F.7). Simple calculations show that the unique steady state of system (F.7) is the FS-RE equilibrium $\bar{z} = (I - \mathrm{M})^{-1}\mathrm{A}$, provided that matrix $(I - \mathrm{M})$ is invertible, i.e. $\phi_\pi > 1$. Stability of the FS-RE equilibrium under trend-following expectations depends on the eigenvalues of matrix N in Eq. (F.7). Fig. F.20 displays the absolute value of the eigenvalues of matrix N as function of parameter ξ under policy regimes of $T1$, $T2$, $T3$ and $T4$. Under the WTR in Table 2, i.e. $\xi = 0.4$, all eigenvalues are within the unit circle in $T2$, $T3$ and $T4$ (local stability in this case is ensured by $\phi_\pi > 1$), meaning that the FS-RE steady state is stable



(a) $T1$ (b) $T2$

(c) $T3$ (d) $T4$

Figure F.20: Absolute value of eigenvalues of matrix N as function of ξ in different treatments. Dashed vertical lines refer to WTR ($\xi = 0.4$) and STR ($\xi = 1.3$).

(although convergence can be slow in $T2$ and $T3$ due to one eigenvalue close to one), while in $T1$ one eigenvalue is exactly on the unit circle, meaning that there is a continuum of stable equilibria. On the opposite, the system is unstable under the STR in Table 2, i.e. $\xi = 1.3$, in all treatments with dynamics exploding monotonically in treatments $T1$, $T2$ and $T3$ due to the presence of explosive real eigenvalues, and oscillating in $T4$ due to the complex explosive eigenvalues (local stability in this case is ensured by a much higher monetary policy reaction coefficient, i.e. $\phi_\pi > 20.85$).

Anchoring and adjustment heuristics

The anchoring and adjustment heuristic considered in Table 2 for a generic variable x has a time-varying component $\bar{x}_{t-1}$ defined as

$$\bar{x}_{t-1} = \frac{1}{t-1} \sum_{i=1}^{t-1} x_i \ . \tag{F.8}$$

Therefore, under the anchoring and adjustment heuristics for both inflation and the output gap we can write the vector of expected future aggregate variables $z^e = (y^e, \pi^e)'$ as

$$z^e_{t+1} = \frac{1}{2}\bar{z}_{t-1} + \frac{3}{2} z_{t-1} - z_{t-2} \ . \tag{F.9}$$

Substituting Eq. (F.9) in the NK model we obtain

$$z_t = \mathrm{A} + \mathrm{M} \left(\frac{1}{2}\bar{z}_{t-1} + \frac{3}{2} z_{t-1} - z_{t-2} \right) \ . \tag{F.10}$$

Although it is trivial to show that that the FS-RE equilibrium $\bar{z} = (I - \mathrm{M})^{-1}\mathrm{A}$ is the unique steady state of system (F.10), provided that matrix $(I - \mathrm{M})$ is invertible, i.e. $\phi_\pi > 1$, it is non-trivial to study its stability properties due to explicit dependence on t. Therefore, we replace $\bar{z}_{t-1}$ with the equilibrium $\bar{z}$ and study whether small perturbations to the FS-RE equilibrium are amplified or re-absorbed. We thus consider the system

$$z_t = \mathrm{A} + \mathrm{M} \left(\frac{1}{2}\bar{z} + \frac{3}{2} z_{t-1} - z_{t-2} \right) \ , \tag{F.11}$$

which can be rewritten, defining $w_t = z_{t-1}$, $\alpha = 1/2\,\bar{z}$, $\beta = 3/2$ and $\beta_2 = -1$, as a 4-dimensional system

$$\begin{aligned} \begin{pmatrix} z_t \\ w_t \end{pmatrix} &= \begin{pmatrix} \mathrm{A} + \mathrm{M}\,\alpha \\ 0 \end{pmatrix} + \begin{pmatrix} \beta_1 \mathrm{M} & \beta_2 \mathrm{M} \\ I & 0 \end{pmatrix} \begin{pmatrix} z_{t-1} \\ w_{t-1} \end{pmatrix} \\ s_t &= \mathrm{B} + \mathrm{N}\, s_{t-1}\ , \end{aligned} \tag{F.12}$$

whose stability depends on the eigenvalues of matrix N. Fig. F.21 depicts the eigenvalues of matrix N as function of the policy parameter ϕ_π. When $\phi_\pi = 1$, two complex eigenvalue are

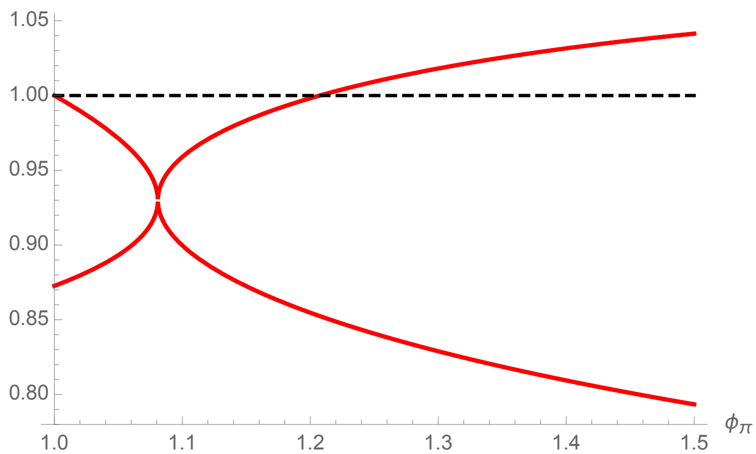


Figure F.21: Absolute value of eigenvalues of matrix N as function of ϕ_π.

exactly on the unit circle, while the others are within the unit circle, meaning that there in $T1$ there is a continuum of stable equilibria under homogeneous LAA forecasts. As ϕ_π increases from 1 to 1.5, eigenvalues move from within to outside the unit circle (the critical value for ϕ_π is about 1.2). Therefore, under the policy regimes implemented in treatments $T2$ and $T3$, the system is stable with homogeneous anchoring and adjustment forecasting heuristics. On the contrary, under the policy regime of $T4$ the system exhibits explosive complex eigenvalues and it is therefore unstable. The intuition for this result is the following. Start from equilibrium and suppose there is a positive shock in inflation expectations. This will cause actual inflation to increase via the NKPC, but at the same time it will lower output via an higher interest rate. When the interest rate is aggressive enough, output fluctuations are large and they are further amplified by trend-extrapolating LAA rule. This has a negative impact on inflation, which can overshoot the target, leading the central bank to lower the interest rate reversing the trend in the output gap. The combination of strong interest rate reaction and trend extrapolation may lead small initial deviations from equilibrium to be amplified over time, causing oscillatory divergence. Simulations of system (F.10) with observable sample mean $\bar{z}_{t-1}$ confirm these results and are reported in Fig. F.22 for $\phi_\pi = 1.015$ and $\phi_\pi = 1.5$.[4] Notice that, in order to initialize system (F.10), we need to set the first two values z_1 and z_2. We fix the initial value at steady state, i.e. $(y_1, \pi_1)' = ((1-\rho)\bar{\pi}/\lambda, \bar{\pi})$, and we define $(y_2, \pi_2)'$ on a grid defined by points $y_2 = \{y_1 - 0.1, y_1, y_1 + 0.1\}$ and $\pi_2 = \{\pi_1 - 0.1, \pi_1, \pi_1 + 0.1\}$. Each line

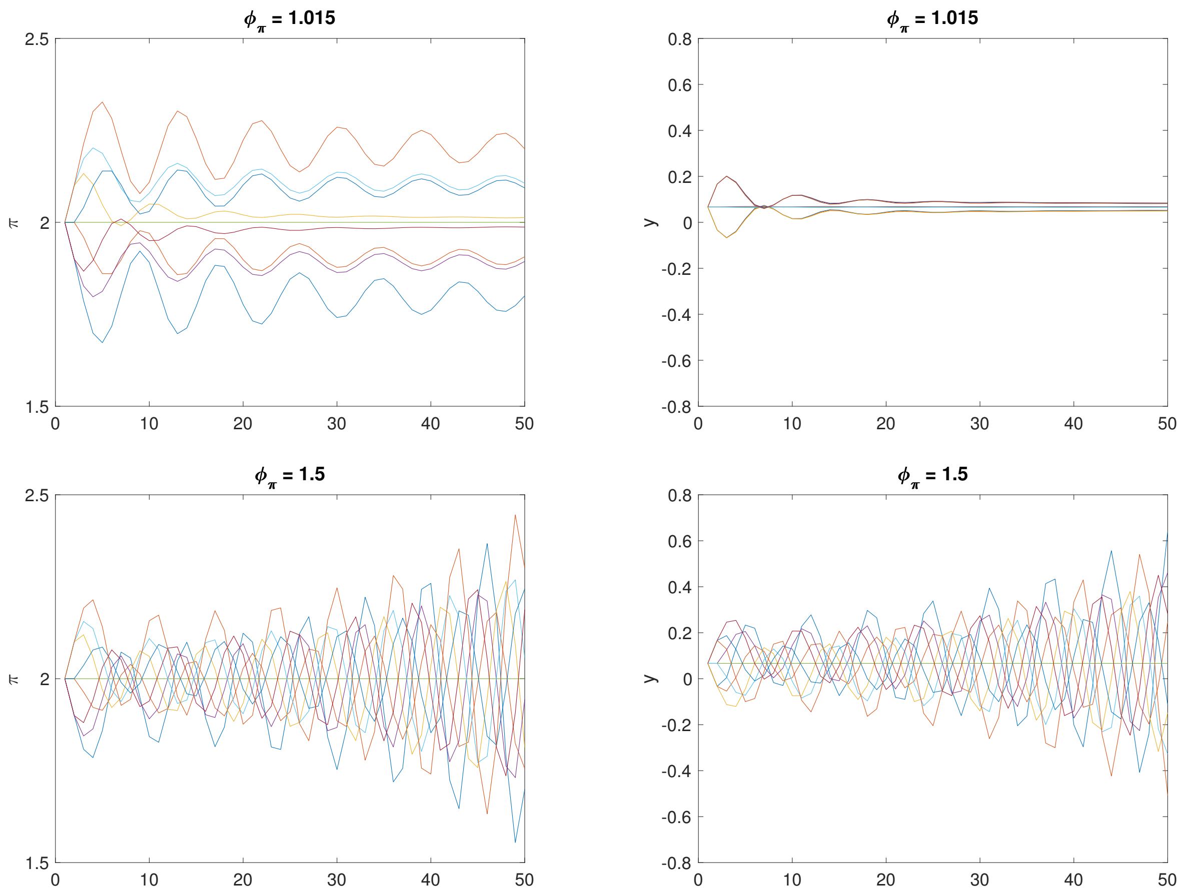


Figure F.22: Simulated dynamics of inflation (left panels) and output gap (right panels) under LAA heuristics for $\phi_\pi = 1.015$ (top panels) and $\phi_\pi = 1.5$ (bottom panels).

corresponds to simulated dynamics for different initial conditions. When monetary policy is not too aggressive the system is stable, although convergence can be very slow due to an eigenvalue almost on the unit circle. On the other hand, when the policy reaction is strong,

[4]Dynamics for $\phi_\pi = 1.005$ are similar to those obtained for $\phi_\pi = 1.015$

the system is unstable displaying oscillatory divergence.

Appendix G. One-step-ahead simulations for all groups

In this section we report the results of one-step ahead predictions for all experimental economies. Left panels in Figs. G.23–G.34 display experimental data together with the one-step-ahead predictions under the HSM, while right panels depict the evolution over time of the weights of the four considered heuristics.

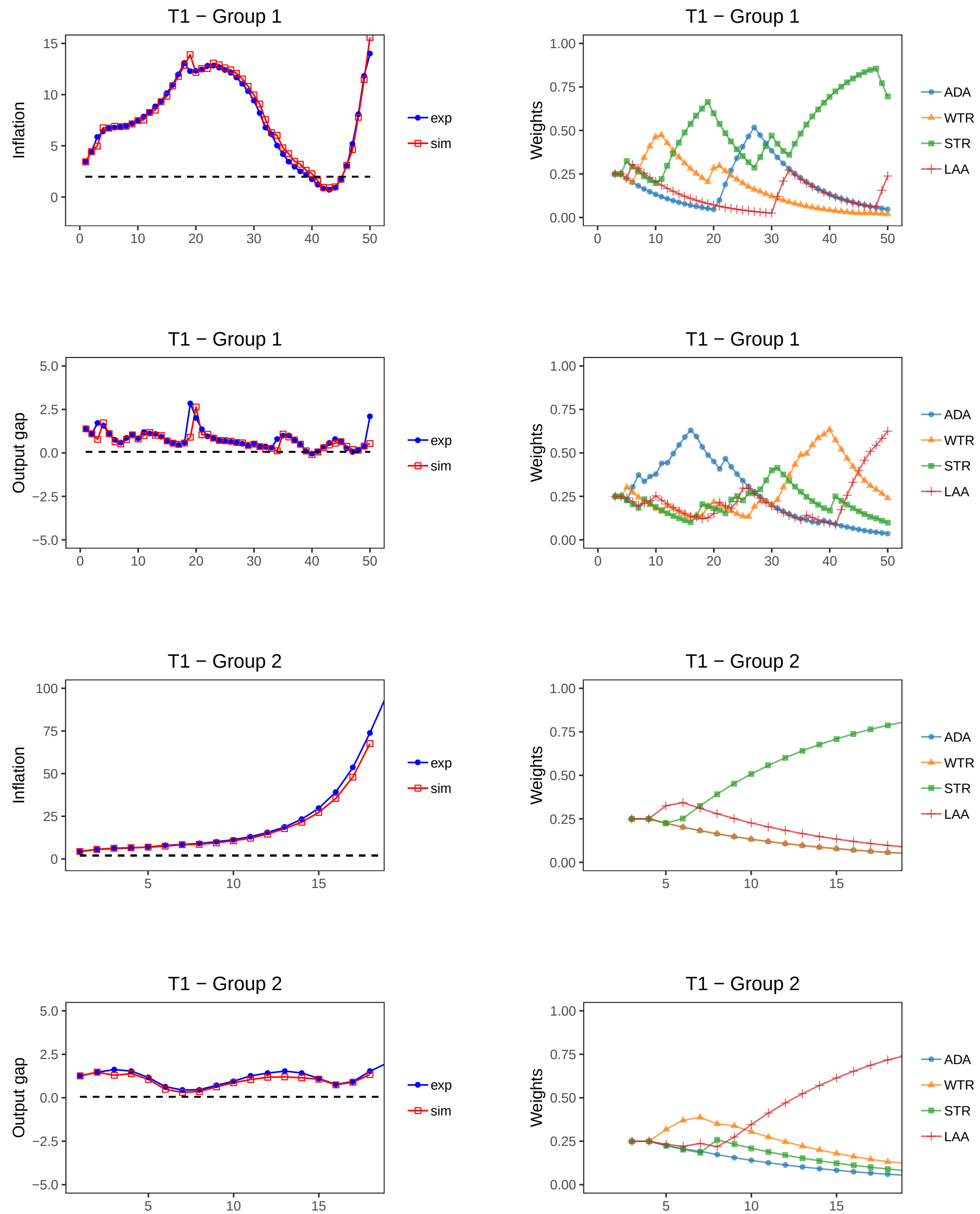


Figure G.23: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T1$ (groups 1–2).

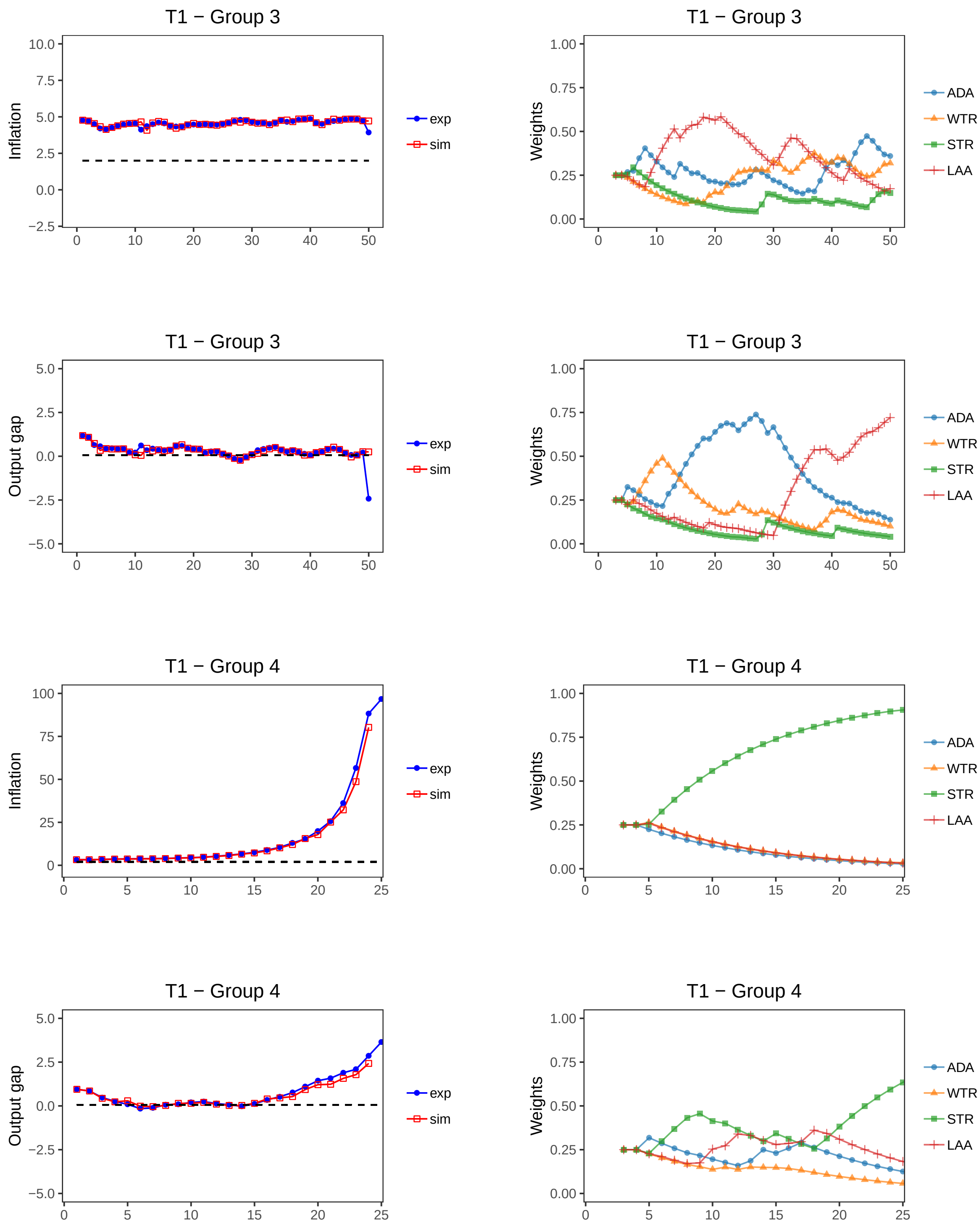


Figure G.24: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T1$ (groups 3–4).

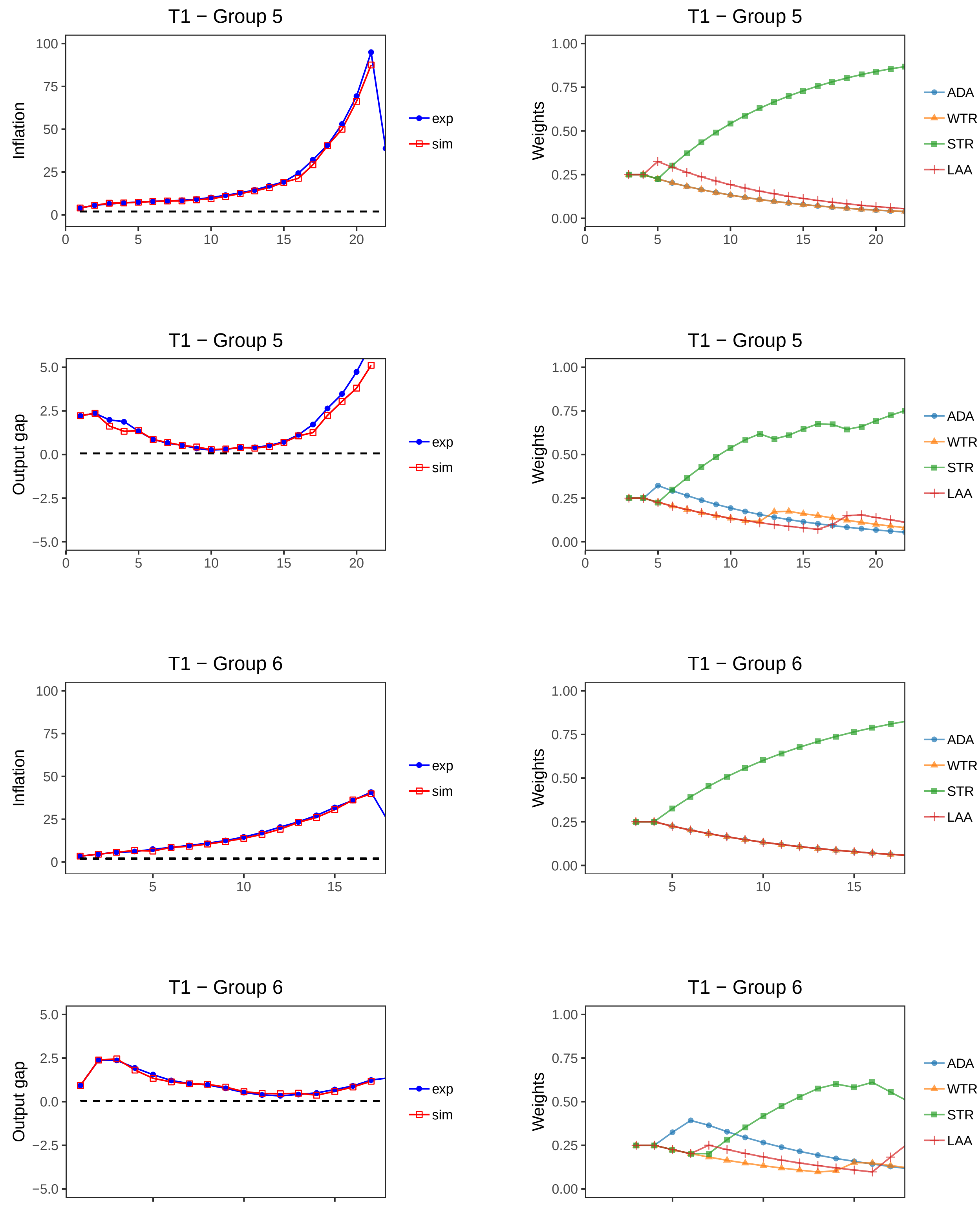


Figure G.25: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T1$ (groups 5–6).

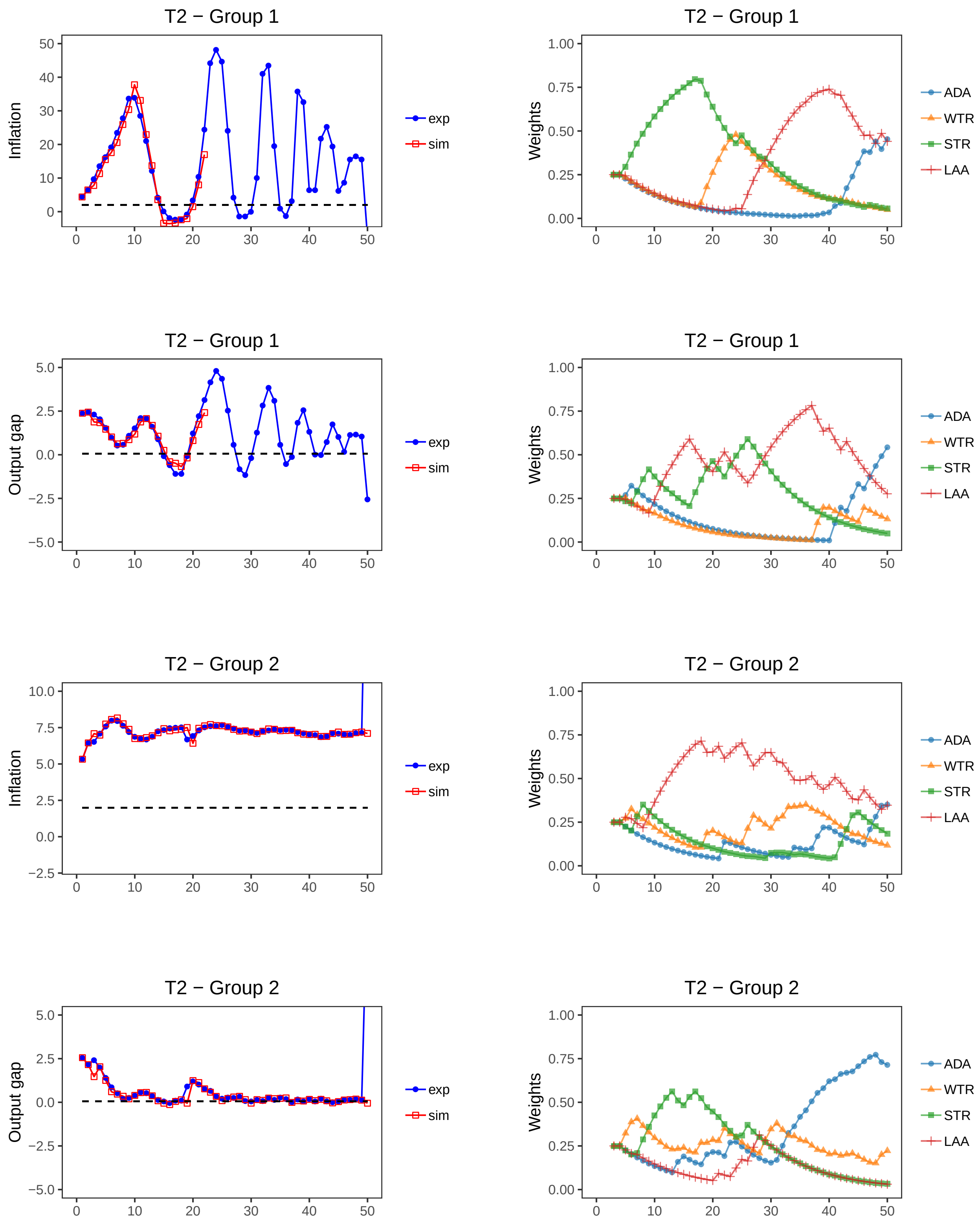


Figure G.26: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T2$ (groups 1–2).

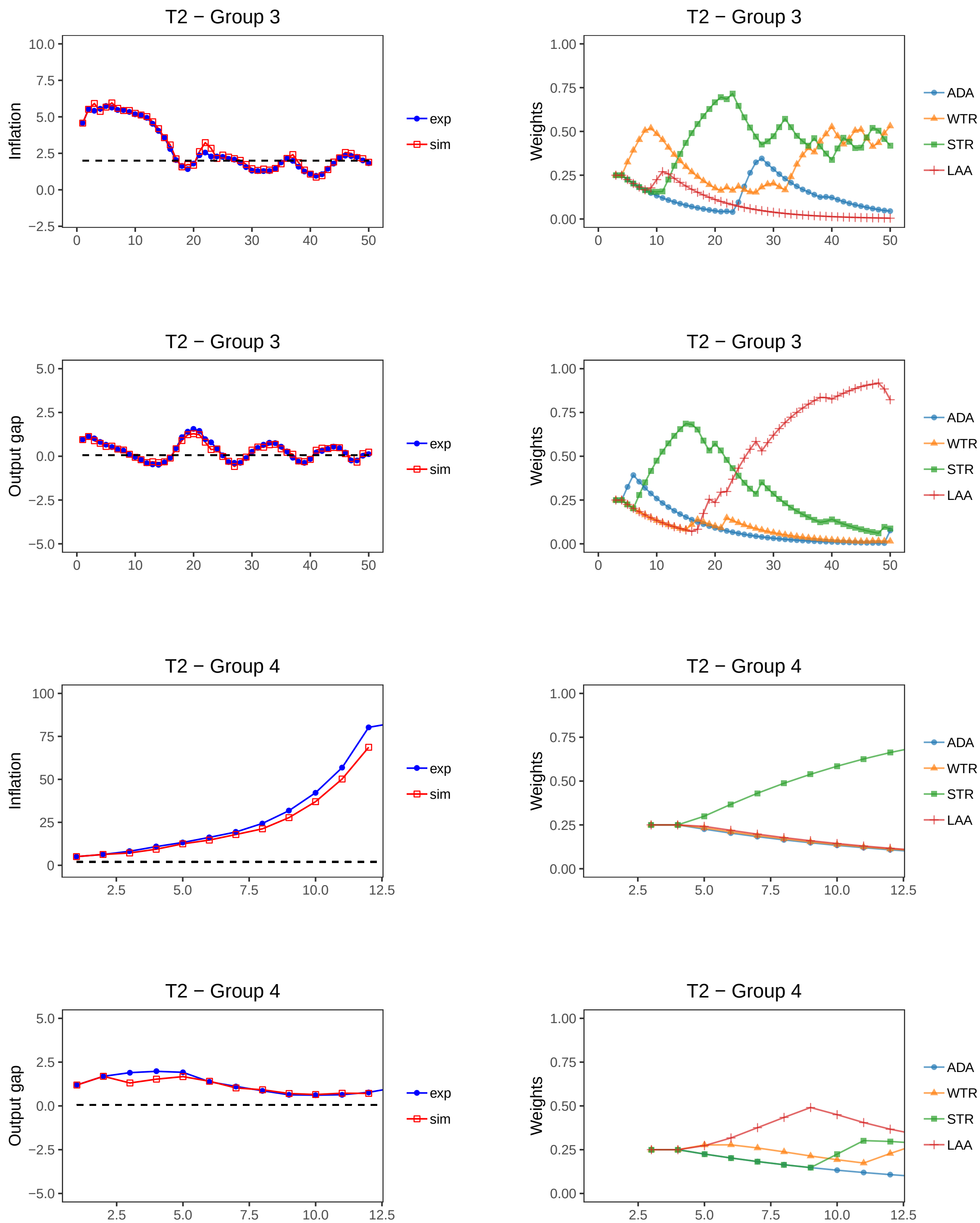


Figure G.27: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T2$ (groups 3–4).

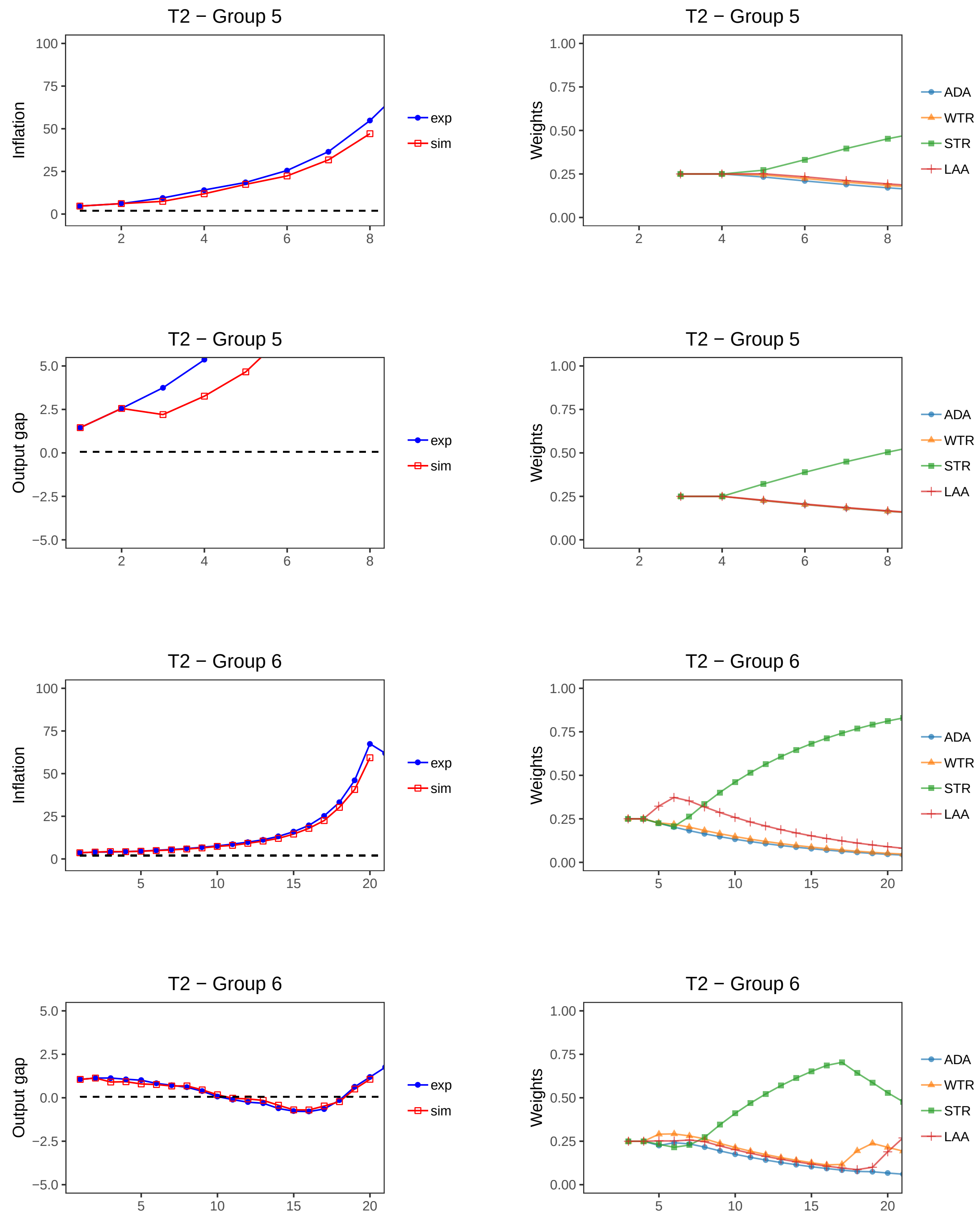


Figure G.28: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T2$ (groups 5–6).

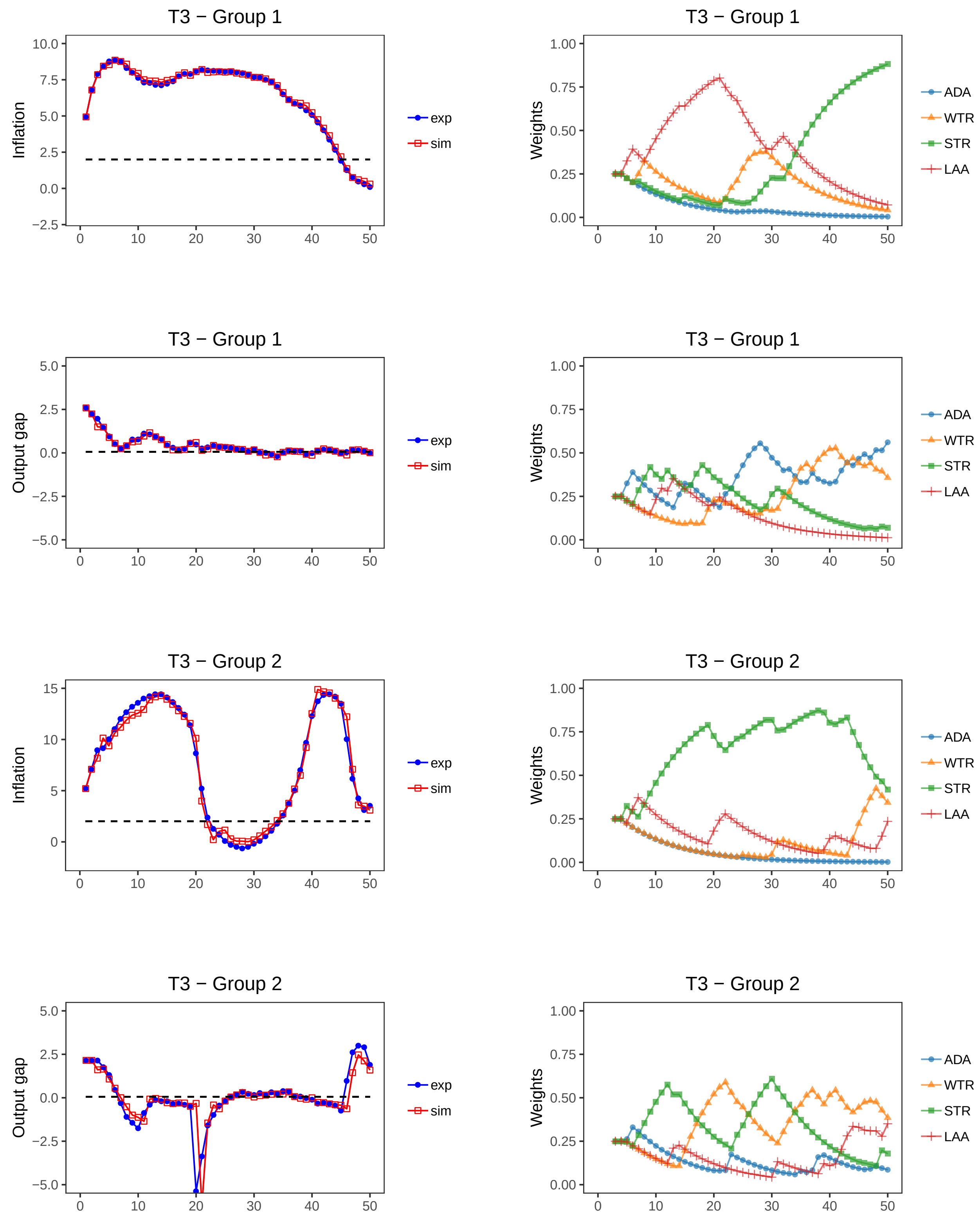


Figure G.29: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T3$ (groups 1–2).

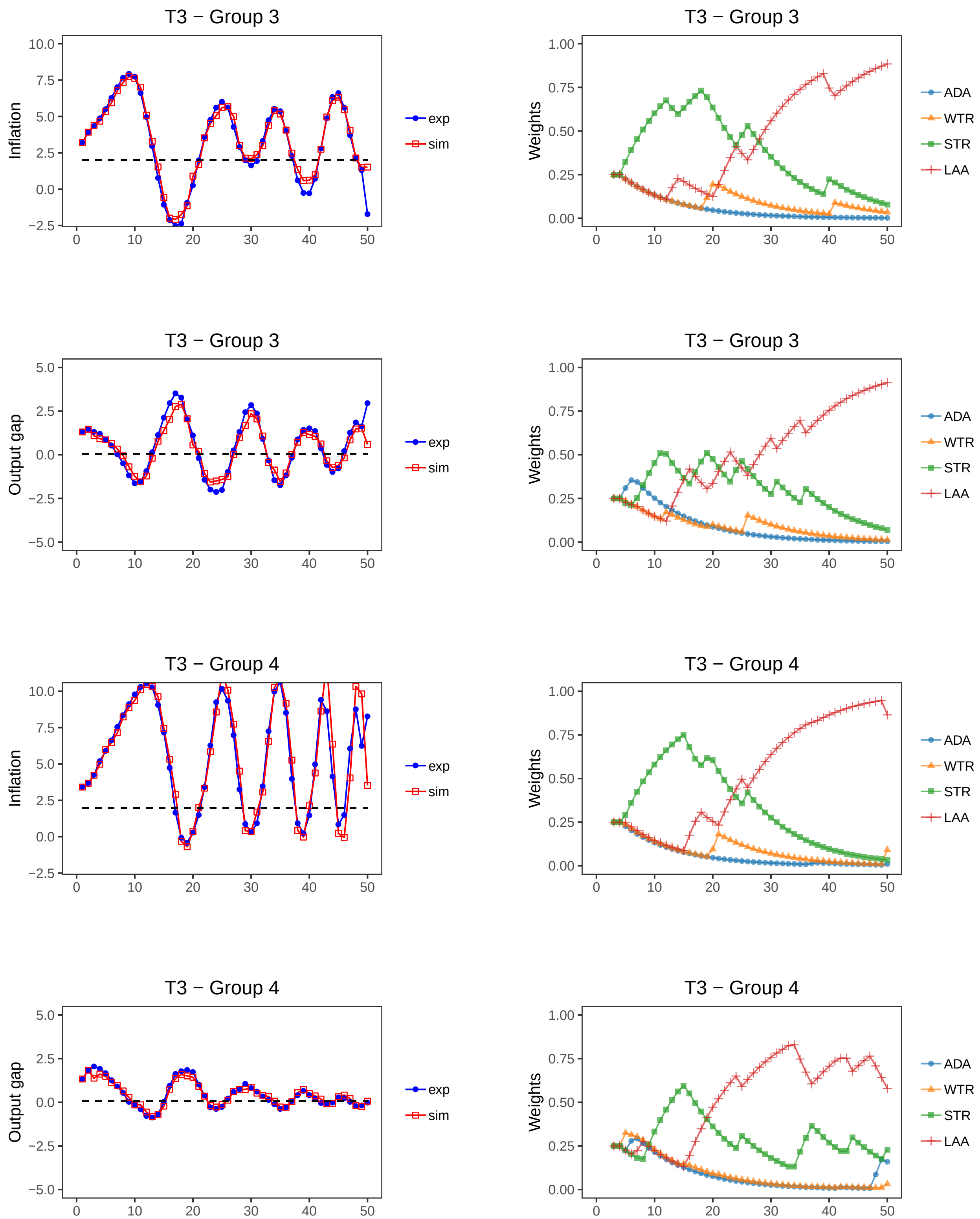


Figure G.30: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T3$ (groups 3–4).

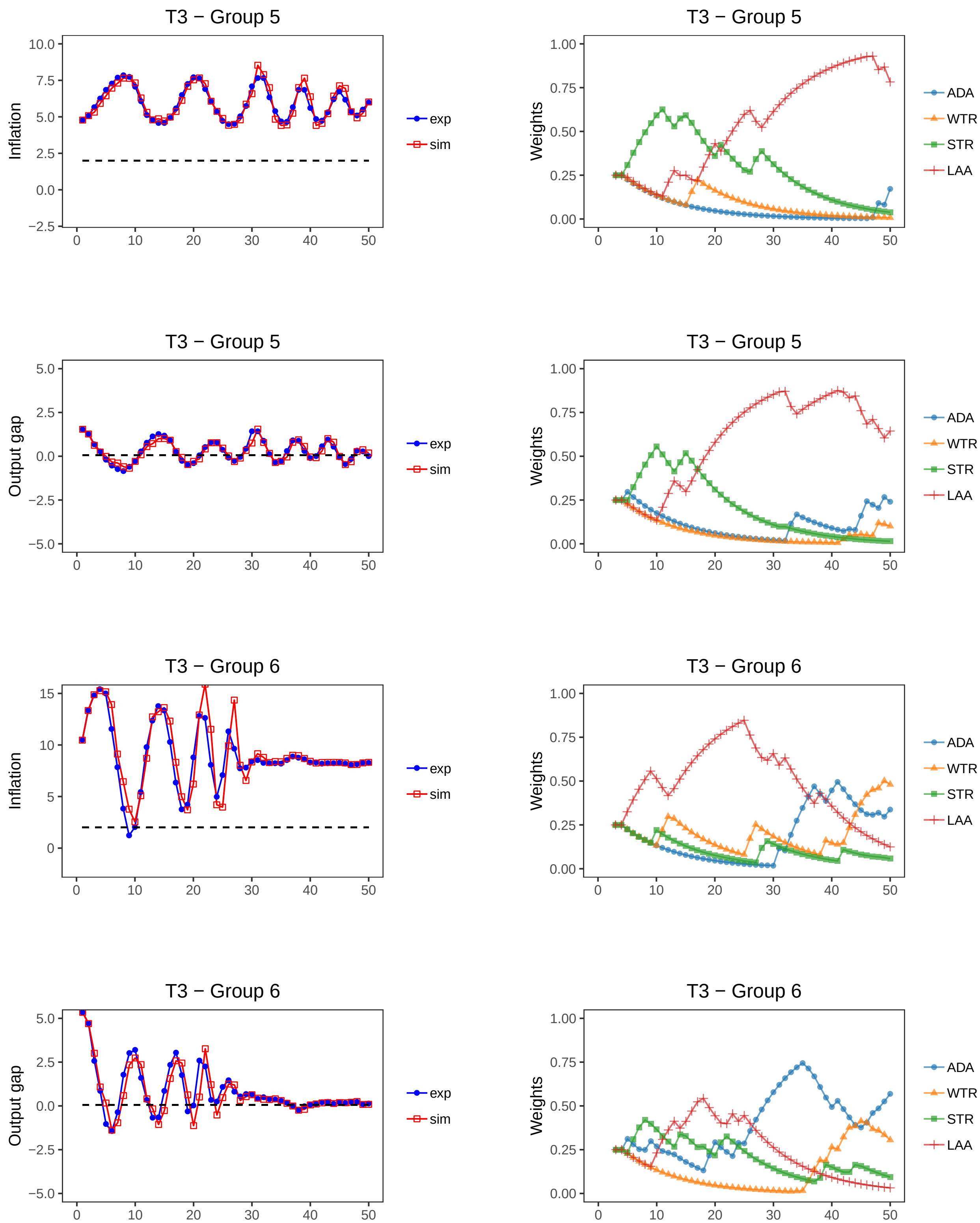


Figure G.31: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T3$ (groups 5–6).

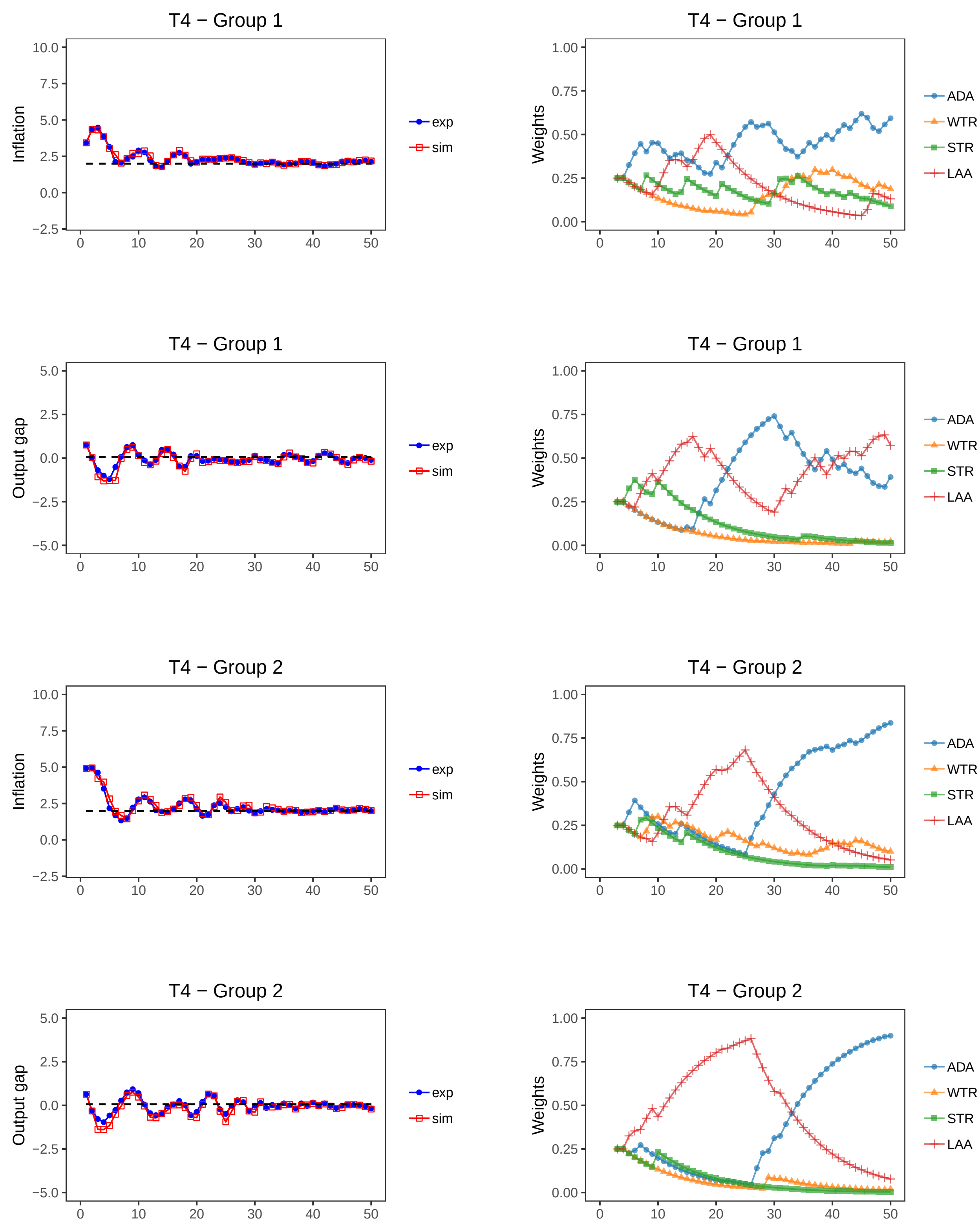


Figure G.32: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T4$ (groups 1–2).

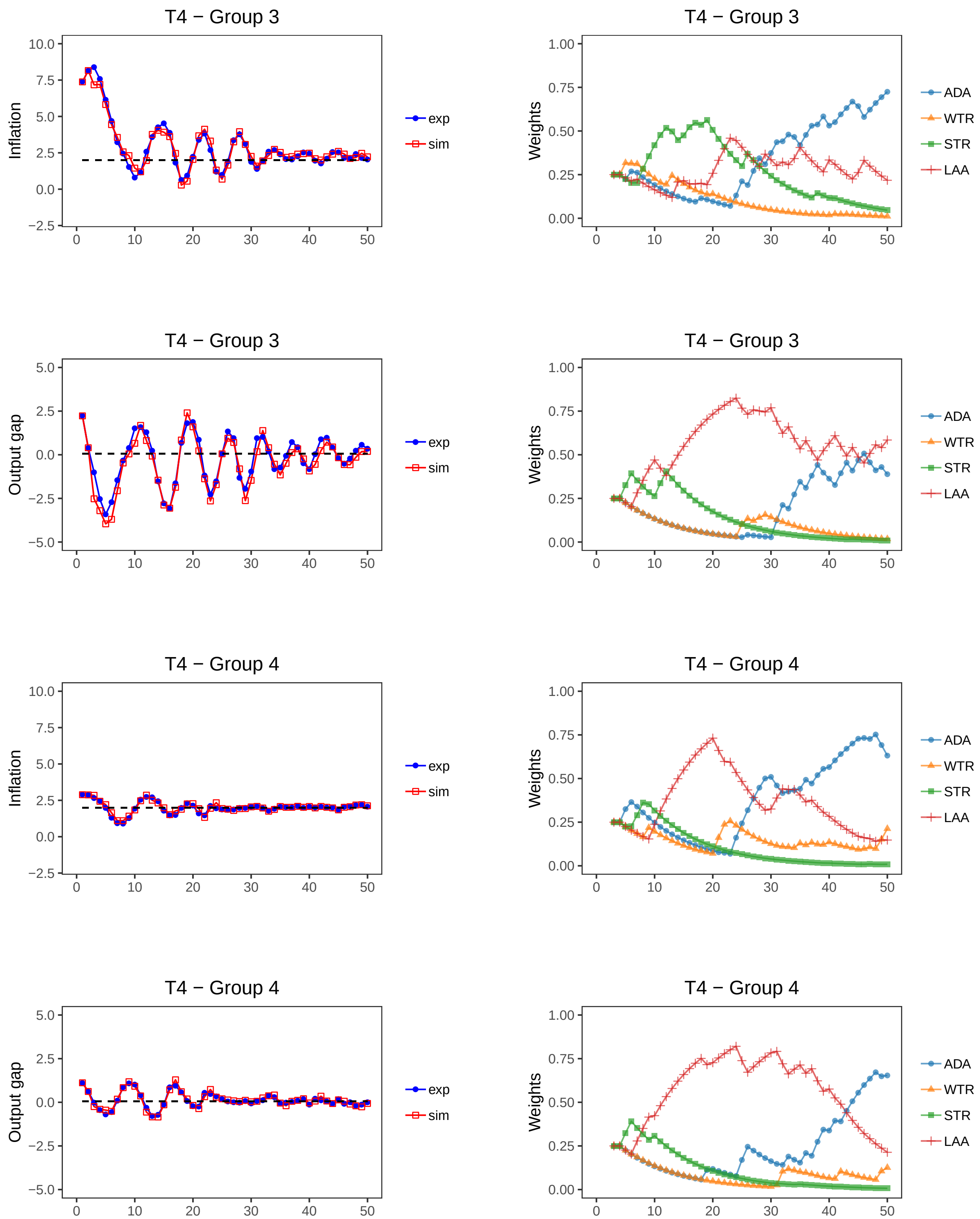


Figure G.33: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T4$ (groups 3–4).

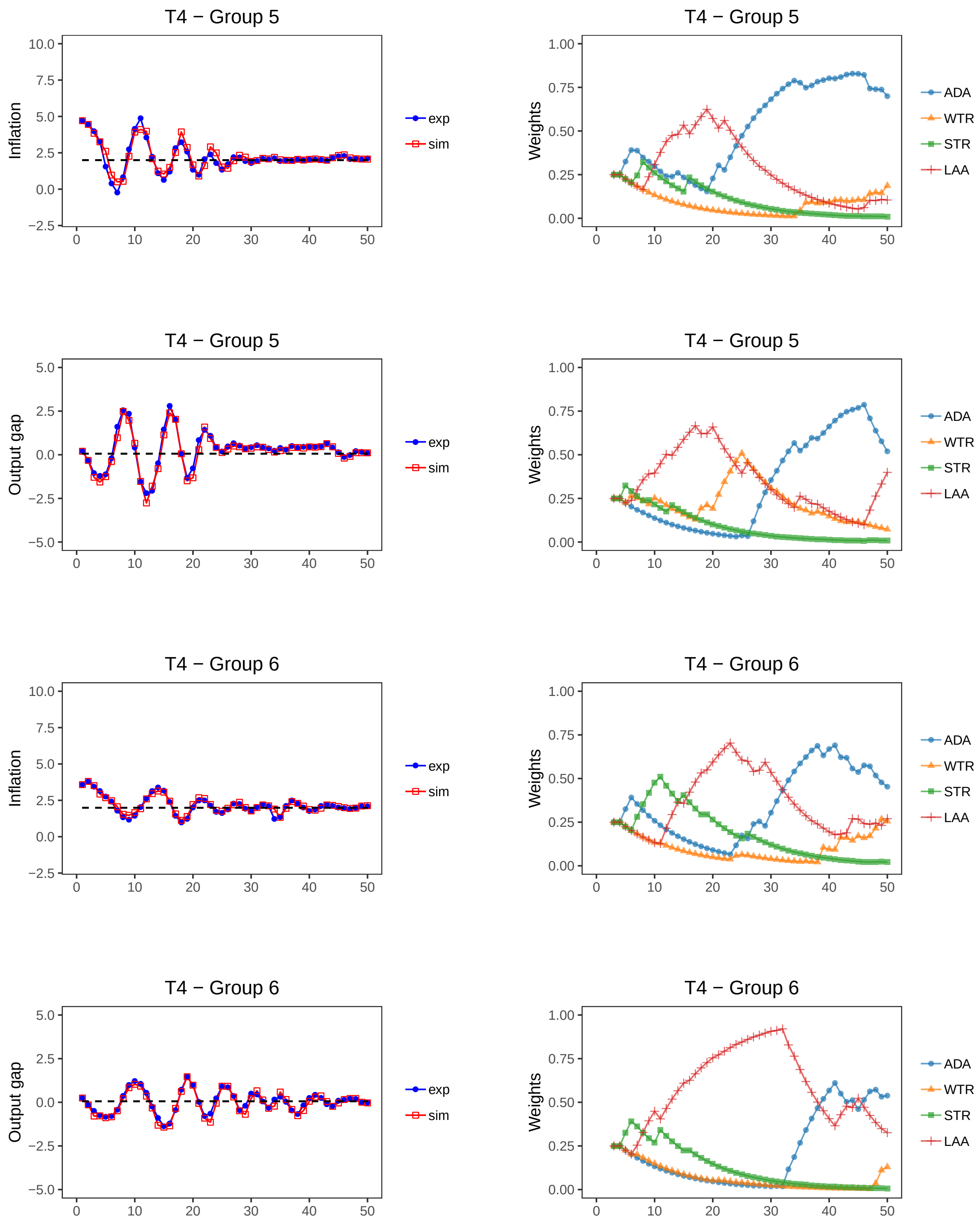


Figure G.34: Realized and simulated inflation and output gap (left panels) with corresponding simulated weights of 4 heuristics for $T4$ (groups 5–6).