Online Appendix: "Two-Stage Model Averaging for Impulse Responses: Local Projections- and VARs-based Approaches"

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Abstract

This online appendix provides the full set of robustness checks that complement the main paper. Appendix D reports Monte Carlo results for the seven individual estimators and for under two alternative identification schemes (IV/Proxy and recursive). Appendix E repeats the simulations with a stationary data-generating process (DGP) instead of the non-stationary DGP used in the main text, whereas Appendix F explores shorter (lag 2) and longer (lag 8) estimation lag lengths.

Appendix D Monte Carlo Simulation Results for Estimation Methods and Identification Schemes

Appendix D.1 Other Individual Estimation Methods

To select individual estimators for comparison alongside the model averaging schemes presented in Section 4, we evaluate the performance of seven LP-based and VAR-based estimators in terms of absolute bias ($aBias$), standard deviation (SD), and unweighted root mean squared error (MSE): LS LP, BC LP, BLP, Pen LP, LS VAR, BC VAR, and BVAR. These estimators are computed under the same DGPs used in our simulation study. Results under observed shock identification with four lags are shown in Figure D.1, while results under IV/Proxy and recursive identification are presented in Appendix D.2 and Appendix D.3, respectively.

In the case of fiscal shocks (Figure D.1), LP-based estimators generally exhibit lower $aBias$, particularly for longer horizons, with the exception of Pen LP. In contrast, VAR-based estimators display lower variability from $h = 7$ onward, with the gap between the two groups widening at longer horizons. Among LP-based estimators, BC LP consistently

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achieves low and steadily increasing bias. Among VAR-based estimators, BVAR shows the lowest SD starting from $h = 4$.

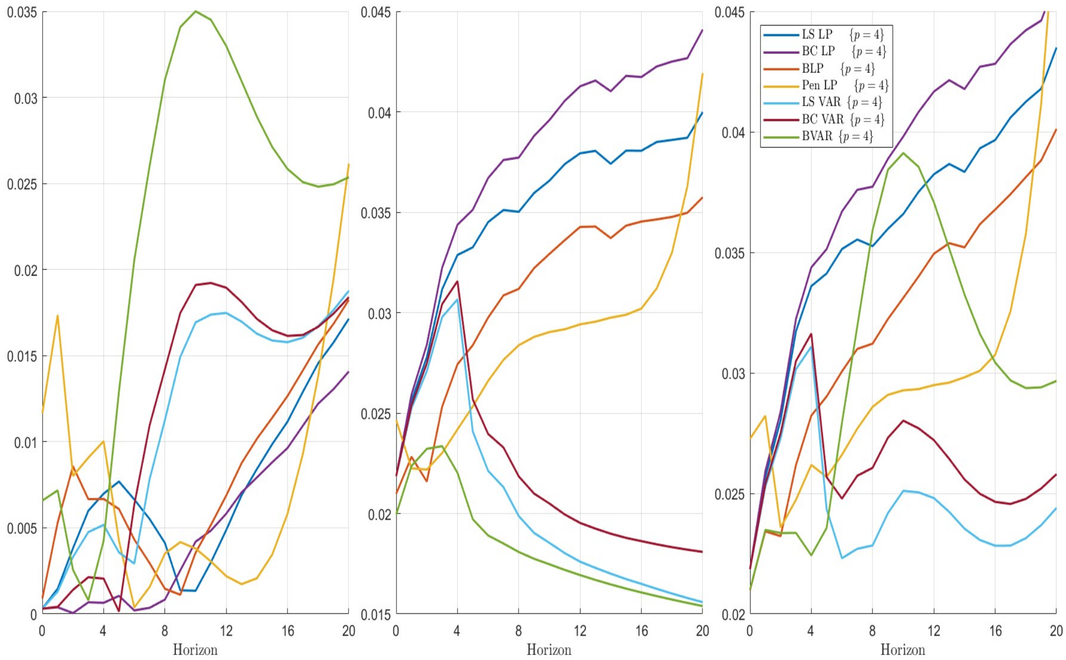
For monetary shocks, the comparison in $aBias$ varies across horizons. BC LP performs best for $3 \leq h < 12$, while BC VAR and BVAR dominate at longer horizons. Notably, BVAR exhibits high bias in intermediate horizons but achieves the lowest bias in the long run due to its large fluctuations. However, it consistently displays the lowest SD across nearly all horizons.

In summary, the SD results clearly indicate that VAR-based estimators are more stable than LP-based estimators for both shock types and most horizons. However, the comparison in terms of $aBias$ depends on the type of shock and the forecast horizon. LP-based estimators perform better at intermediate horizons in terms of bias, while VAR-based estimators are more favorable at intermediate and long horizons in terms of variability.

Based on these findings, we select BVAR and BC LP as representative single estimators to be presented alongside the model averaging estimators in the main simulation results.

Observed Fiscal Shock

$aBias$ **(Left) ,** SD **(Middle) and MSE (Right) of Estimators**



Observed Monetary Shock

$aBias$ **(Left) ,** SD **(Middle) and MSE (Right) of Estimators**

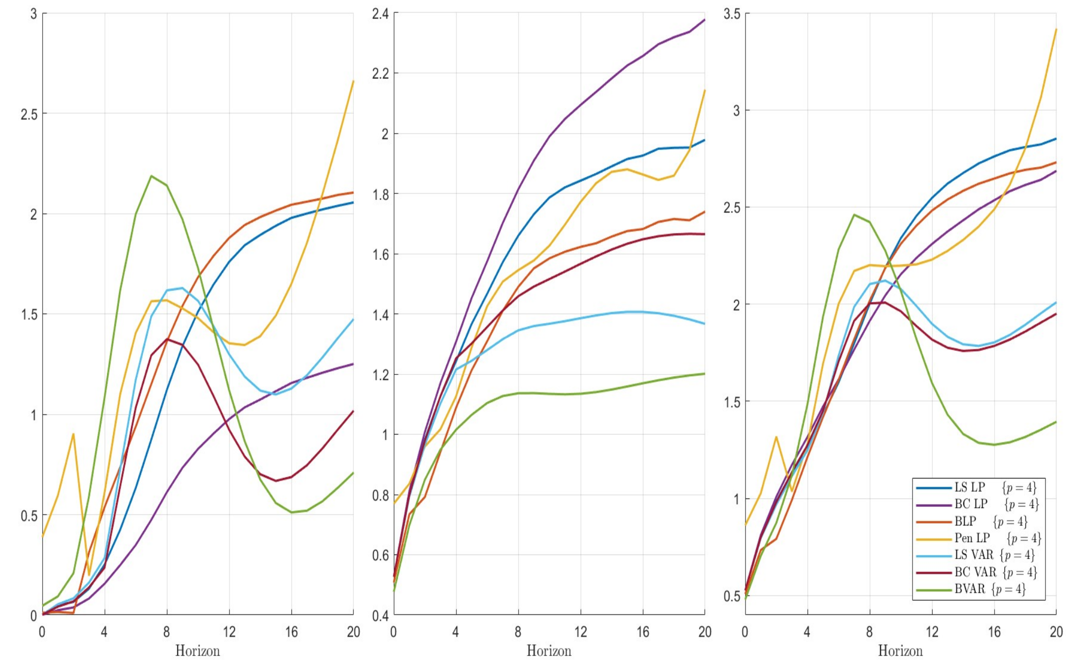


Figure D.1: Average absolute bias, standard deviation and MSE when a shock is observed.

Appendix D.2 IV Identification Results

In our baseline analysis, we conduct simulation studies using a non-stationary dynamic factor model (DFM), assuming that the shock is observed. As a robustness check, this subsection and the following section present results obtained under IV/Proxy and recursive identification schemes. For VAR estimators, we implement an internal IV procedure rather than relying on external SVAR-IV approach. Given that the variance of some estimators may overshadow bias due to outliers, we apply trimmed IRFs by winsorizing each row to the 1st and 99th percentiles—replacing extreme values with threshold cutoffs.

Figure D.2 reports the bias, standard deviation, and MSE of seven estimators, including LP- and VAR-variants. Under fiscal shocks, LS LP shows a relatively low and stable increase in bias in the intermediate horizon, while LS VAR achieves the lowest variability for $h \geq 8$. For monetary shocks, BC LP delivers the lowest and most stable bias among LP-variants, while BVAR exhibits the lowest variability after $h = 4$. Overall, the results suggest a bias-variance trade-off between LPs and VARs in intermediate horizons under fiscal shocks, while VAR-based estimators outperform in both bias and variance in longer horizons ($h \geq 12$) under monetary shocks.

In line with these findings, Figure D.3 reveals a clear bias-variance trade-off between MAVG_{LP} and MAVG_{VAR} in the intermediate horizon for fiscal shocks. By contrast, for monetary shocks, MAVG_{VAR} estimators outperforms in both dimensions beyond $h = 8$, indicating the absence of such trade-offs.

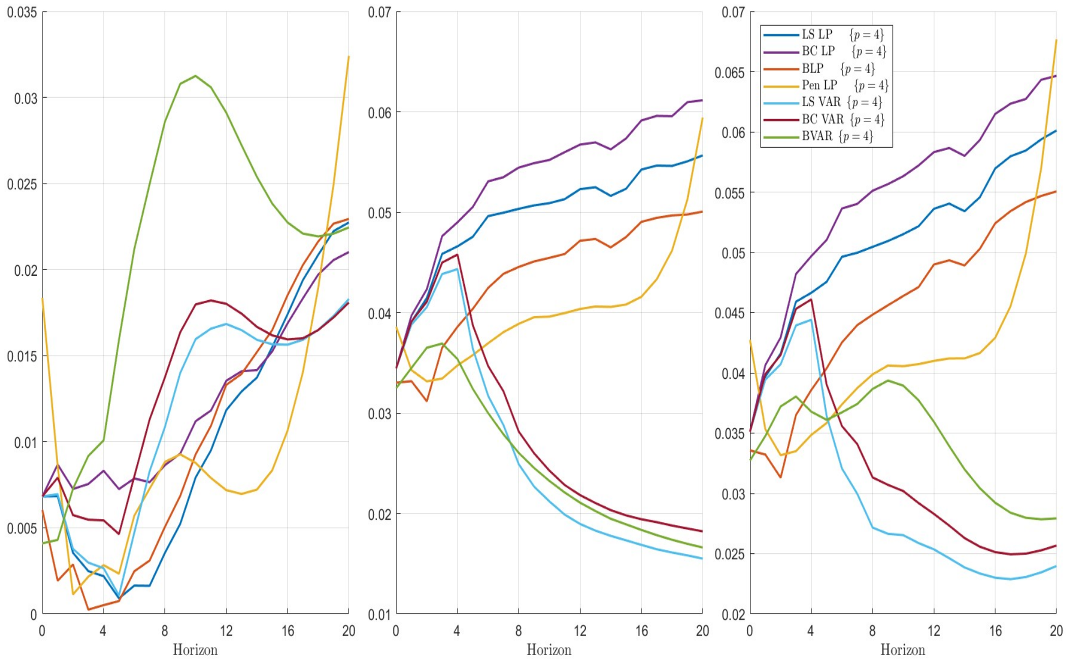
Figures D.4 to D.7 compare model averaging estimators with selected single estimators. While single estimators can be efficient when minimizing either bias or variance individually, none dominate in bias across all horizons, regardless of the shock type. For fiscal shocks (Figures D.4 to D.5), estimators in MAVG_{LP} and MAVG_{ALL} achieve lower $aBias$ and SD than LS VAR and LS LP, respectively. For monetary shocks (Figures D.6 to D.7), MAVG estimators also outperform BVAR and BC LP in both evaluations at short and intermediate horizons. These results suggest that when researchers consider both bias and variance in their loss function, MAVG estimators offer superior performance in the intermediate horizon.

Figures D.8 to D.9 compare the performance of different MAVG estimators. In the fiscal shock case, α_{LP} schemes show relatively lower bias in intermediate horizons and comparable variability to MAVG_{VAR} across horizons. Under monetary shocks, all MAVG estimators perform similarly up to $h = 8$ in bias and $h = 4$ in variance. Beyond these ranges, MAVG_{VAR} estimators become dominant in both evaluations, suggesting that under such conditions, GMA_{VAR} may be preferable.

Finally, Figure D.10 presents a comparison among four α_{LP} schemes that combine both LP- and VAR-based estimators. Schemes that incorporate both model fit and prediction accuracy tend to outperform others or remain competitive across evaluation metrics, consistent with the findings from the main analysis.

IV: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators



IV: Monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

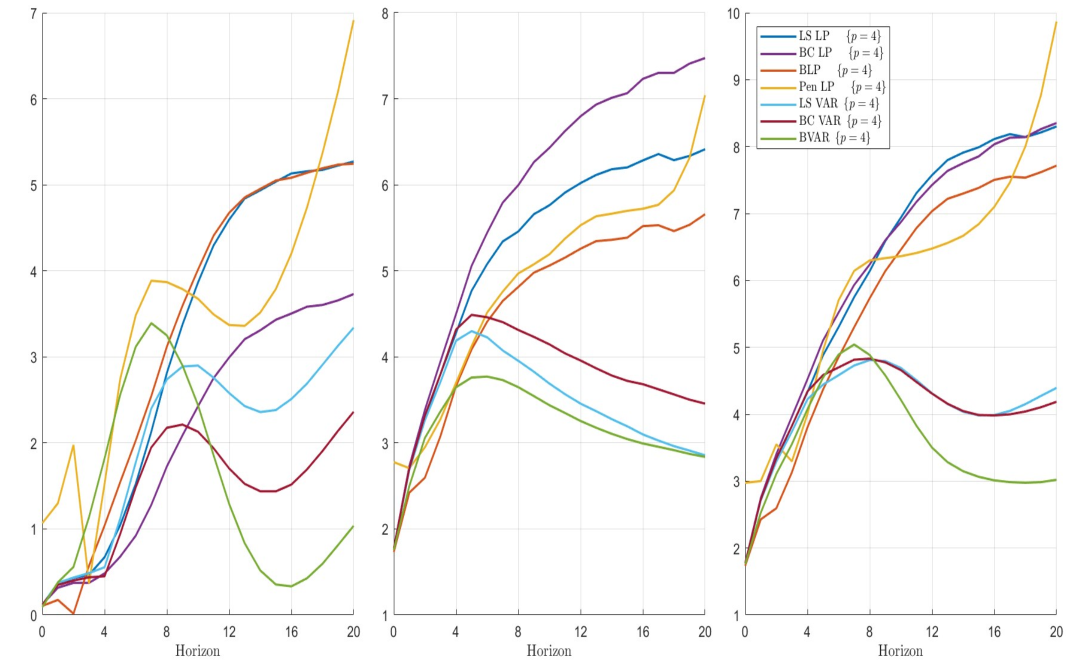
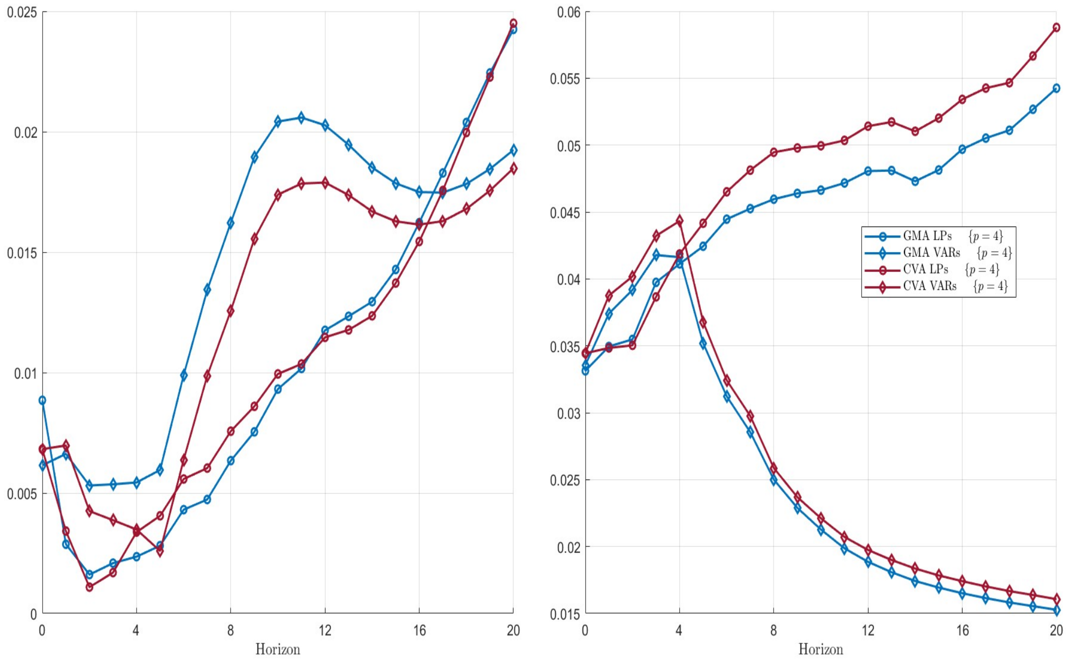


Figure D.2: Average absolute bias, standard deviation and MSE when a shock is proxied.

IV: Fiscal Shock

$aBias$ **(Left) and** SD **(Right) of Estimators**



IV: Monetary Shock

$aBias$ **(Left) and** SD **(Right) of Estimators**

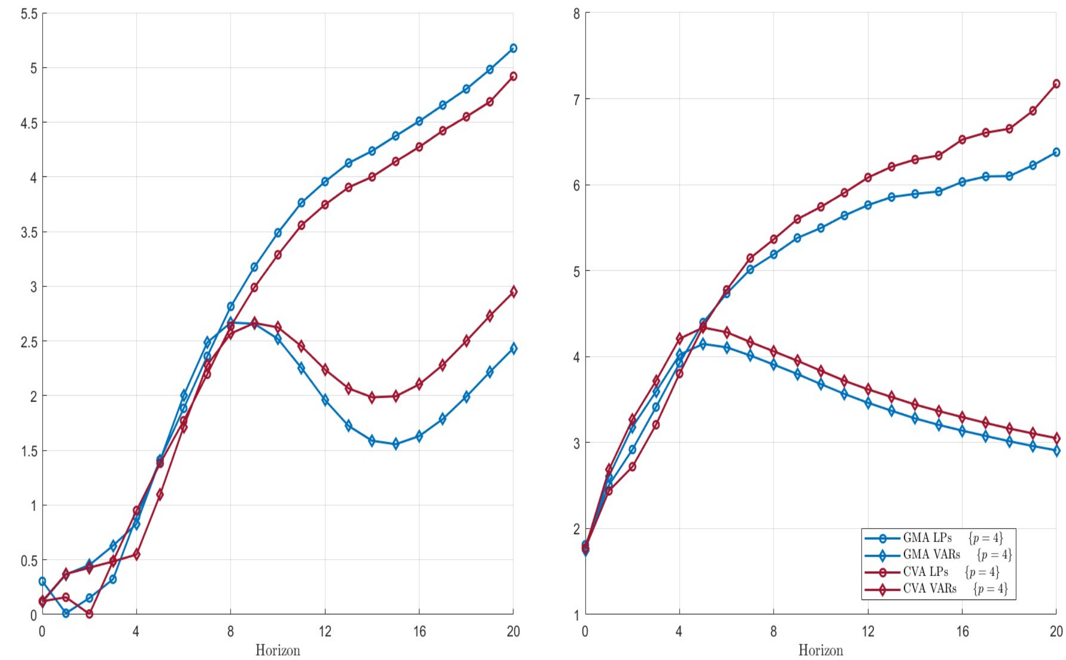


Figure D.3: Average absolute bias and standard deviation when a shock is proxied.

IV: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

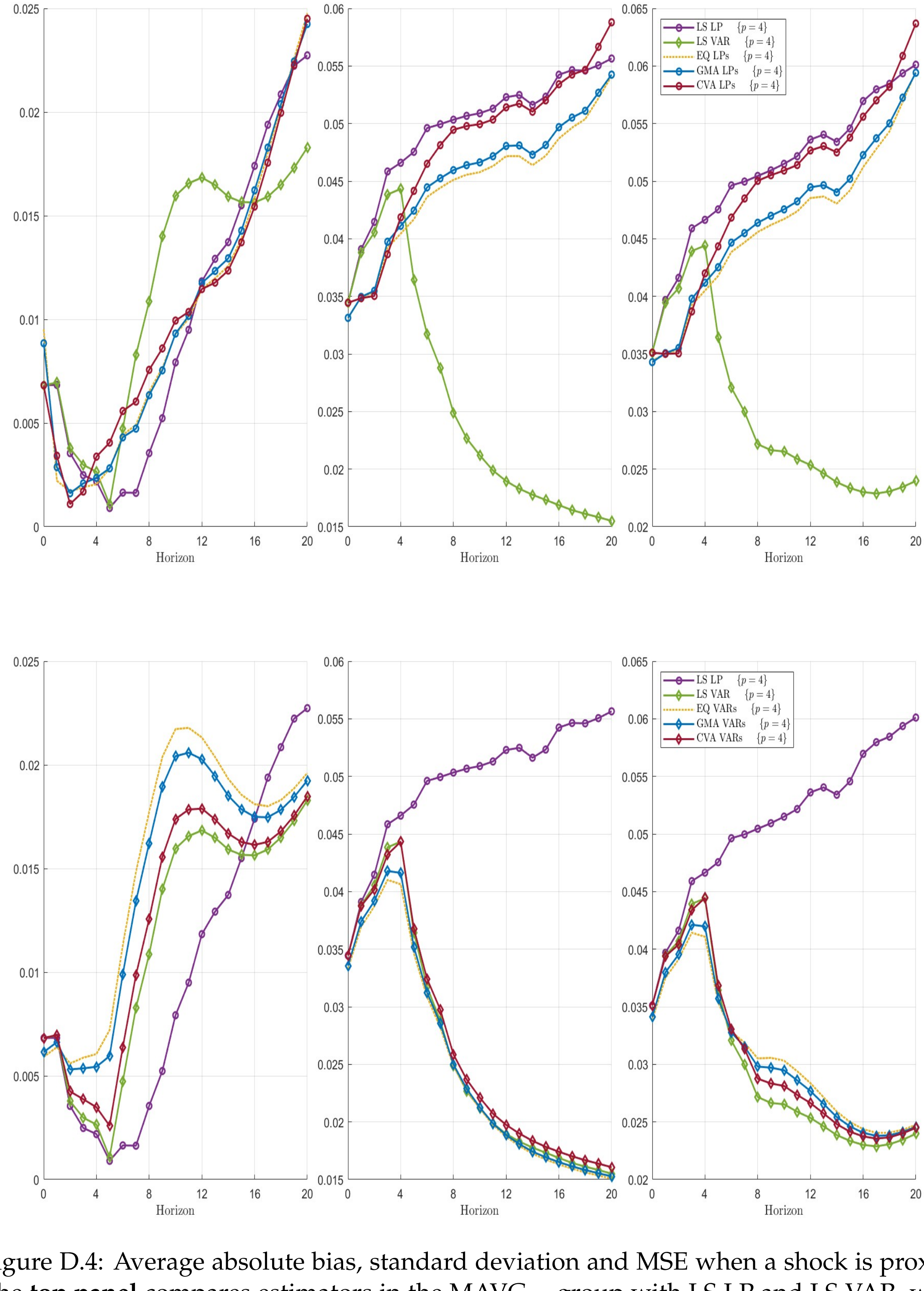


Figure D.4: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{LP} group with LS LP and LS VAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

IV: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

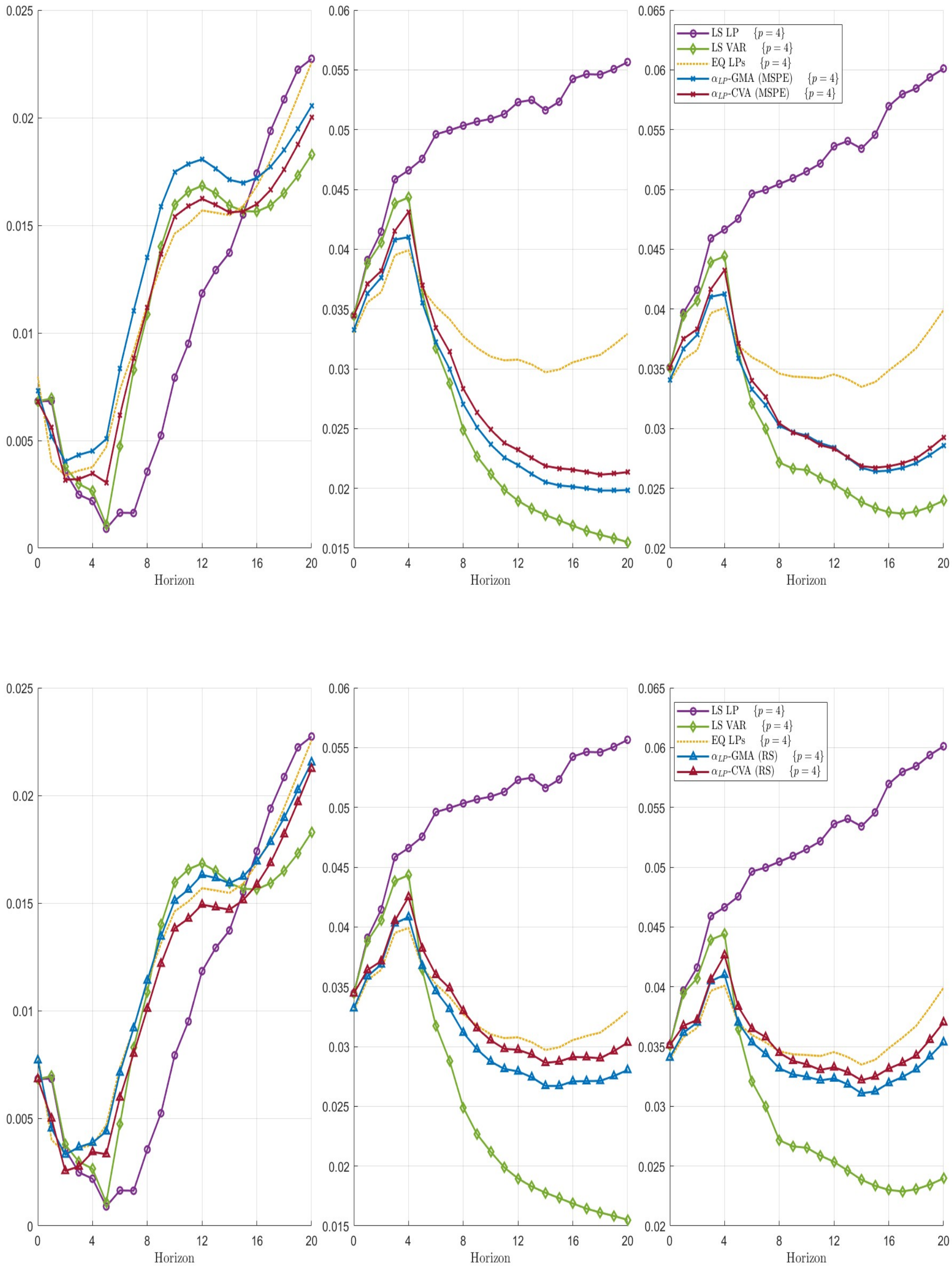


Figure D.5: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with LS LP and LS VAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

IV: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

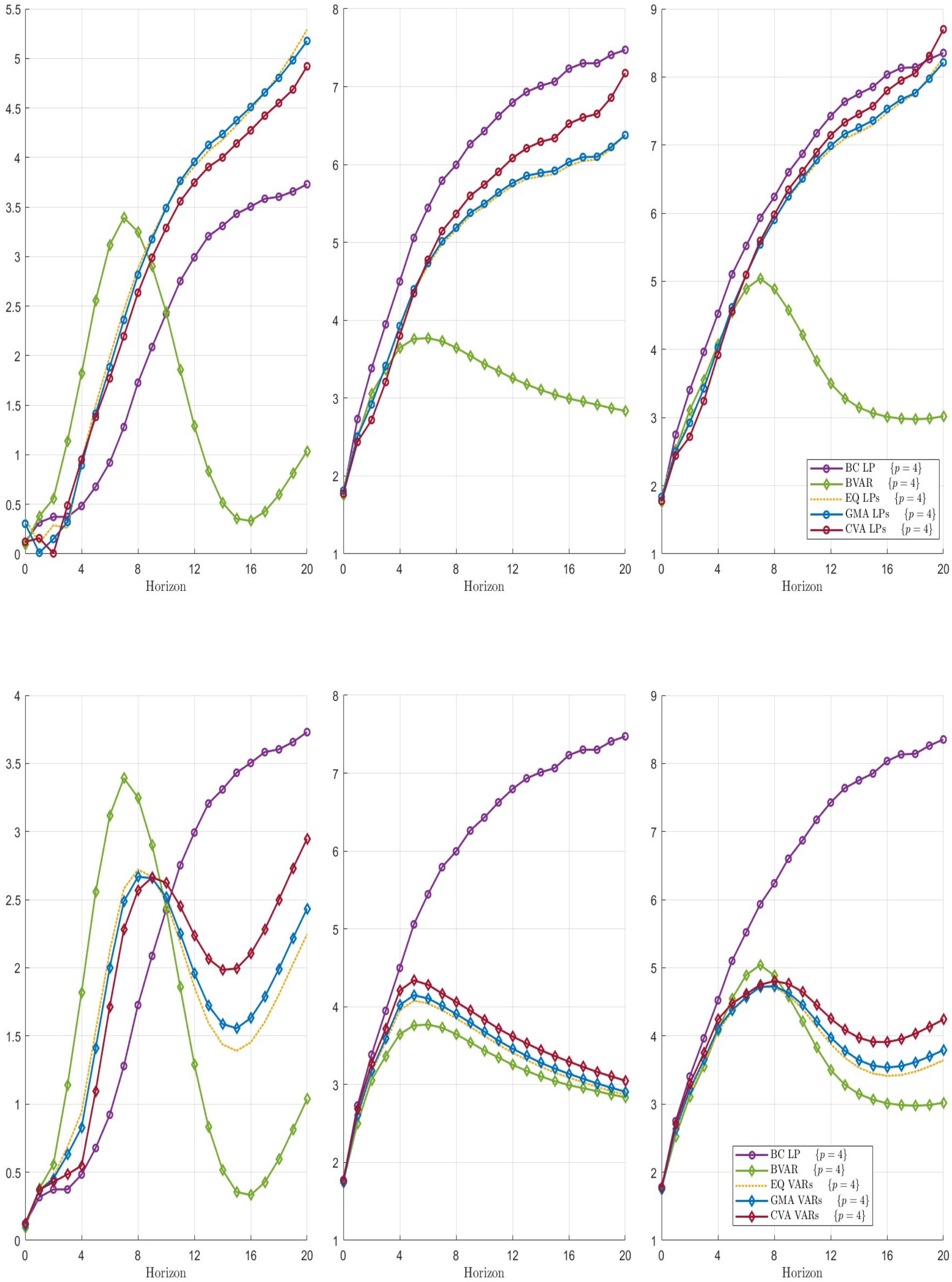


Figure D.6: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

IV: monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

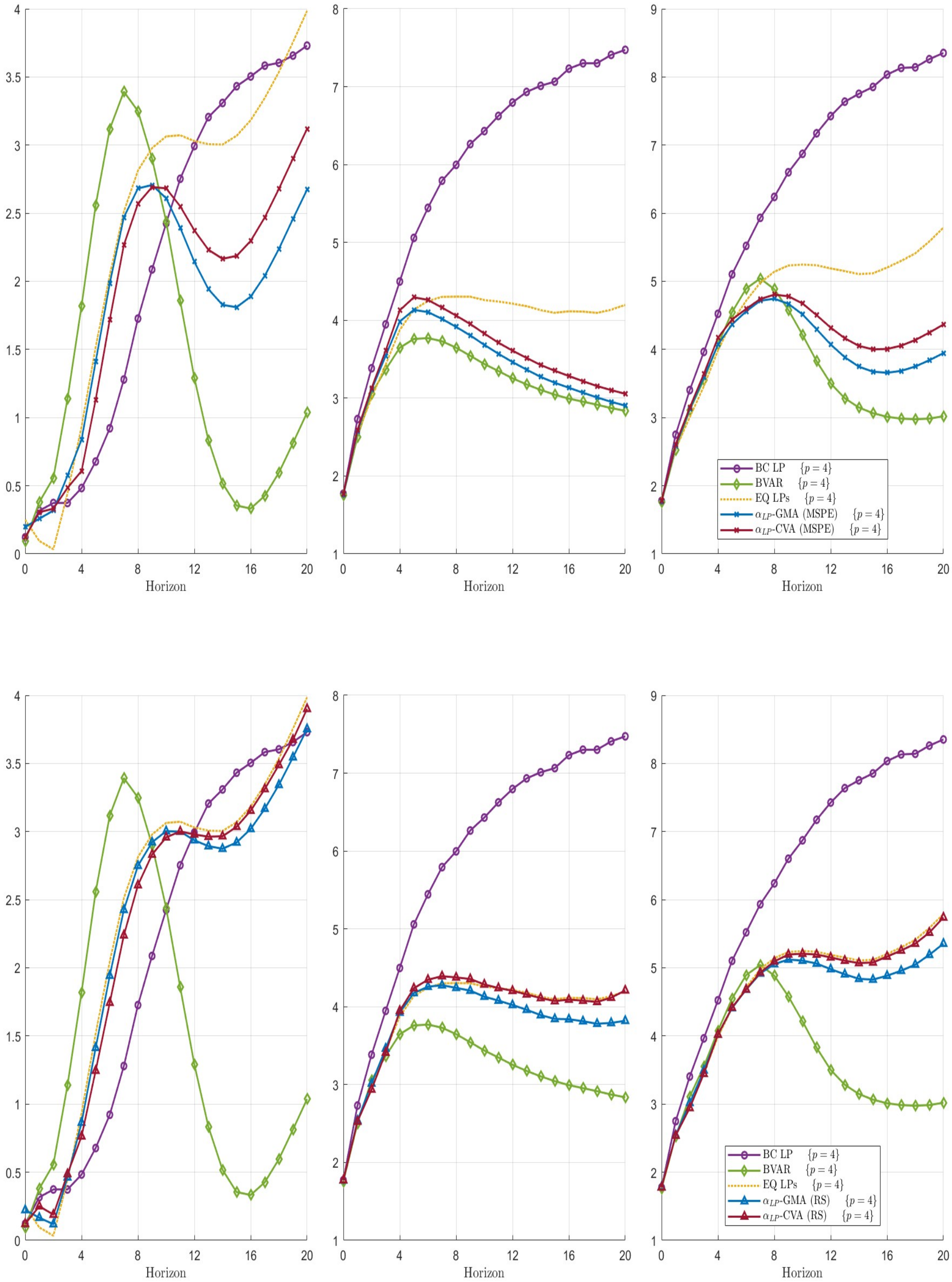


Figure D.7: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

IV: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

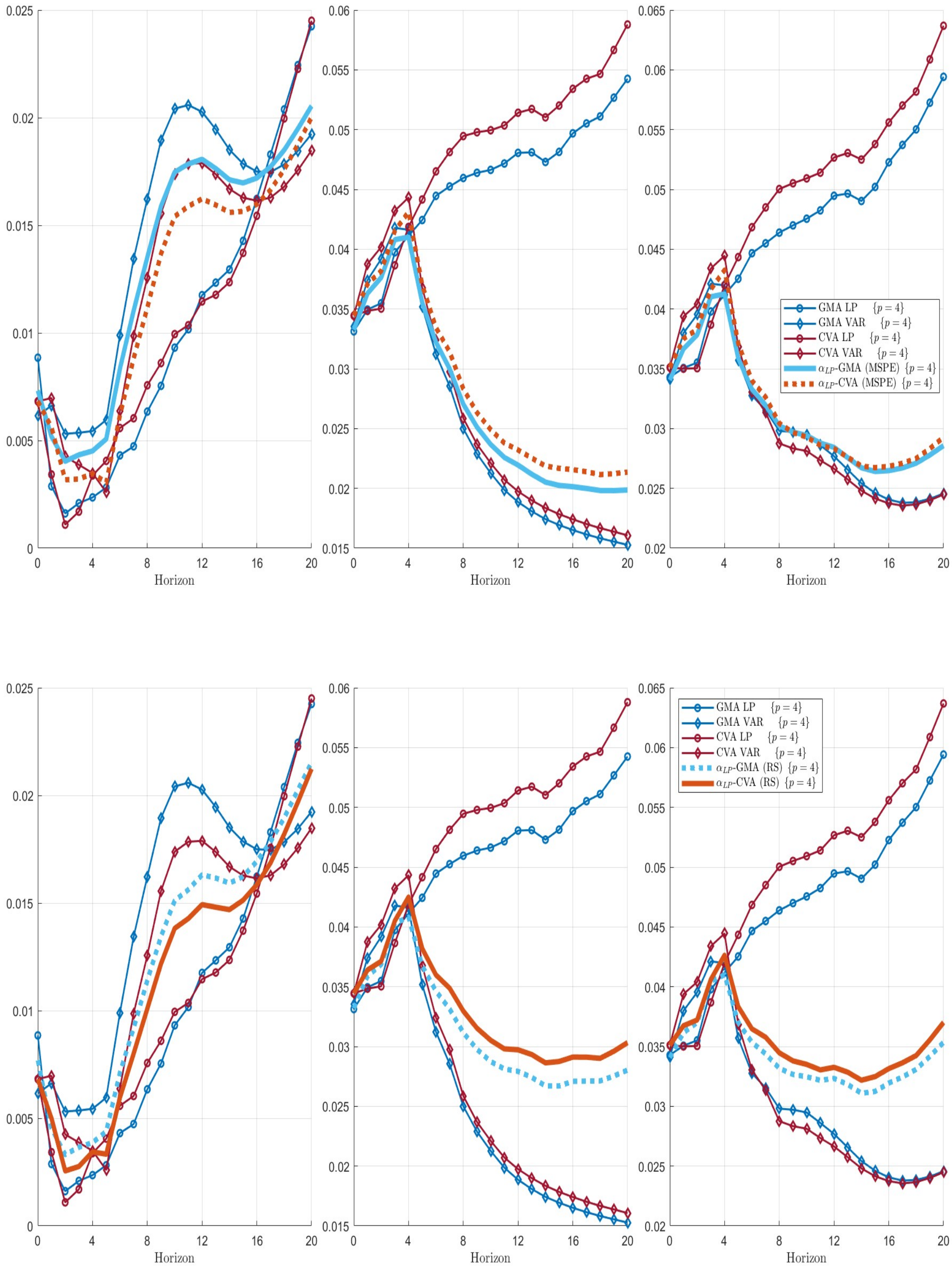


Figure D.8: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

IV: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

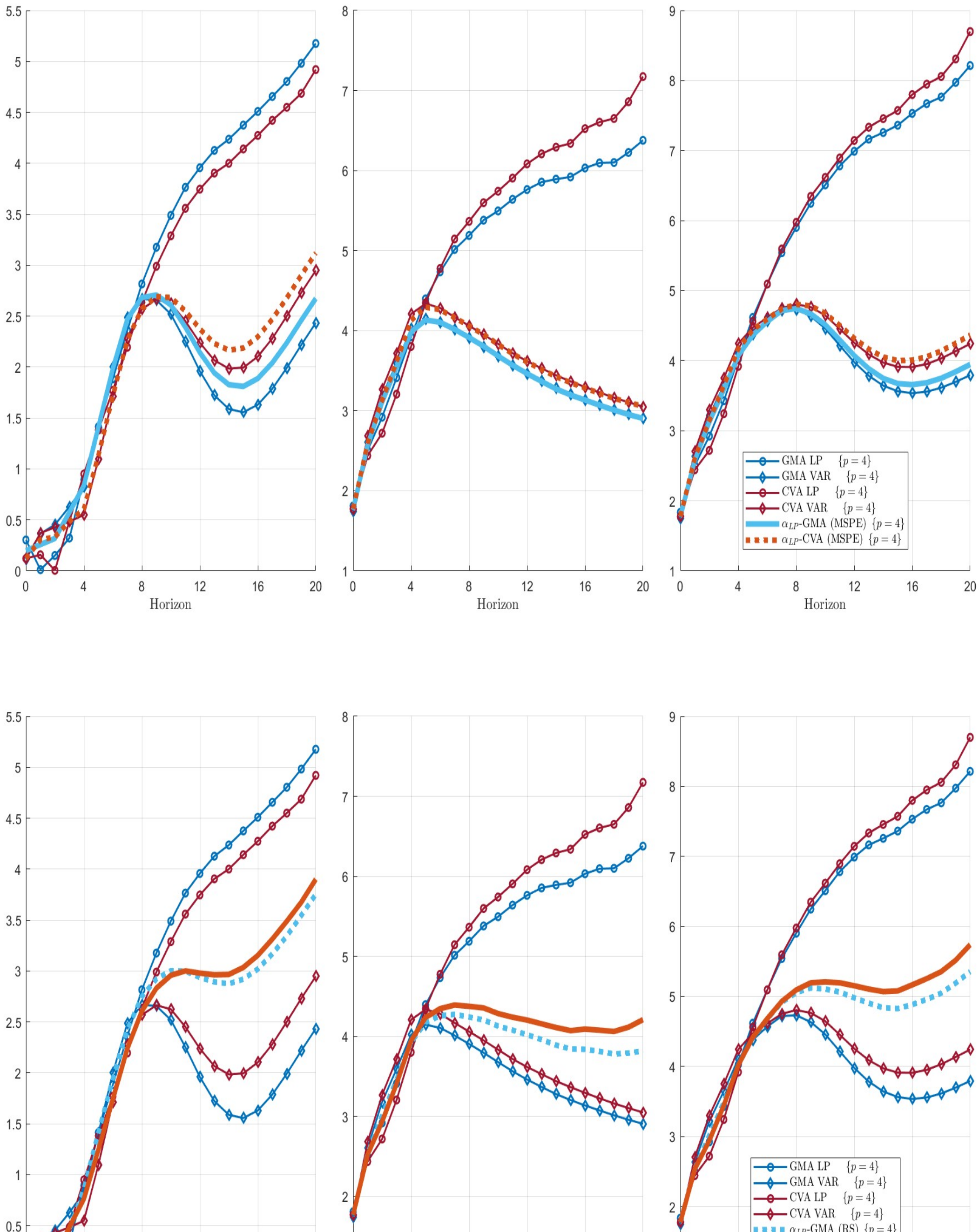
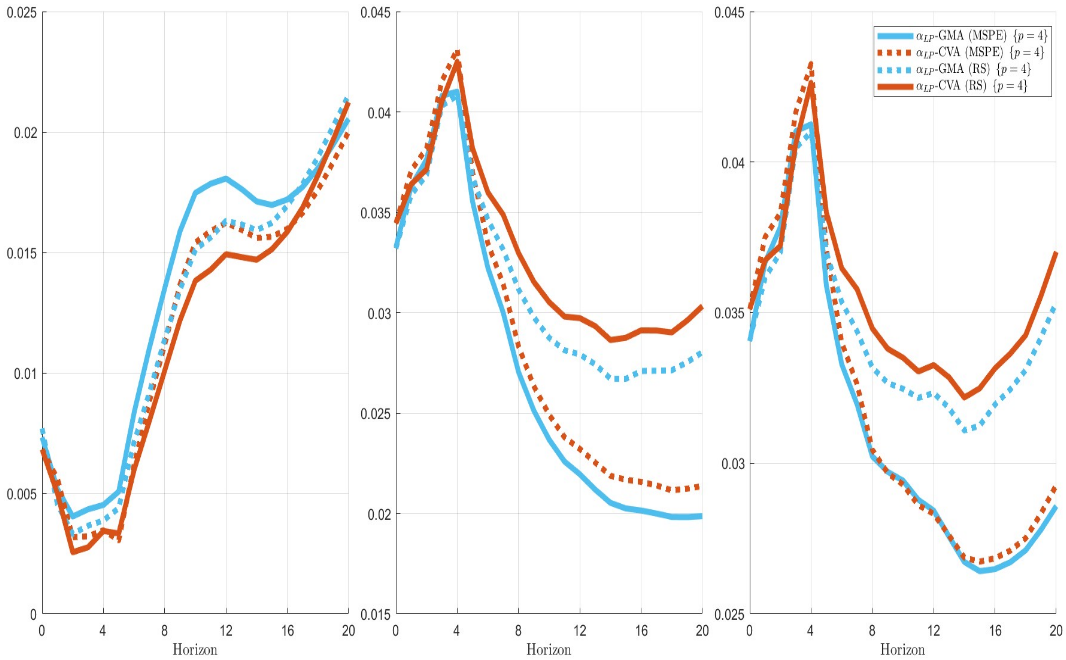


Figure D.9: Average absolute bias, standard deviation and MSE when a shock is proxied. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

IV: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



IV Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

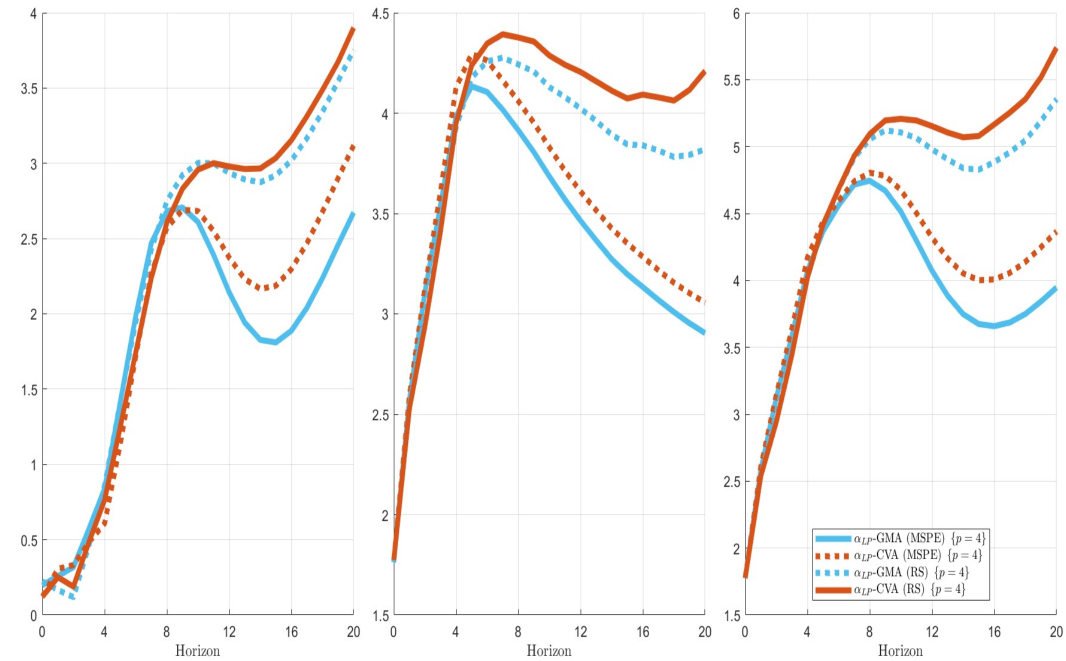


Figure D.10: Average absolute bias, standard deviation and MSE when a shock is proxied.

Appendix D.3 Recursive Identification Results

Figure D.11 illustrates the performance of seven LP-based or VAR-based estimators in terms of average absolute bias, standard deviation, and MSE when a shock is not observed and recursive identification is used. Regardless of the shock type, bias-corrected estimators (BC LP, BC VAR) tend to show relatively low bias, while Bayesian estimators (BLP, BVAR) exhibit relatively low variability. Unlike the main paper and Appendix D.2, we do not observe a clear bias-variance trade-off between LP- and VAR-based estimators.

Figure D.12 shows that a bias-variance trade-off between MAVG_{LP} and MAVG_{VAR} is not evident for fiscal shocks in the intermediate horizon, in contrast to the main and IV/Proxy identification results. However, when the shock is monetary, estimators in MAVG_{VAR} clearly outperforms in both bias and variability after $h = 9$, consistent with findings in the main paper and Appendix D.2.

Figures D.13 to D.16 compare the MAVG estimators to single estimators. When the shock is fiscal (Figures D.13 to D.14), single estimators may be suitable if researchers prioritize minimizing either bias or variance. However, no single estimator consistently outperforms across all horizons in both metrics. When the shock is monetary (Figures D.15 to D.16), MAVG estimators achieve lower average bias and standard deviation than selected single estimators in nearly all horizons. This suggests that MAVG estimators can more effectively lower researchers' loss, particularly at longer horizons.

Figures D.17 to D.18 compare the various MAVG estimators. When the shock is fiscal, both MAVG_{VAR} and α_{LP} estimators exhibit relatively lower bias. When the shock is monetary, α_{LP} estimators display lower bias after $h = 8$. In terms of variability, GMA_{VAR} and $\alpha_{\text{LP,MSPE}}$ estimators generally achieve lower standard deviations across both shock types.

Figure D.19 compares the four α_{LP} schemes that incorporate both LP- and VAR-based estimators. Estimators that combine model fit and prediction accuracy in their weighting schemes tend to outperform the others or at least compete closely in each evaluation, which is consistent with the main results.

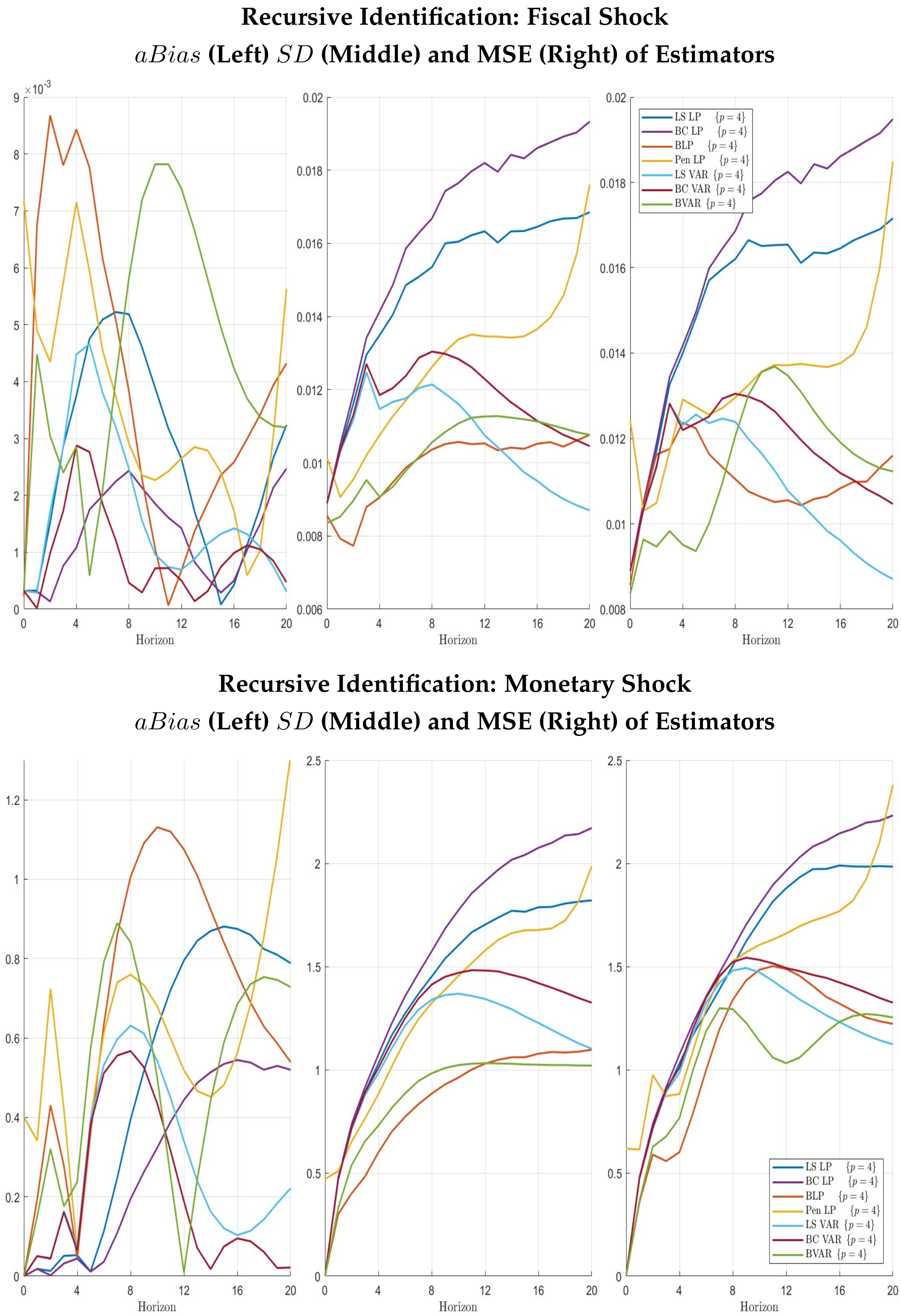
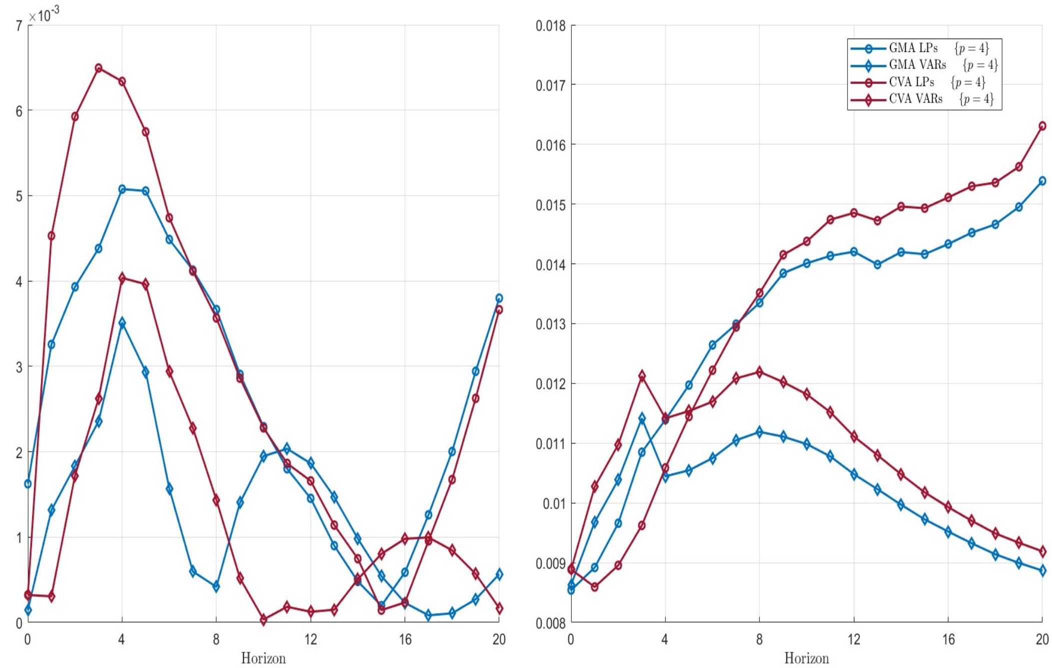


Figure D.11: Average absolute bias, standard deviation and MSE when a shock is not observed.

Recursive Identification: Fiscal Shock

$aBias$ (Left) and SD (Right) of Estimators



Recursive Identification: Monetary Shock

$aBias$ (Left) and SD (Right) of Estimators

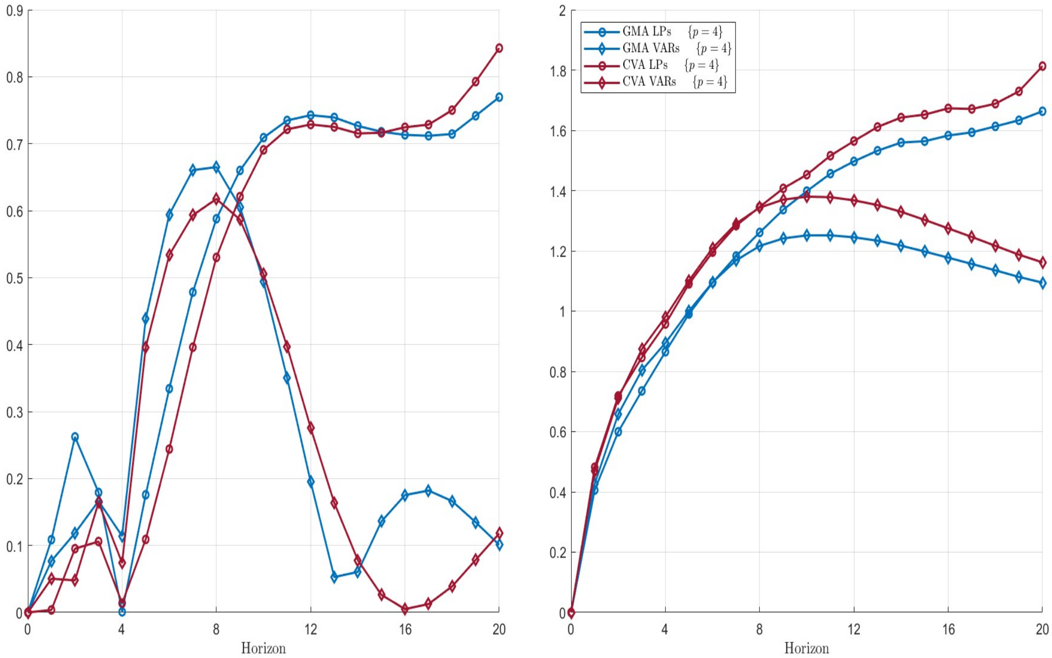


Figure D.12: Average absolute bias and standard deviation when a shock is not observed.

Recursive Identification: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

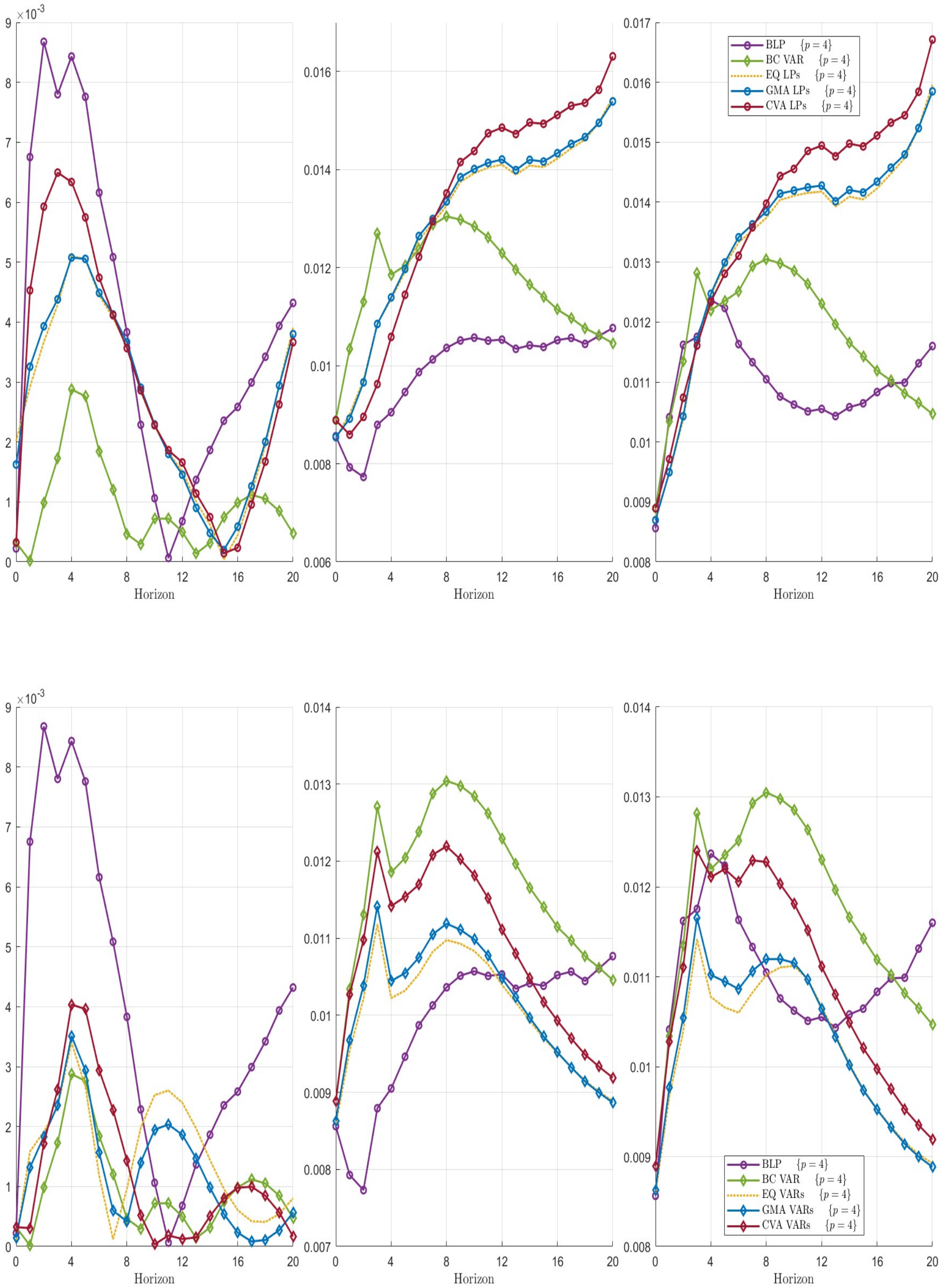


Figure D.13: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{LP} group with BLP and BC VAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Recursive Identification: Fiscal Shock
$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

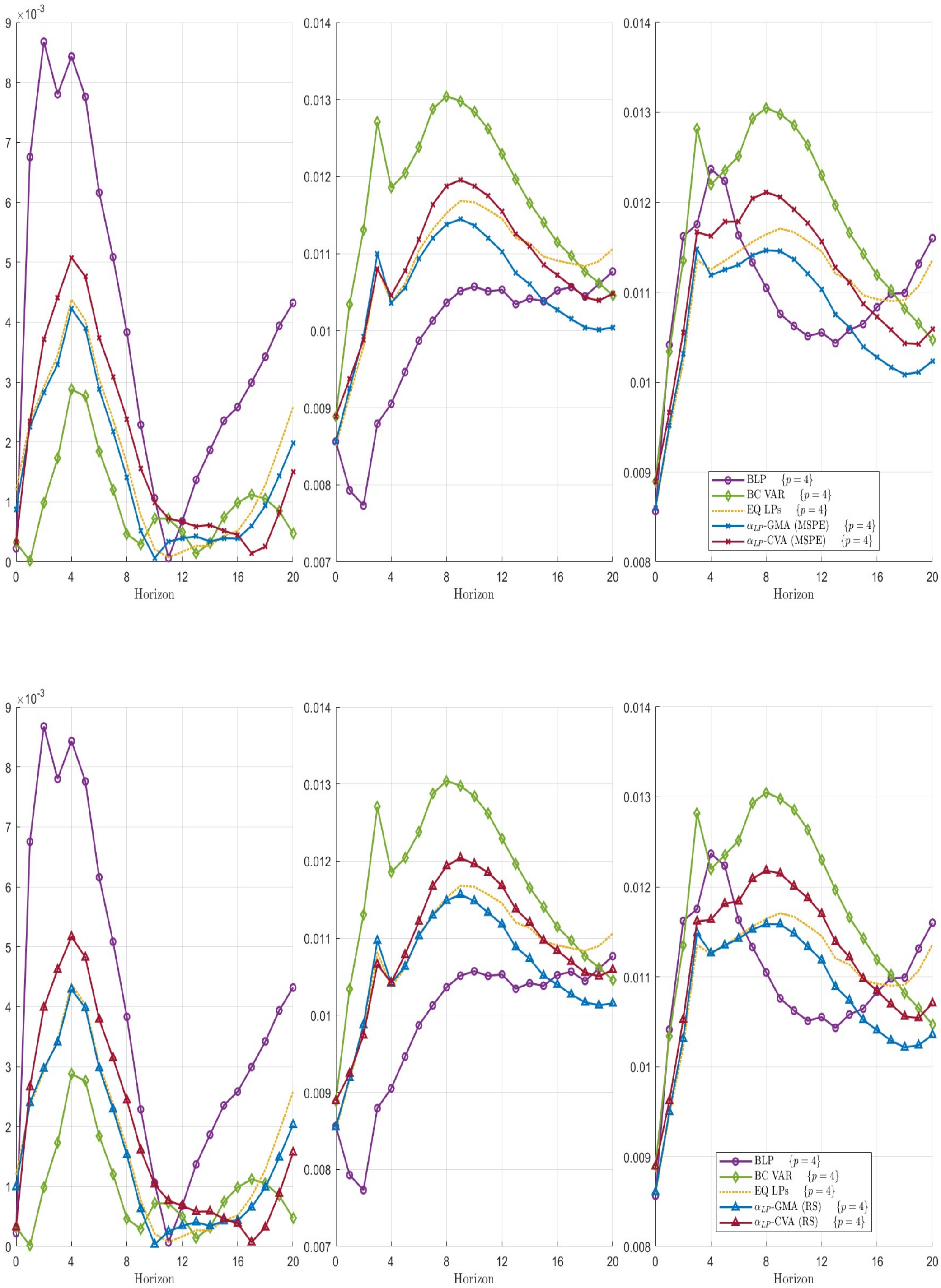


Figure D.14: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BLP and BC VAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Recursive Identification: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

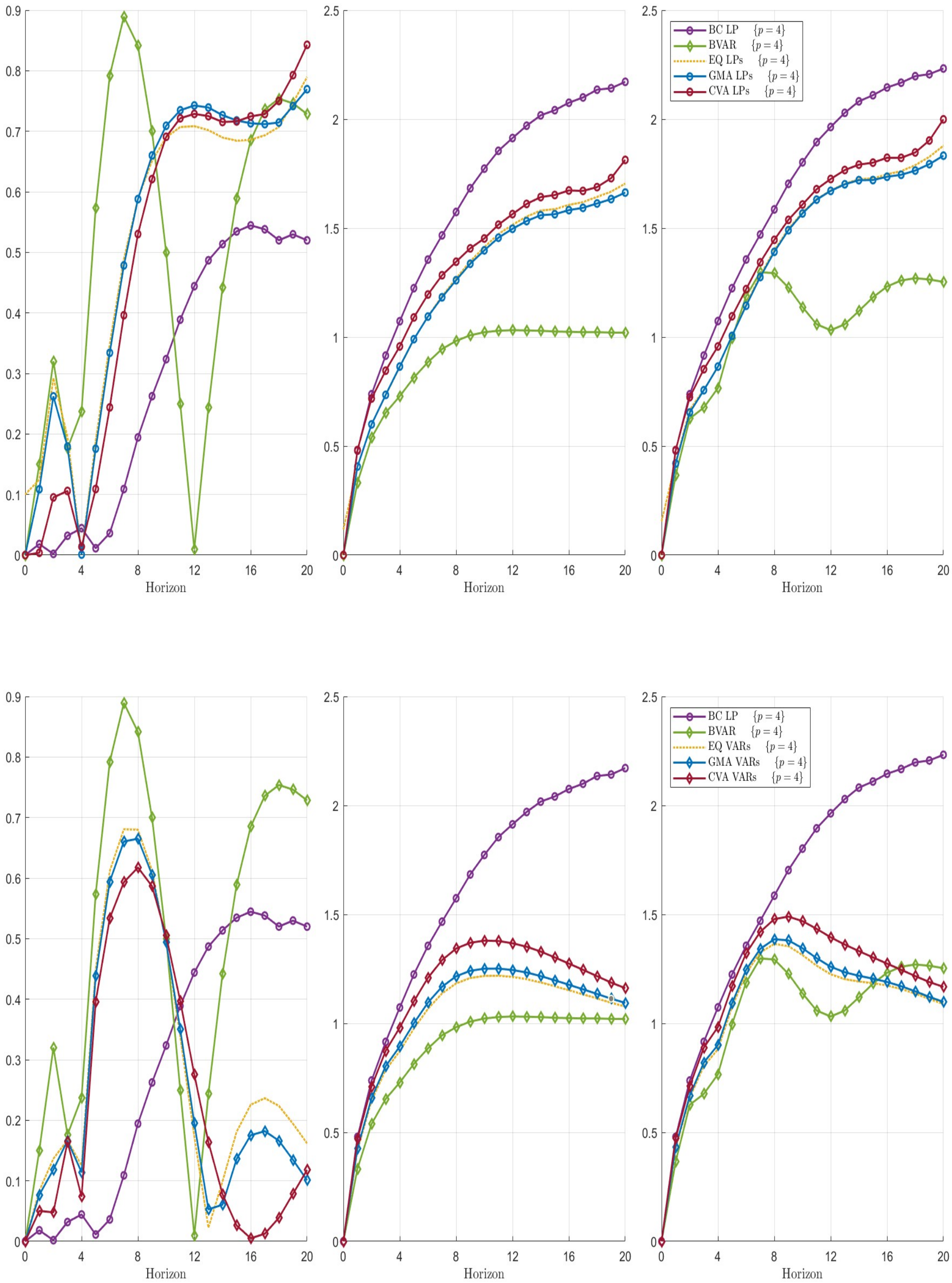


Figure D.15: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Recursive Identification: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

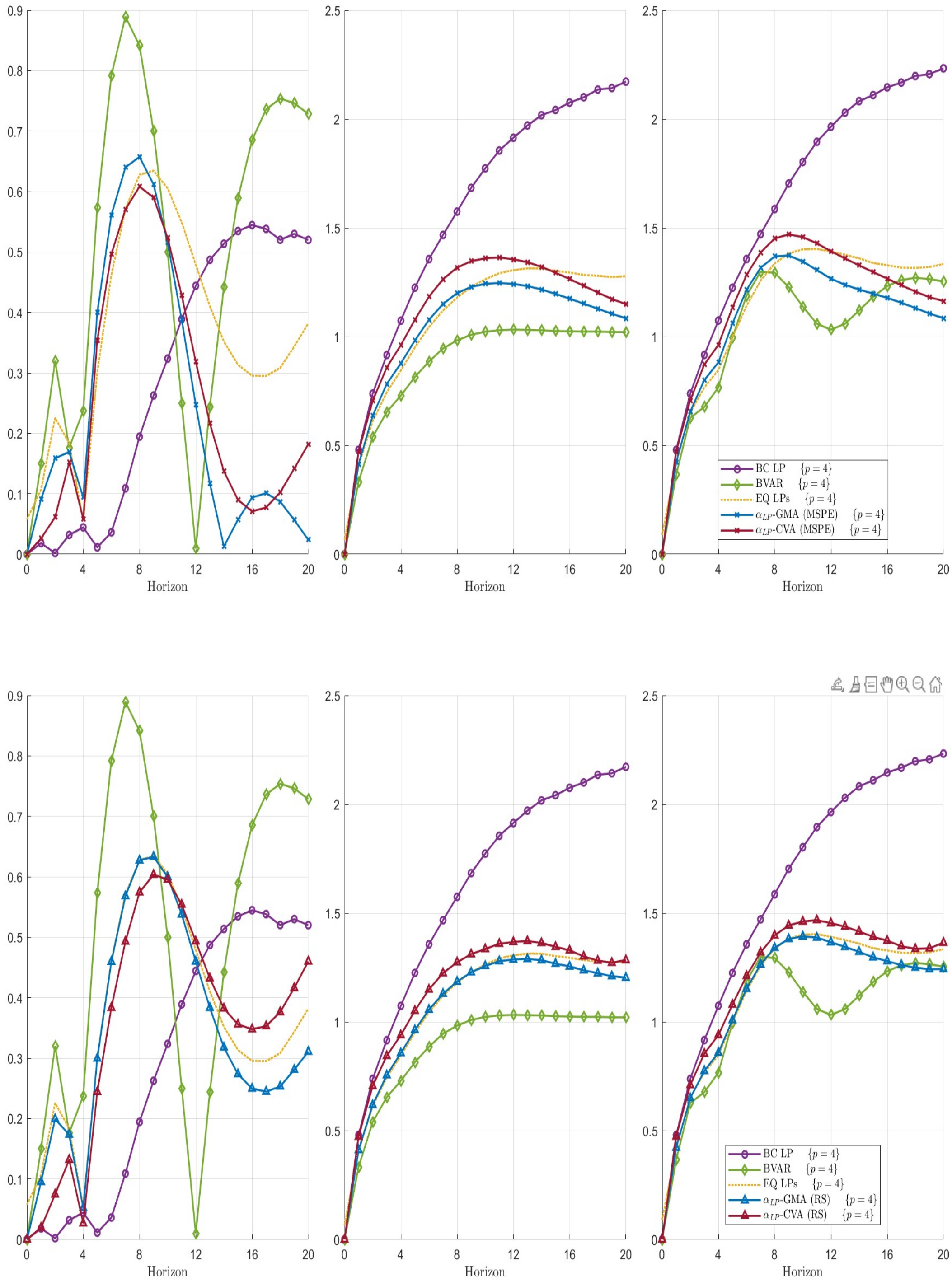


Figure D.16: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Recursive Identification: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

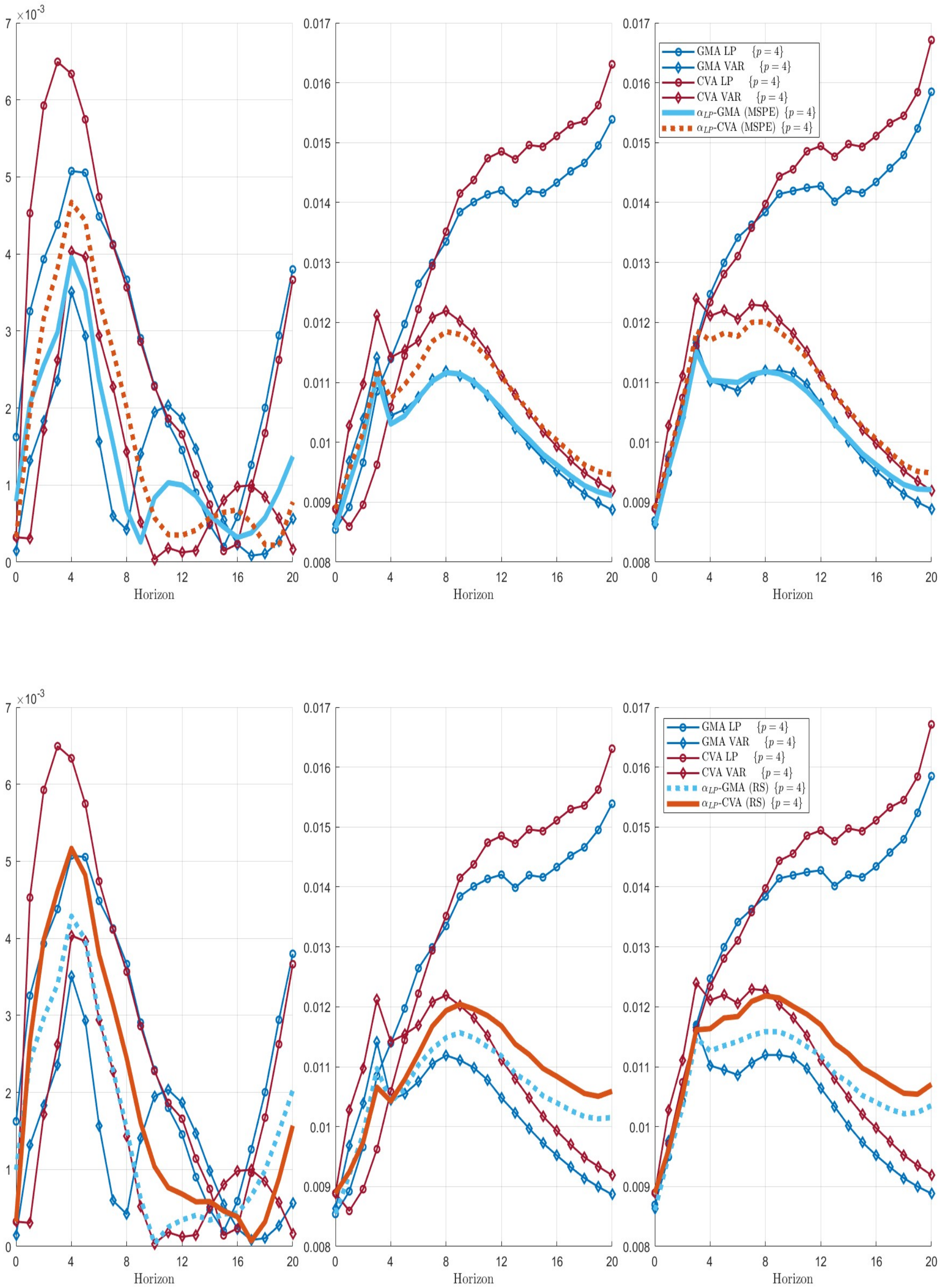


Figure D.17: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Recursive Identification: Monetray Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

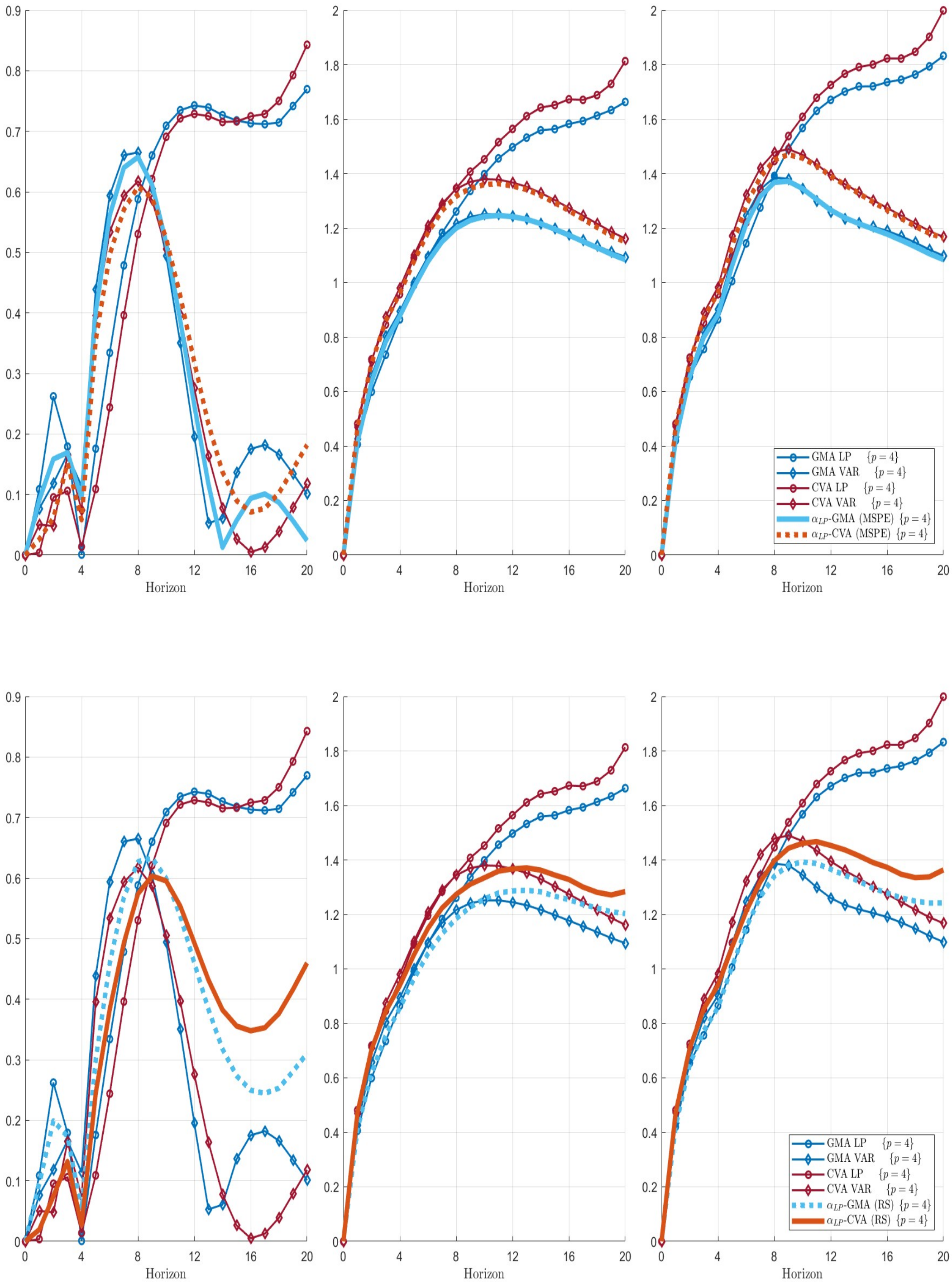
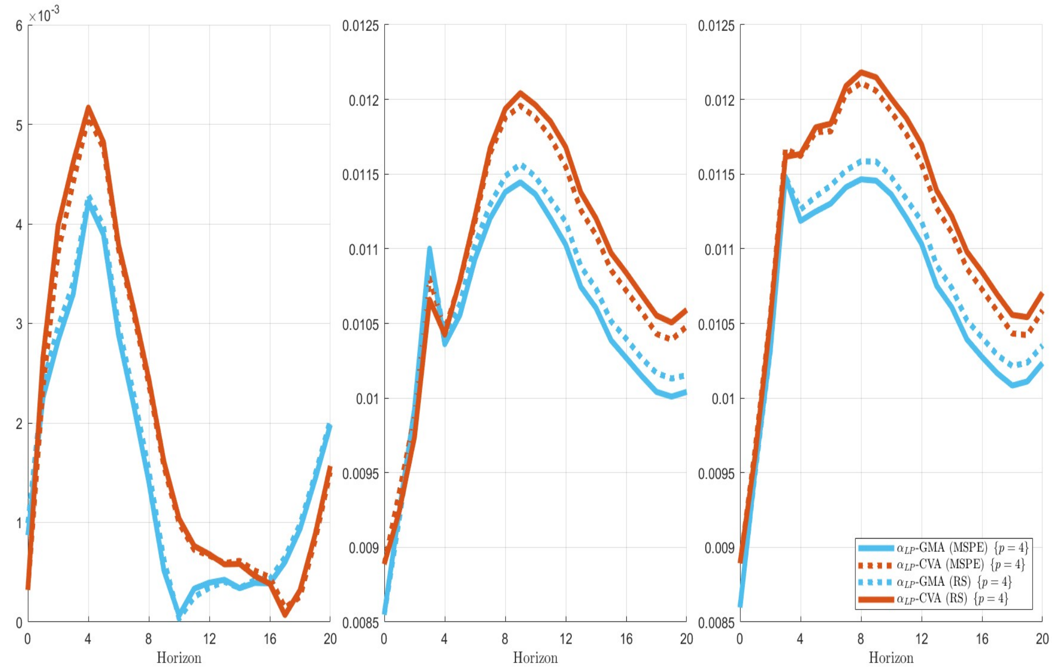


Figure D.18: Average absolute bias, standard deviation and MSE when a shock is not observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Recursive Identification: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators



Recursive Identification: Monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

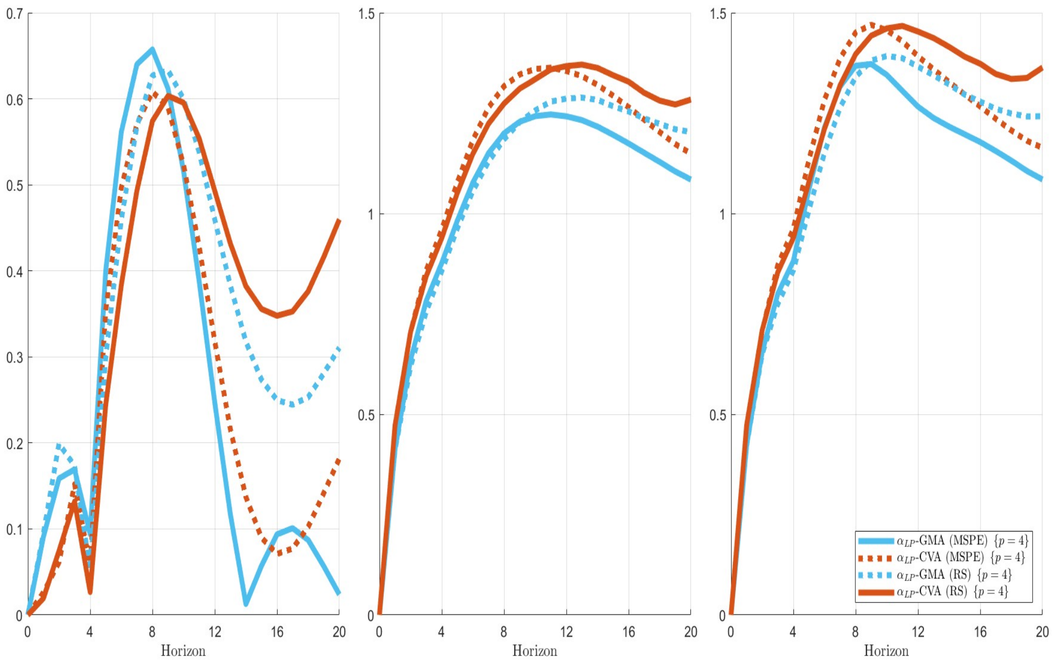


Figure D.19: Average absolute bias, standard deviation and MSE when a shock is not observed.

Appendix E Simulation Results with Stationary DGPs

Figure E.1 illustrates the performance of seven LP- or VAR-based estimators in terms of average absolute bias, standard deviation, and MSE when the shock is observed in stationary data. We employ trimmed IRFs by winsorizing each row to the 1st and 99th percentiles, replacing extreme values with the corresponding cutoff thresholds.

We do not observe a clear bias-variance trade-off between LP and VAR estimators. However, LS LP and BC LP display stable and relatively low bias, alongside high variability across horizons, regardless of the shock type. Meanwhile, shrinkage and Bayesian estimators reduce variability within each group (e.g., MAVG_{LP} and MAVG_{VAR}), but their bias fluctuates substantially across horizons, which is consistent with the results in the main text and other robustness exercises.

Figure E.2 further confirms that the typical bias-variance trade-off between MAVG_{LP} and MAVG_{VAR} is not evident in this setting. When the shock is fiscal and $h \geq 4$, MAVG_{LP} estimators exhibit higher bias than their MAVG_{VAR} counterparts, contrary to expectations. However, MAVG_{VAR} consistently outperforms in terms of standard deviation after $h = 4$, regardless of the shock type.

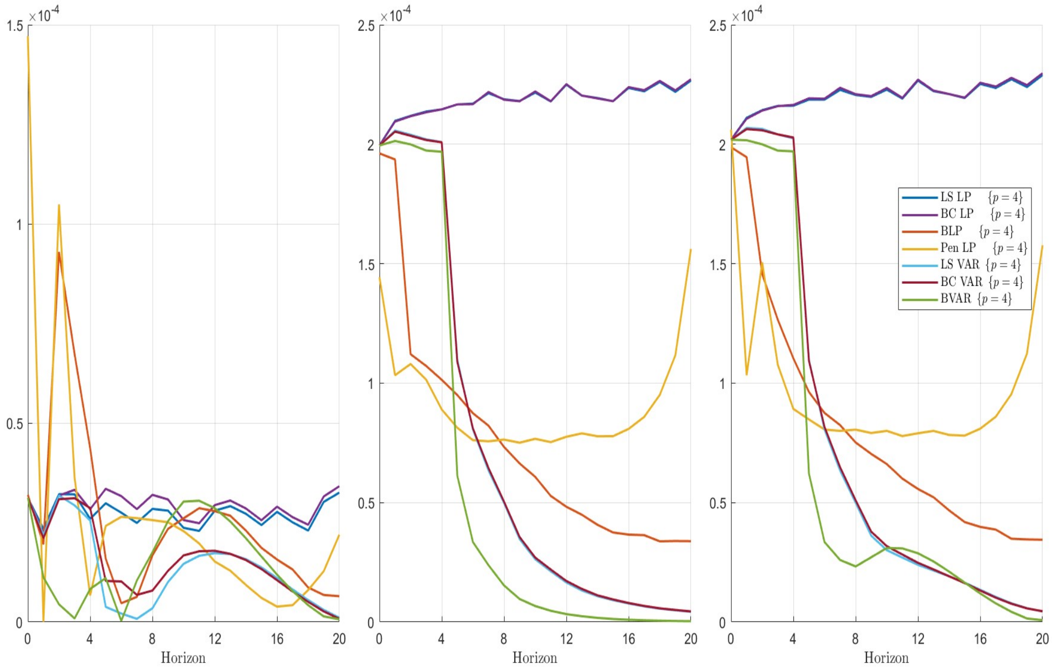
Figures E.3 to E.6 compare MAVG estimators with selected single estimators. When the shock is fiscal (Figures E.3 to E.4), MAVG_{VAR} estimators show lower bias than LS LP and BVAR and exhibit more stable bias trends than BVAR for $h \geq 7$. When the shock is monetary (Figures E.5 to E.6), MAVG_{LP} and α_{LP} estimators achieve lower bias than BC LP in the long horizon ($h \geq 10$). Across both shock types, BVAR consistently demonstrates the lowest variability across all horizons. These results suggest that MAVG estimators can effectively lower loss function values for researchers, when both bias and variance are considered.

Figures E.7 to E.8 compare the MAVG estimators. When the shock is fiscal, MAVG_{VAR} estimators generally outperform all α_{LP} schemes in terms of both bias and variability. When the shock is monetary, α_{LP} estimators exhibit lower bias for $h \geq 12$, while GMA_{VAR} achieves the lowest variability. However, α_{LP} estimators often produce smoother trajectories, offering a more balanced trade-off between bias and variance than MAVG_{VAR}.

Figure E.9 compares four α_{LP} schemes that incorporate both LP and VAR variants. When the shock is fiscal, $\alpha_{\text{LP,RS}}$-GMA, which emphasizes model fit, tends to outperform in both bias and variance. In contrast, when the shock is monetary, the advantages of considering both model fit and prediction accuracy—as highlighted in the main results—appear to be less pronounced.

Observed Identification, Stationary DGPs: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

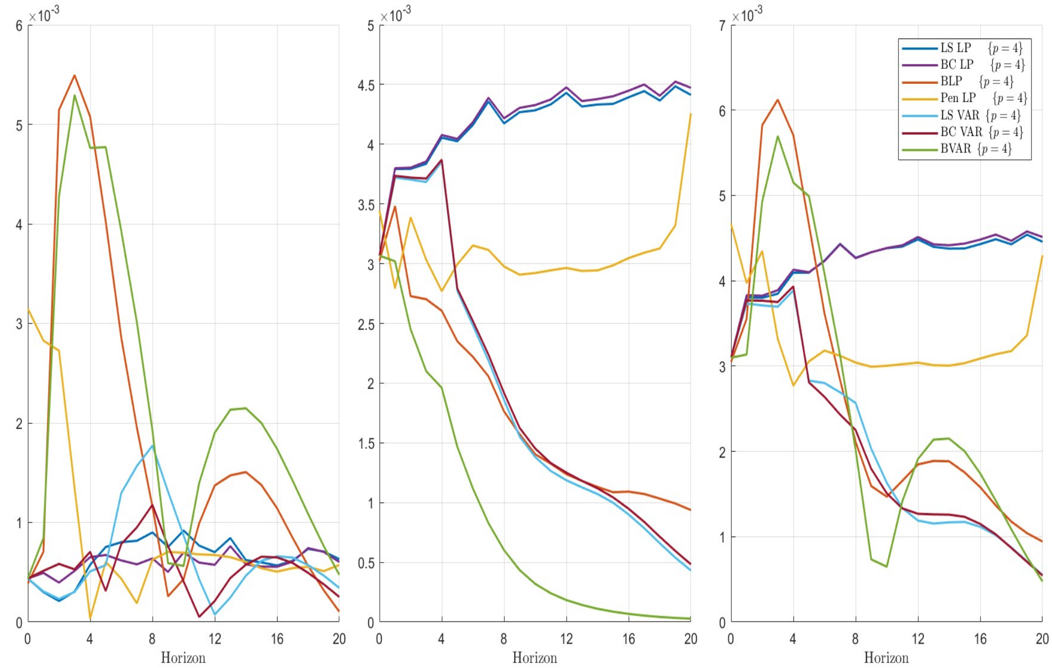
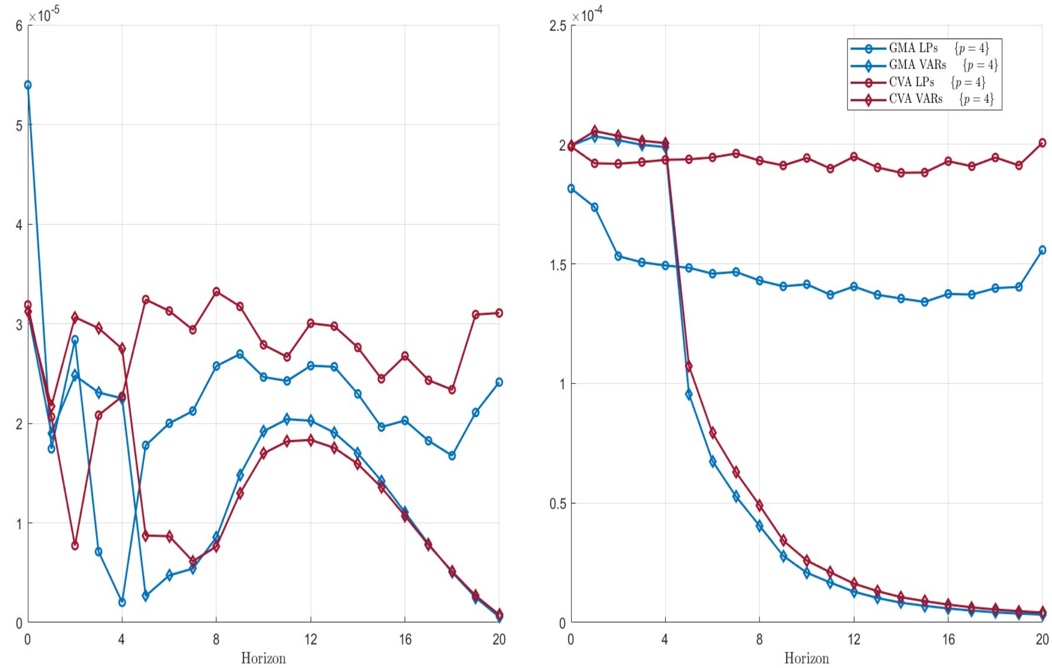


Figure E.1: Average absolute bias and standard deviation when a shock is observed.

Observed Identification, Stationary DGPs: Fiscal Shock

$aBias$ **(Left) and** SD **(Right) of Estimators**



Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left) and** SD **(Right) of Estimators**

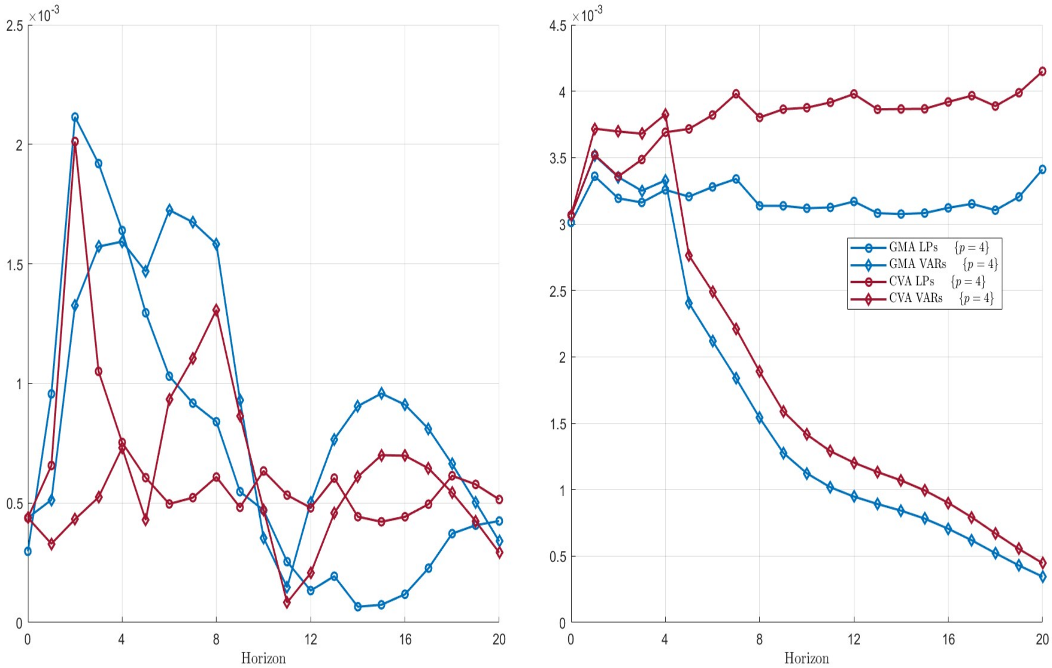
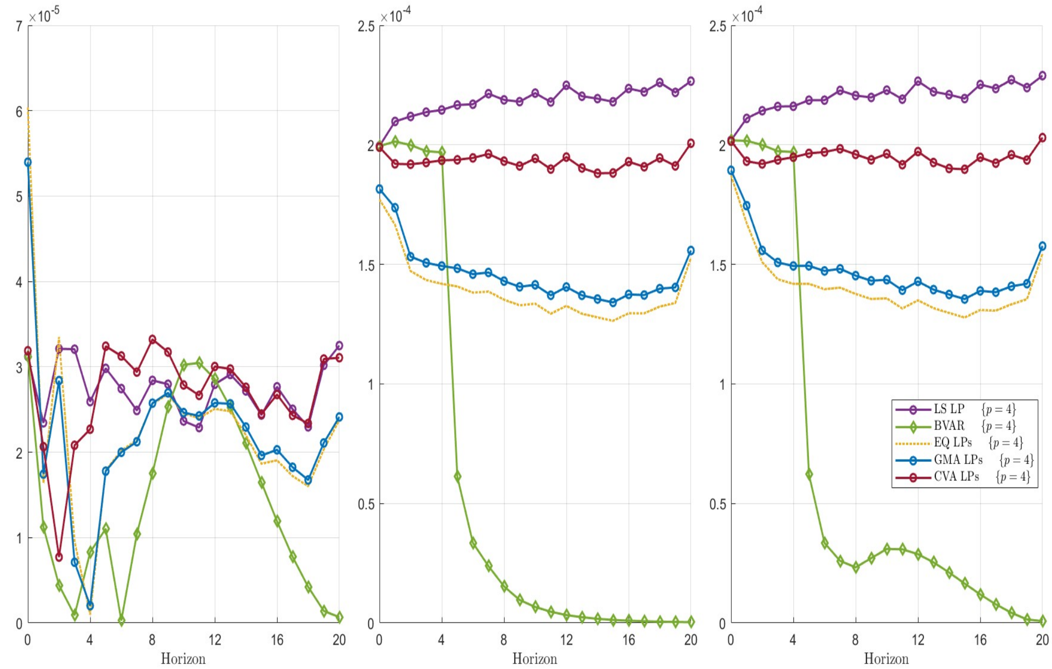


Figure E.2: Average absolute bias and standard deviation when a shock is observed.

Observed Identification, Stationary DGPs: Fiscal Shock
$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



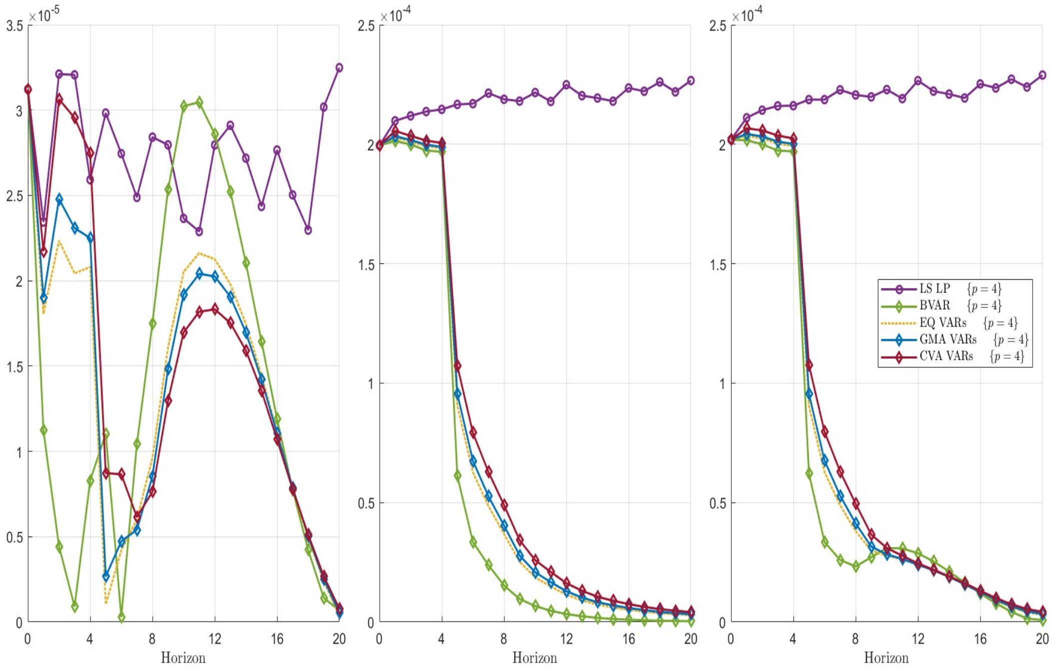


Figure E.3: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with LS LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, Stationary DGPs: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

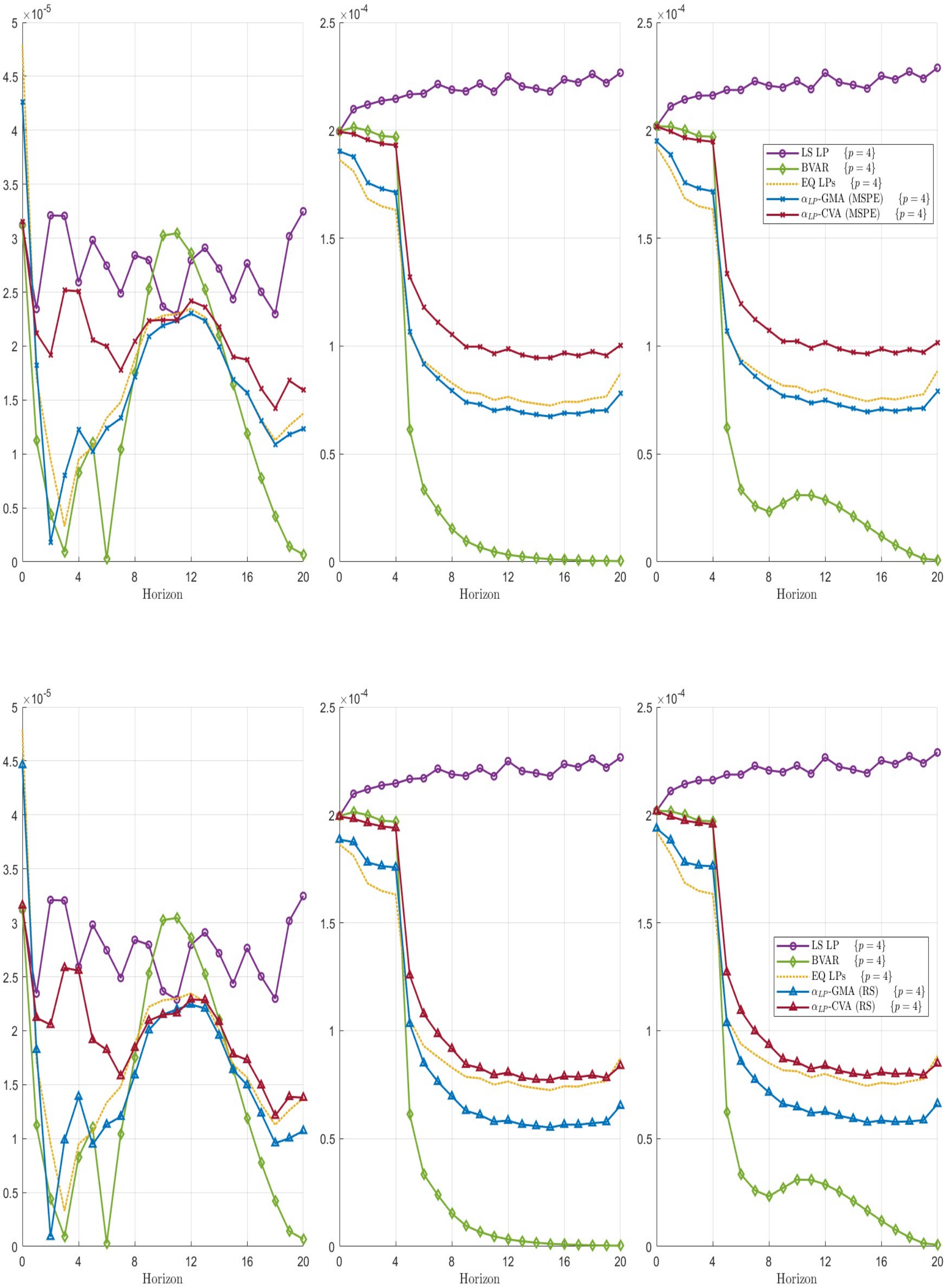
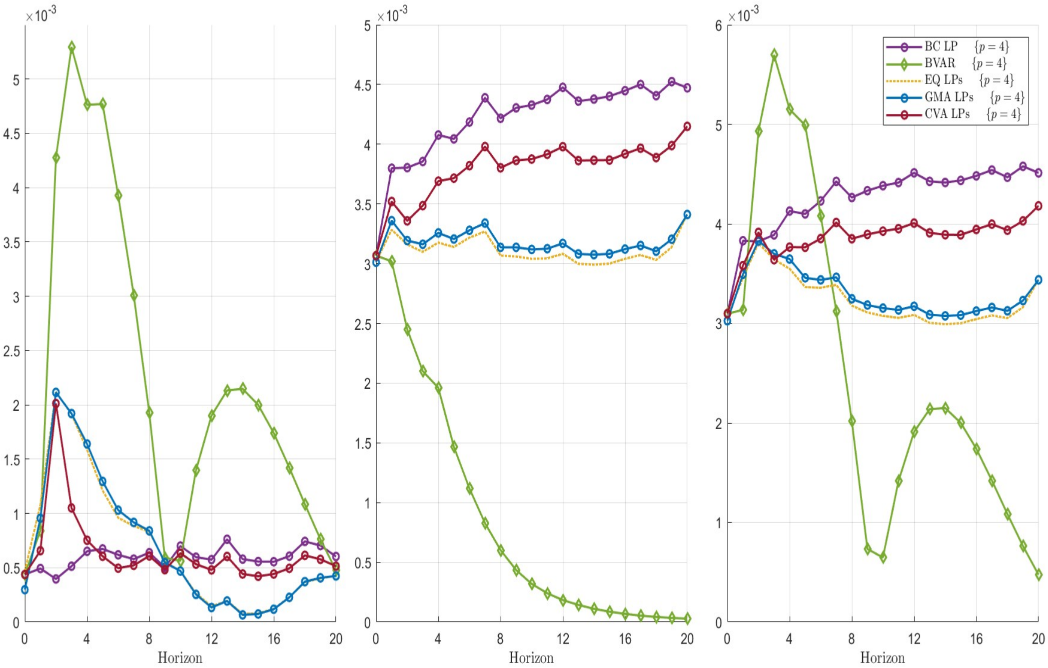


Figure E.4: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with LS LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



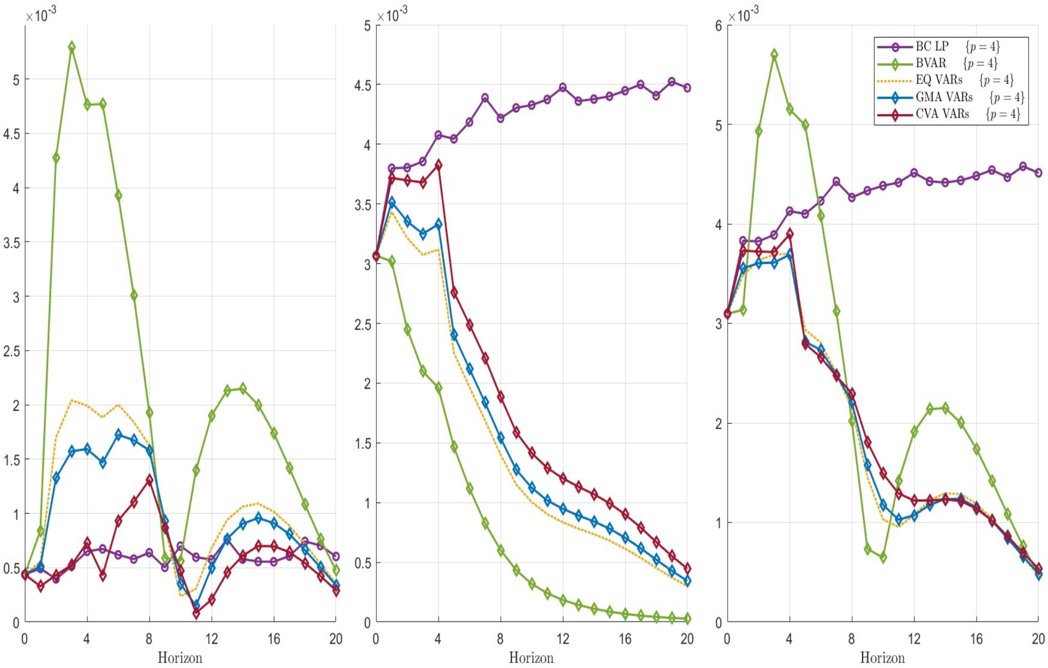


Figure E.5: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

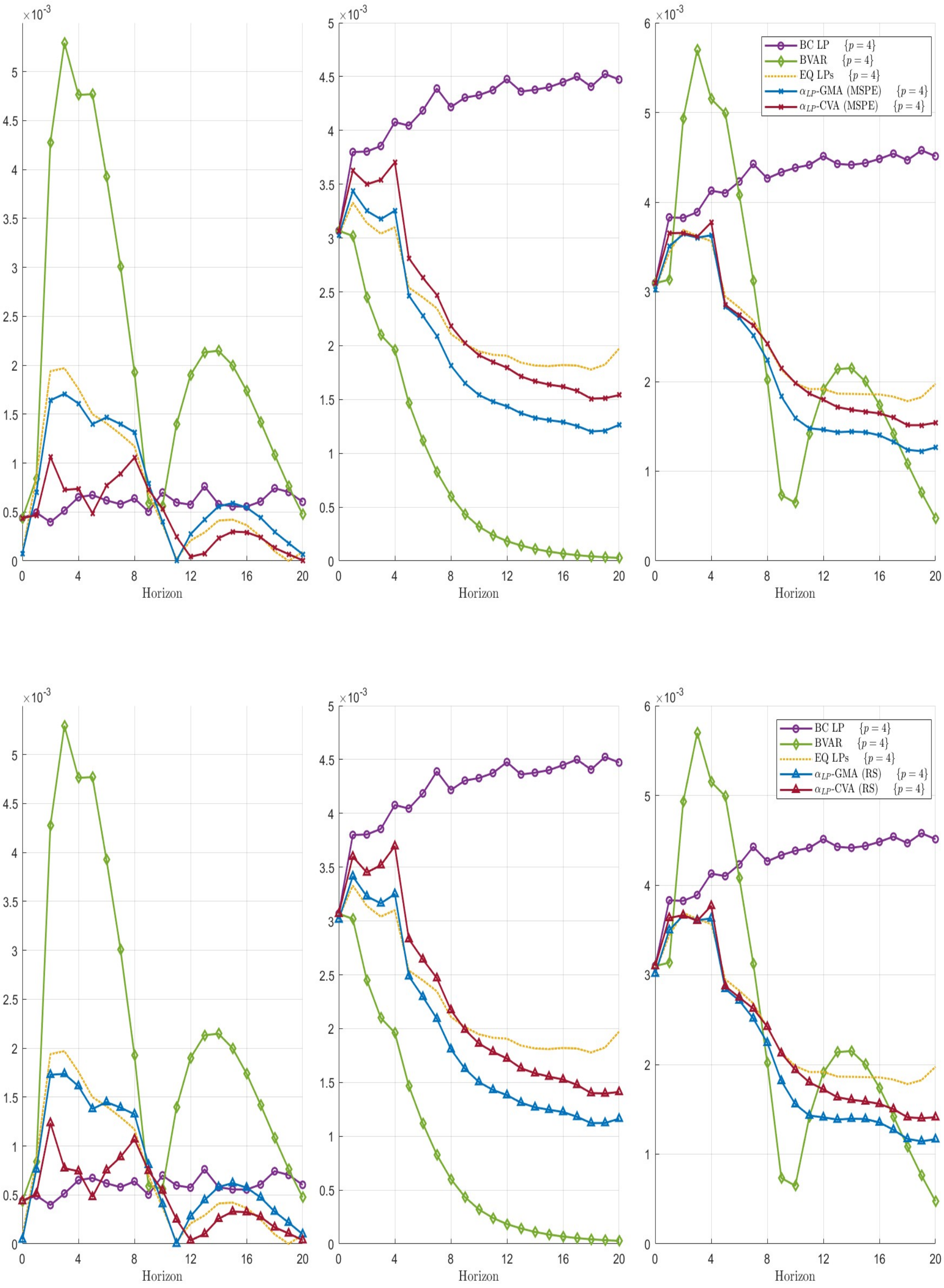


Figure E.6: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, Stationary DGPs: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

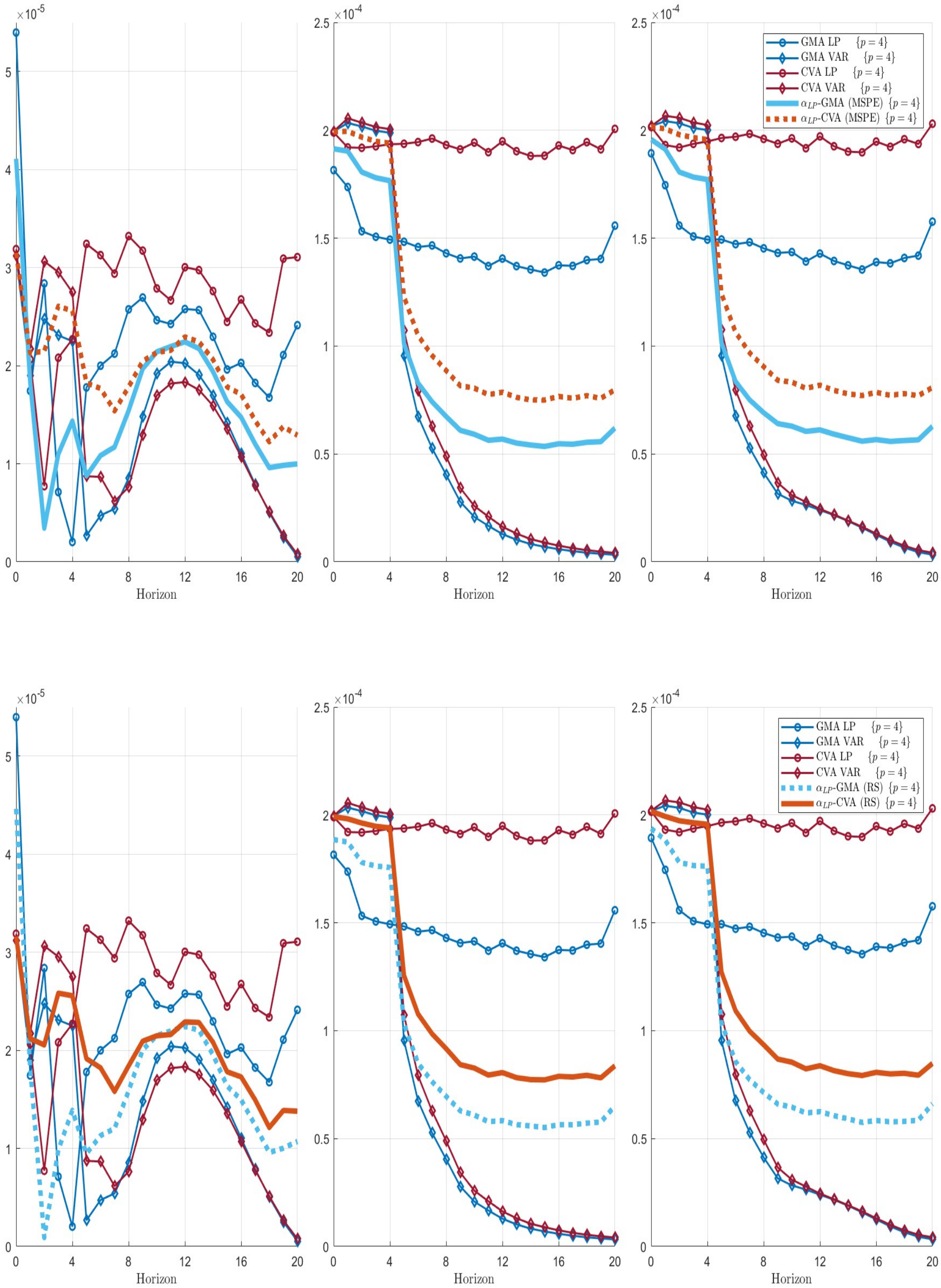


Figure E.7: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

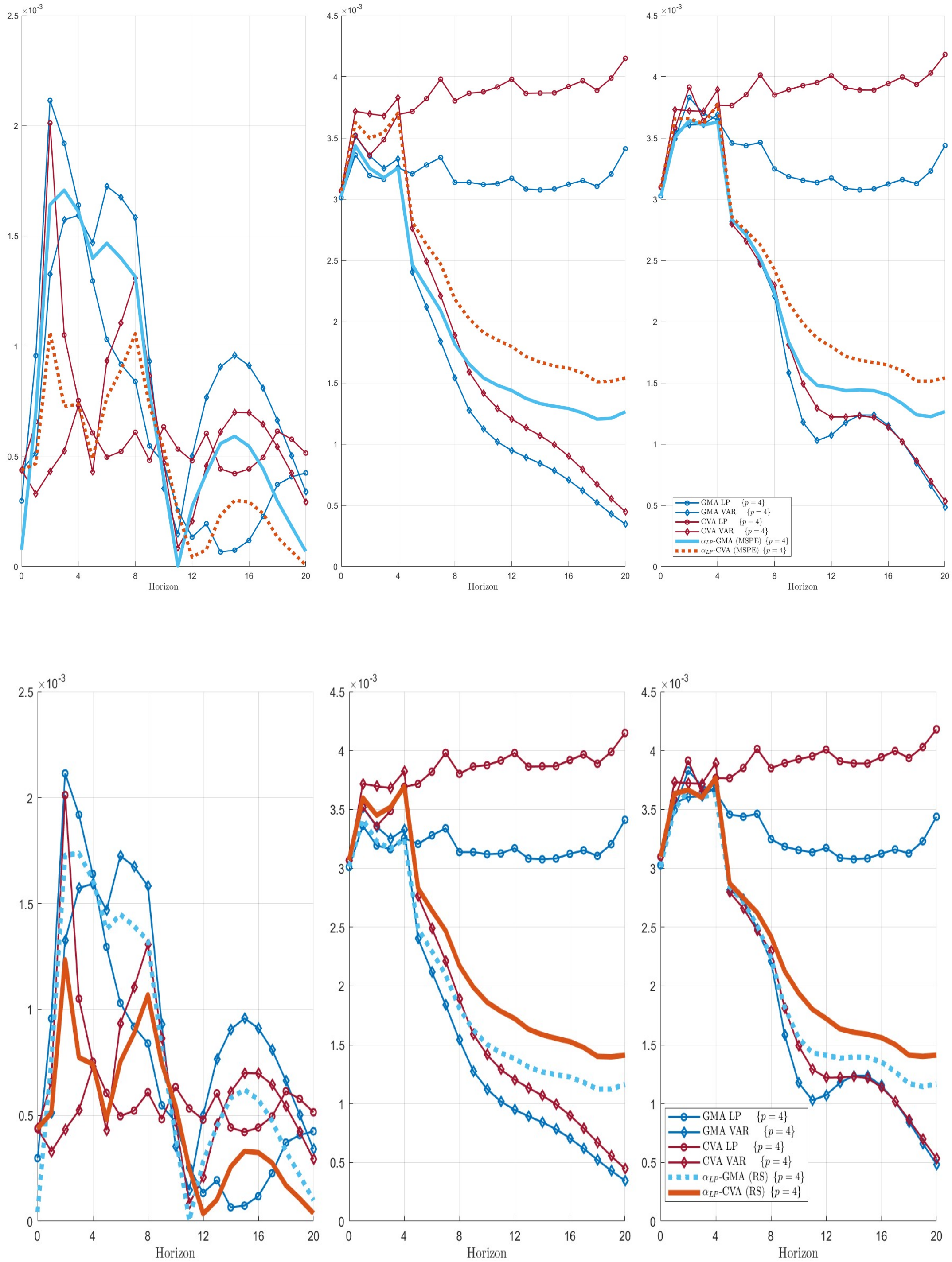
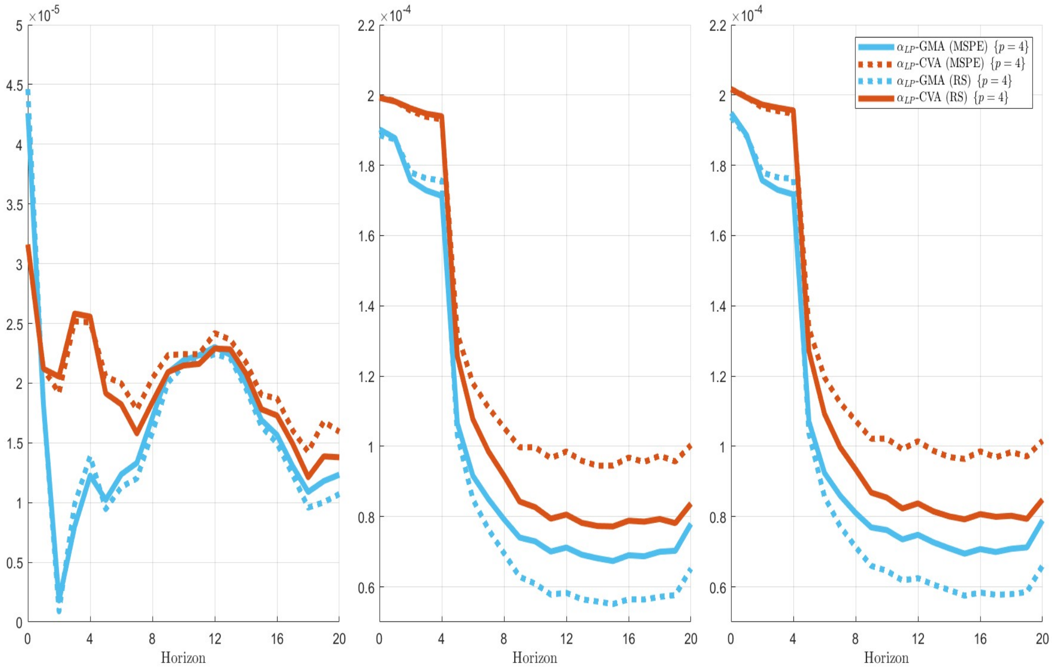


Figure E.8: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, Stationary DGPs: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



Observed Identification, Stationary DGPs: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

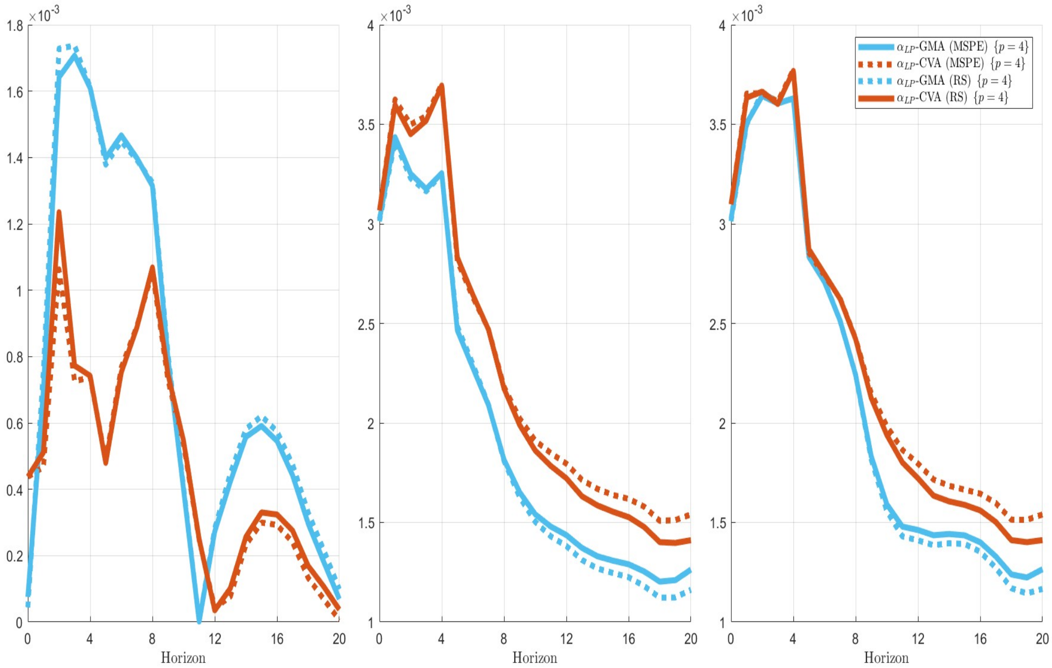


Figure E.9: Average absolute bias, standard deviation and MSE when a shock is observed.

Appendix F Further Monte Carlo Simulation Results and Robustness

Appendix F.1 Shorter estimation lag length

Figure F.1 illustrates the performance of seven LP-variant and VAR-variant estimators in terms of bias, standard deviation, and MSE when the shock is observed and a shorter lag length of 2 is used for estimation (compared to the lag length of 4 used in the main analysis). Regardless of the shock type, LP-variant estimators exhibit slightly improved bias, while VAR-variant estimators show worsened bias. In contrast, the variance of both LP- and VAR-variants is slightly improved under the shorter lag setting relative to the main results.

In Figure F.2, we observe a clear bias-variance trade-off between MAVG_{LP} and MAVG_{VAR}, particularly in intermediate horizons. This pattern is consistent with the results obtained with a lag length of 4. When the shock is fiscal, the two estimators in the MAVG_{LP} group display lower bias but higher variability than the two estimators in the MAVG_{VAR} group for all horizons beyond $h = 4$. When the shock is monetary, the MAVG_{LP} group maintains a bias advantage up to $h = 12$, after which the ranking reverses; by contrast, the MAVG_{VAR} group exhibits consistently lower variability from $h = 4$ onward.

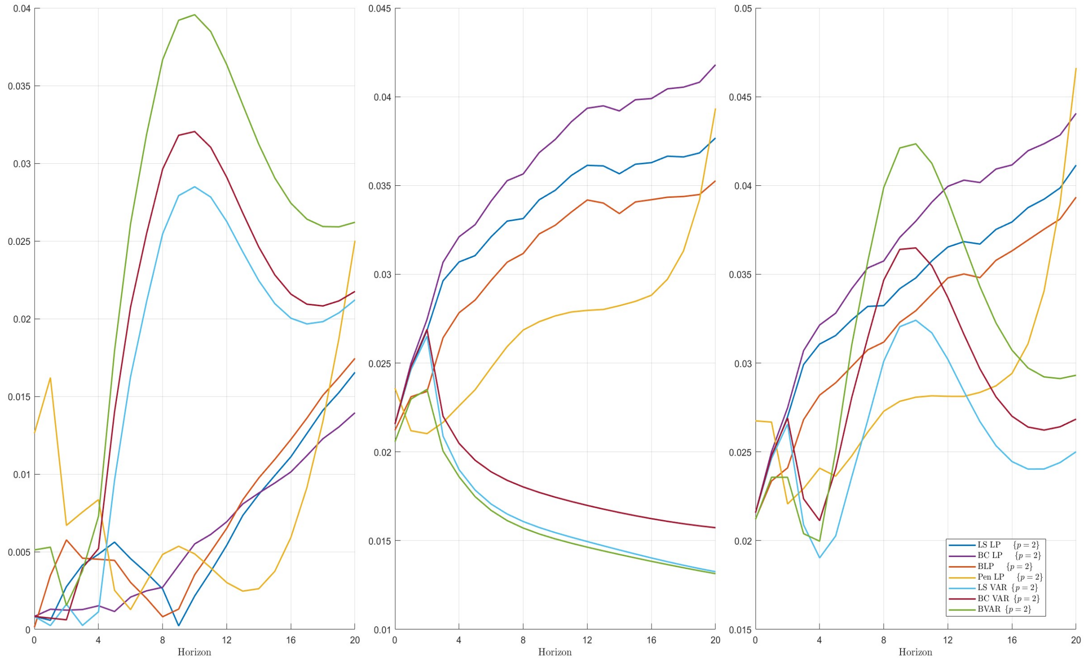
Figures F.3 to F.6 compare the MAVG estimators with selected single estimators. The MAVG_{LP} group clearly outperforms BVAR in terms of bias, whereas the MAVG_{VAR} group clearly outperforms BC LP in terms of variance for both types of shock. This pattern is especially evident at intermediate horizons under monetary shocks. These findings indicate that the α_{LP} estimators effectively reduce the MSE, consistent with the main results even when the lag length is reduced.

Figures F.7 to F.8 compare the model-averaging estimators that incorporate α_{LP}. Because these estimators display lower bias than the MAVG_{VAR} group and lower variance than the MAVG_{LP} group, they more effectively minimize the researcher's loss function when both types of error are considered. This advantage is most pronounced under fiscal shocks in our simulation settings.

Figure F.9 compares the four α_{LP} schemes that combine LP- and VAR-based estimators. The results are consistent with those obtained using a lag length of 4. Schemes that consider both model fit and predictive accuracy—specifically $\alpha_{\text{LP,MSPE}}$-GMA and $\alpha_{\text{LP,RS}}$-CVA—tend to outperform the alternatives in at least one evaluation metric for both shock types.

Observed Identification, 2 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



Observed Identification, 2 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

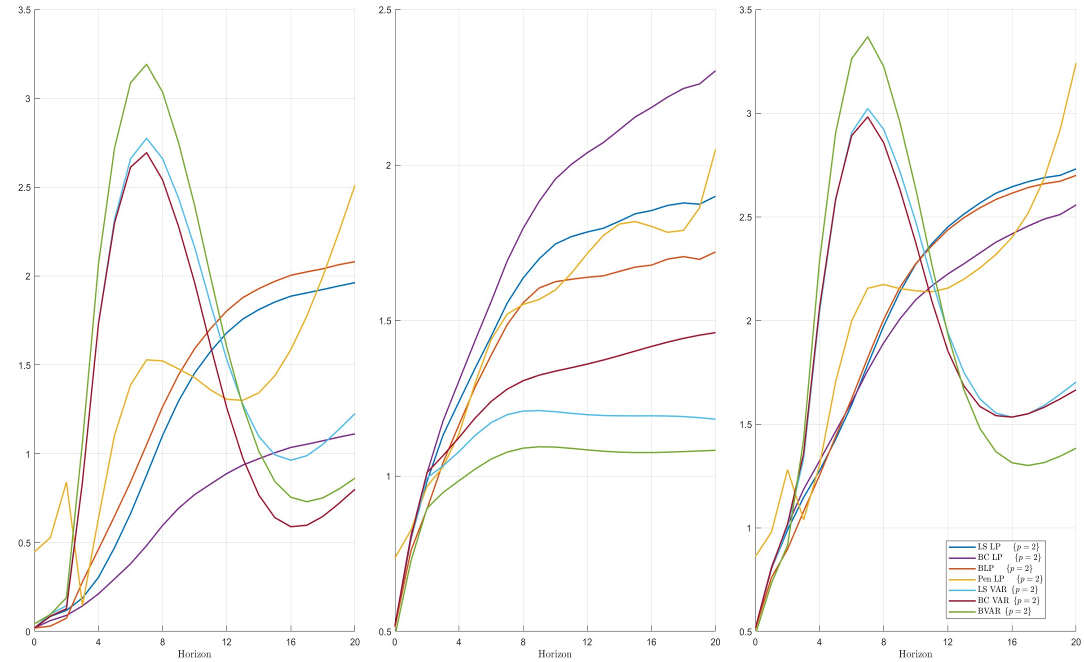
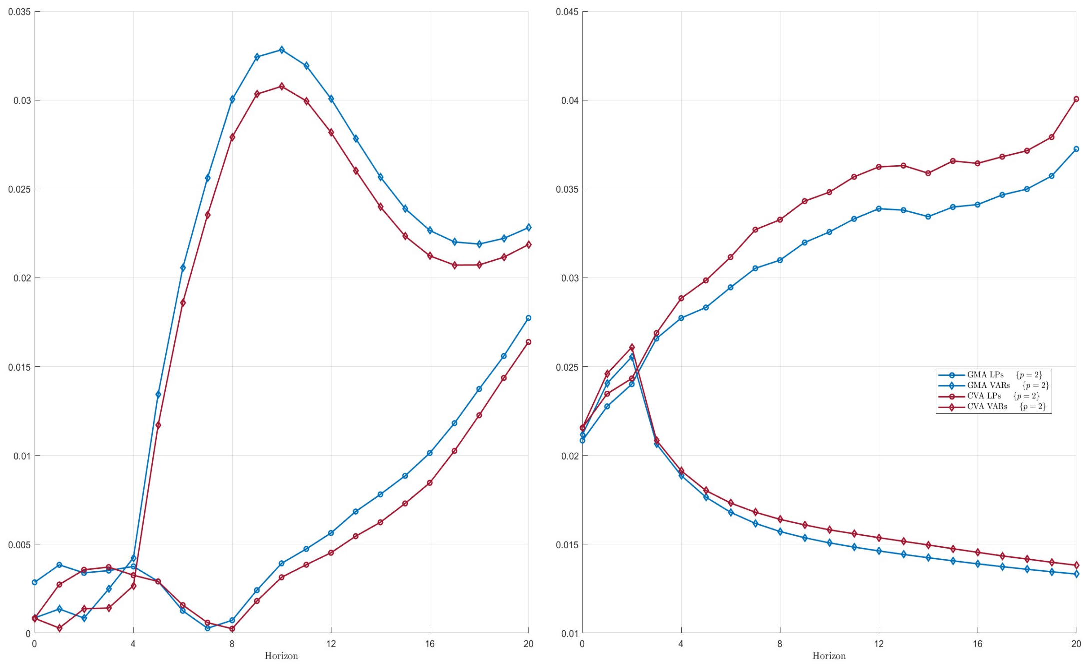


Figure F.1: Average absolute bias, standard deviation and MSE when a shock is observed.

Observed Identification, 2 lags: Fiscal Shock
$aBias$ (Left) and SD (Right) of Estimators



Observed Identification, 2 lags: Monetary Shock
$aBias$ (Left) and SD (Right) of Estimators

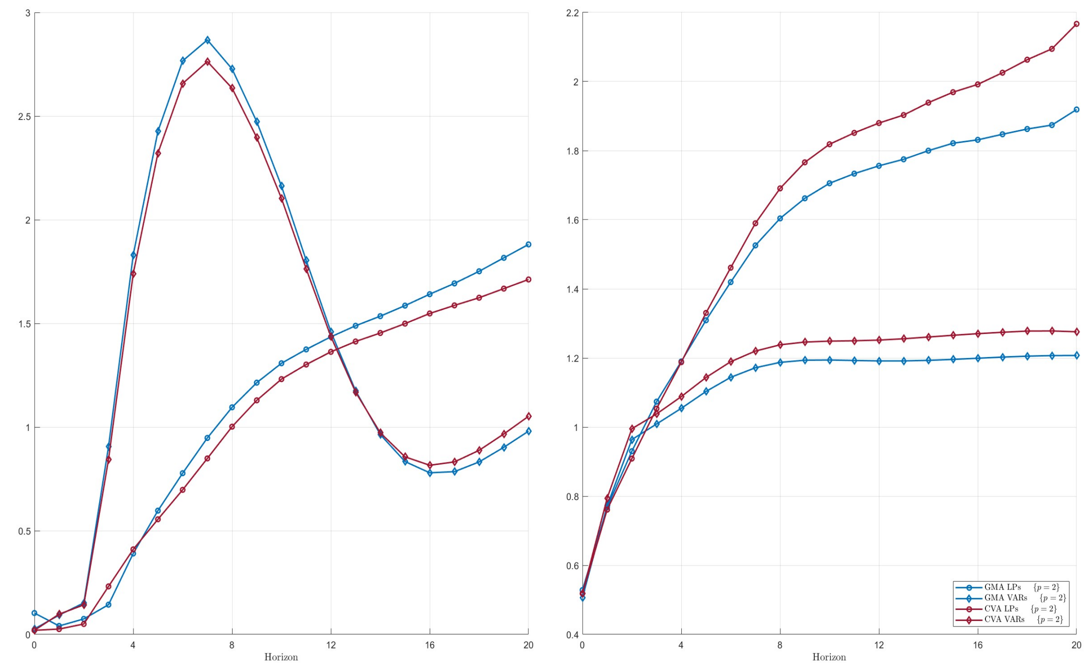


Figure F.2: Average absolute bias and standard deviation when a shock is observed.

Observed Identification, 2 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

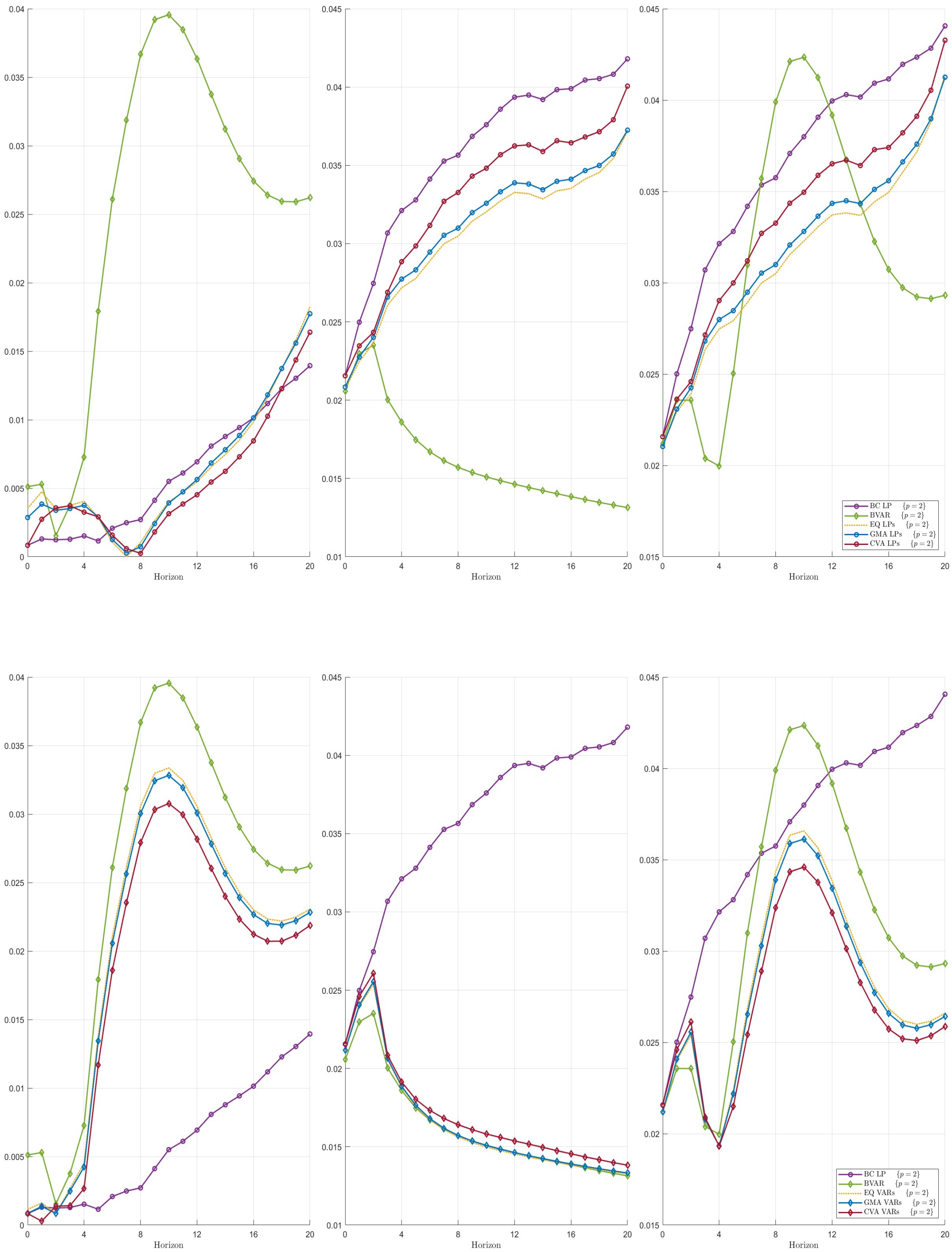


Figure F.3: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, 2 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

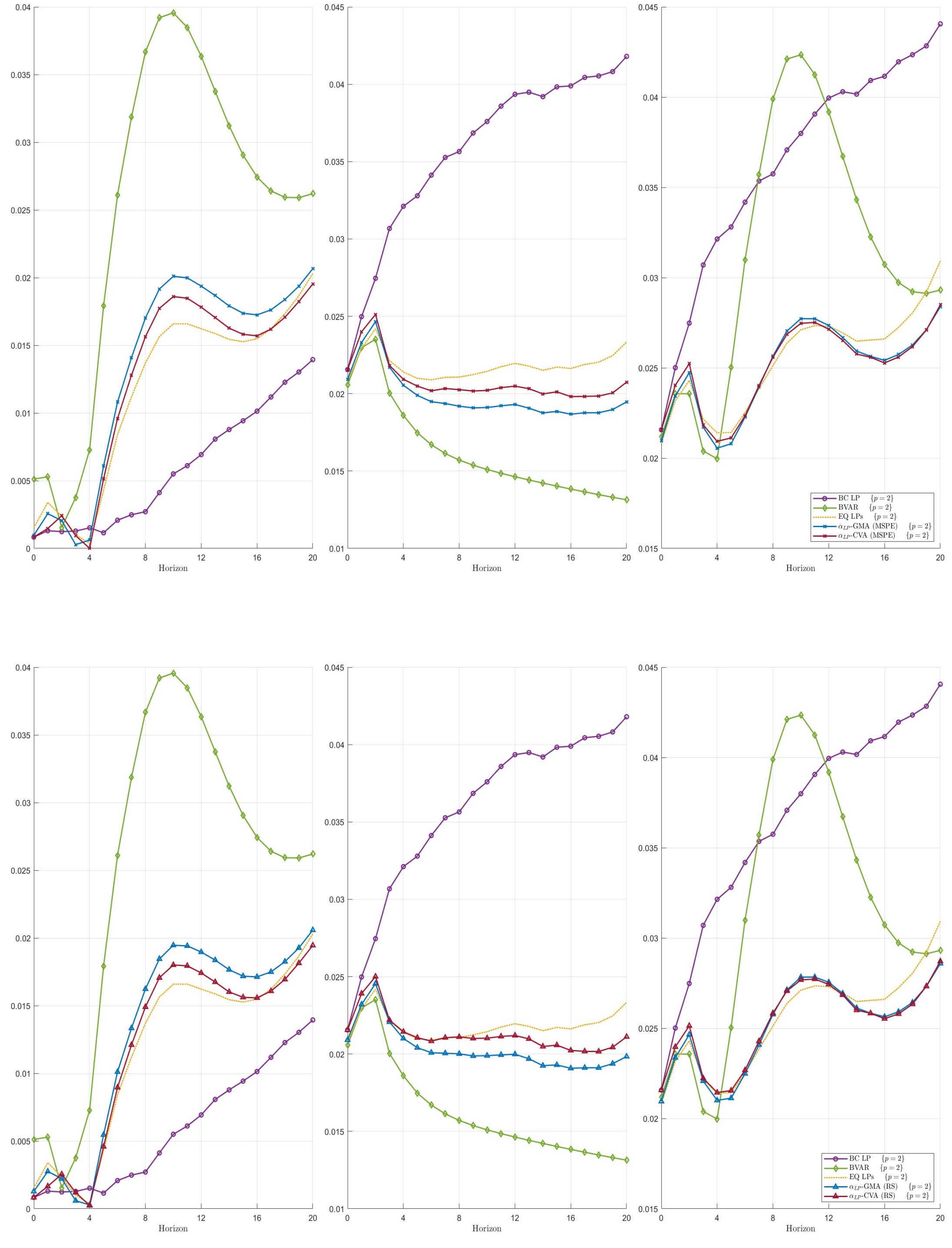


Figure F.4: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, 2 lags: Monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

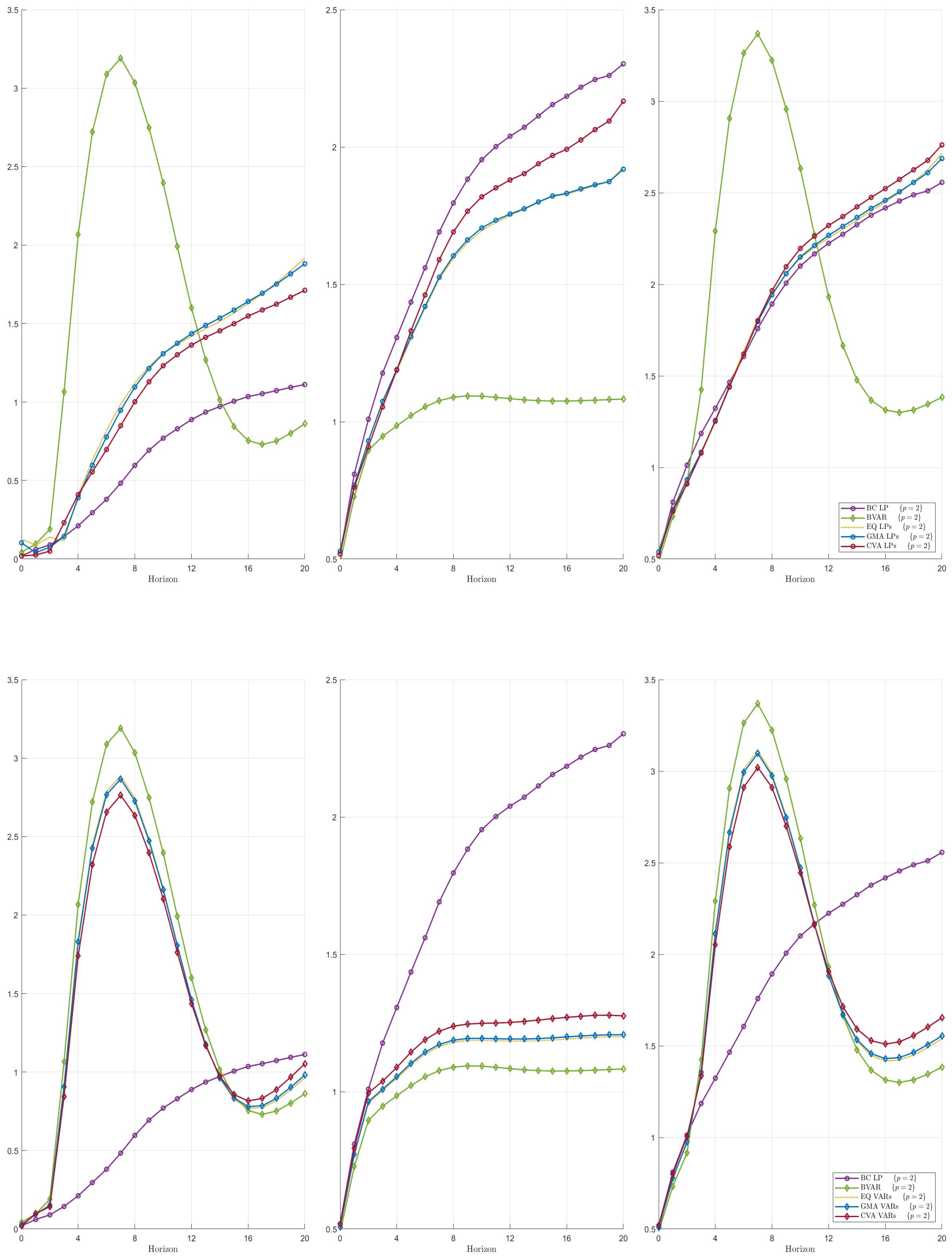


Figure F.5: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, 2 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

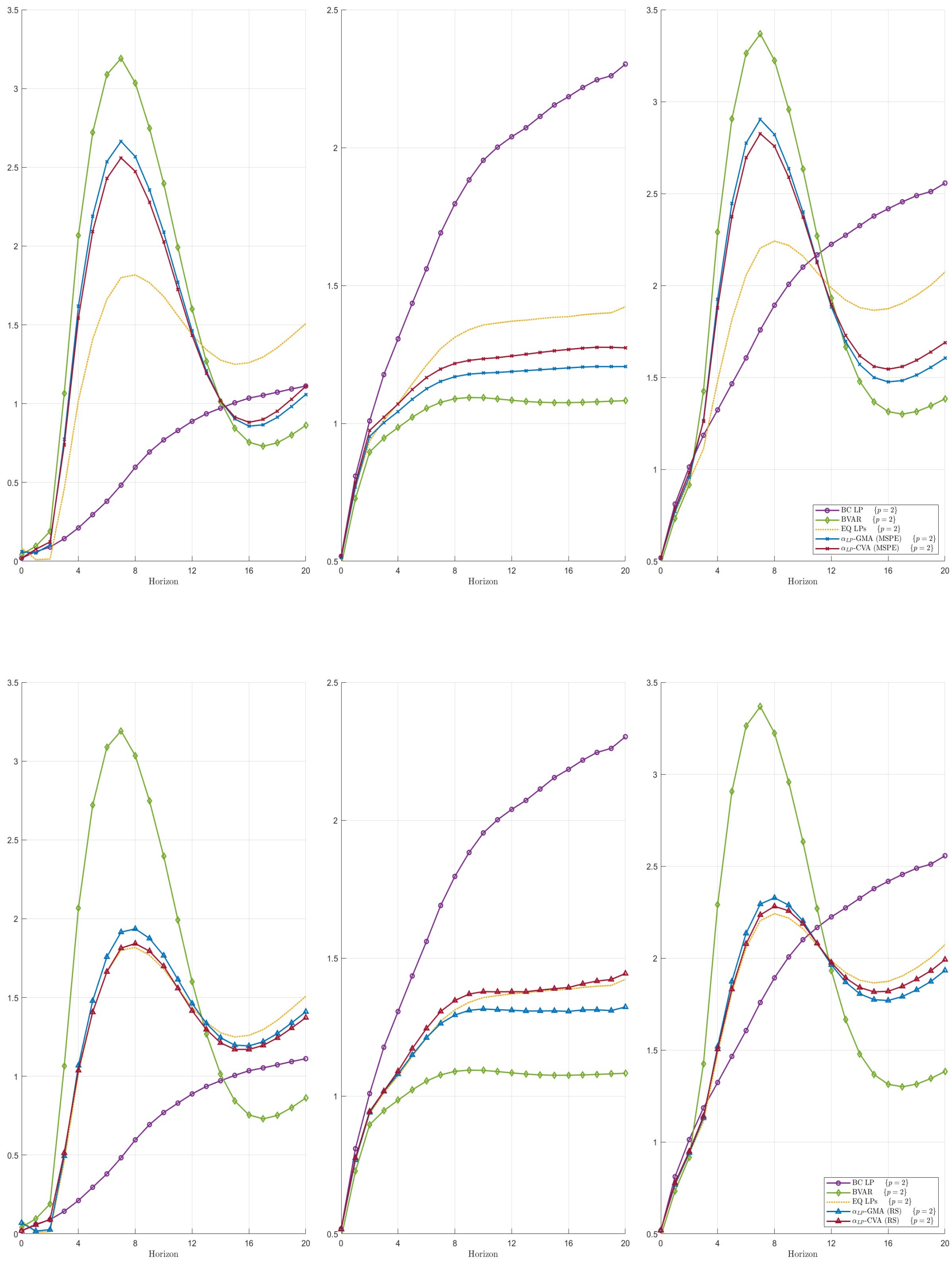


Figure F.6: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, 2 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

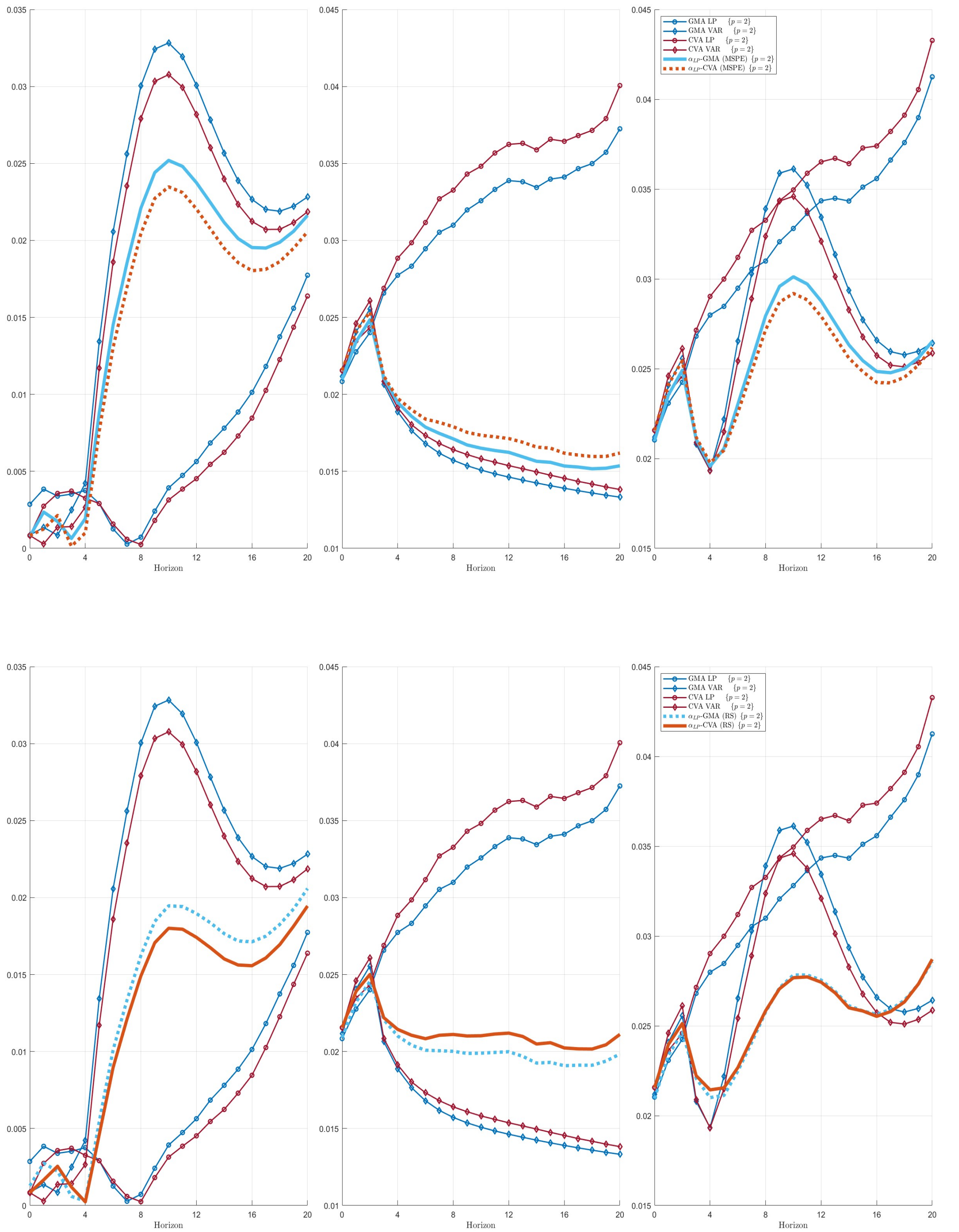


Figure F.7: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, 2 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

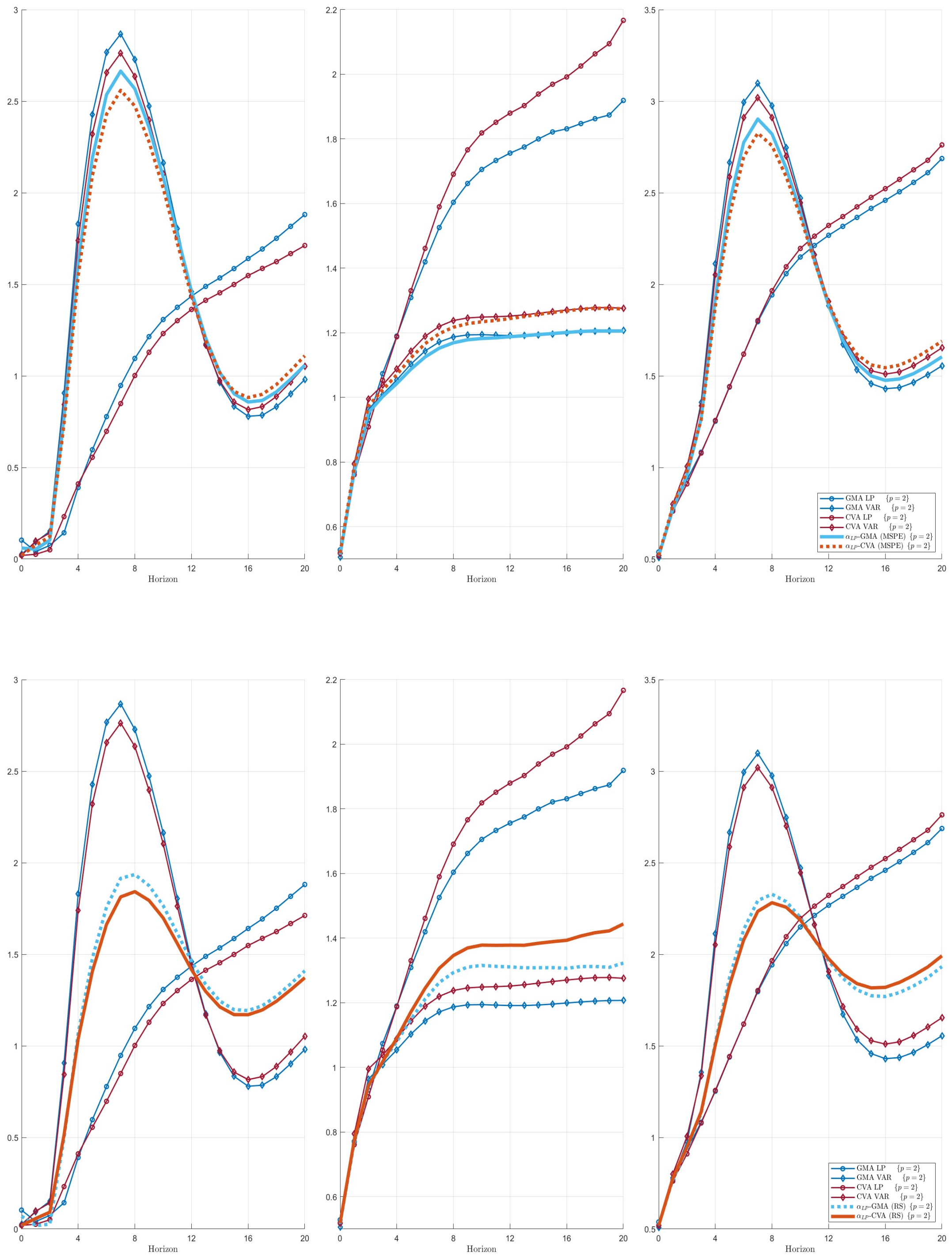
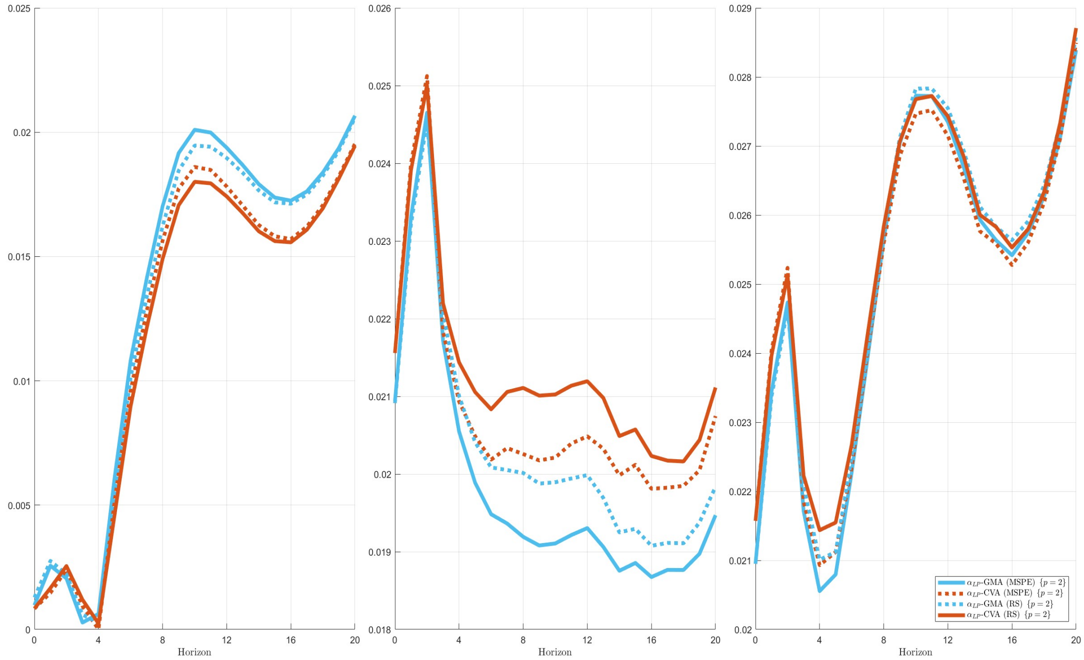


Figure F.8: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, 2 lags: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators



Observed Identification, 2 lags: Monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

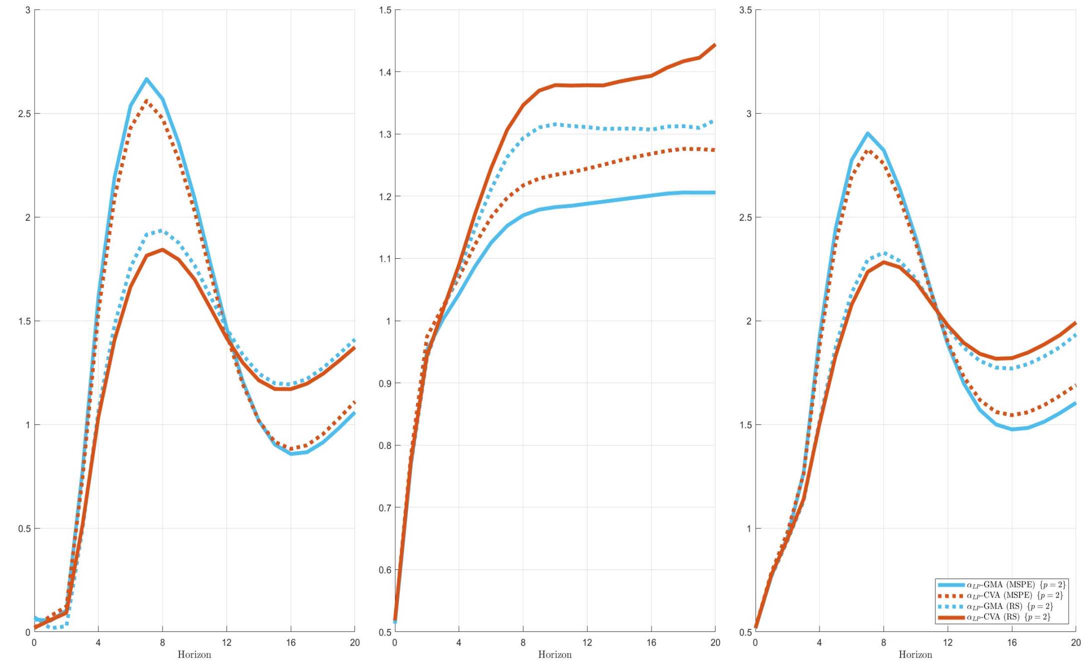


Figure F.9: Average absolute bias, standard deviation and MSE when a shock is observed.

Appendix F.2 Longer estimation lag length

Figure F.10 illustrates the performance of seven LP-variant and VAR-variant estimators in terms of average absolute bias, standard deviation, and MSE when the shock is observed and the estimation lag length is increased to eight (compared with four in the main analysis). Regardless of the shock type, bias for LP-based estimators deteriorates slightly. Bias for VAR-based estimators improves under fiscal shocks and fluctuates less, though not necessarily improving, under monetary shocks. Variance trends remain broadly similar.

Figure F.11 shows a clear bias–variance trade-off between MAVG_{LP} and MAVG_{VAR} in intermediate and long horizons when the shock is fiscal. In contrast, for monetary shocks the trade-off is less pronounced, with the MAVG_{VAR} group outperforming in both bias and variance for horizons $h > 12$. Compared with the four lags case, the bias–variance trade-off observed at intermediate horizons is therefore diluted at the longer lag length.

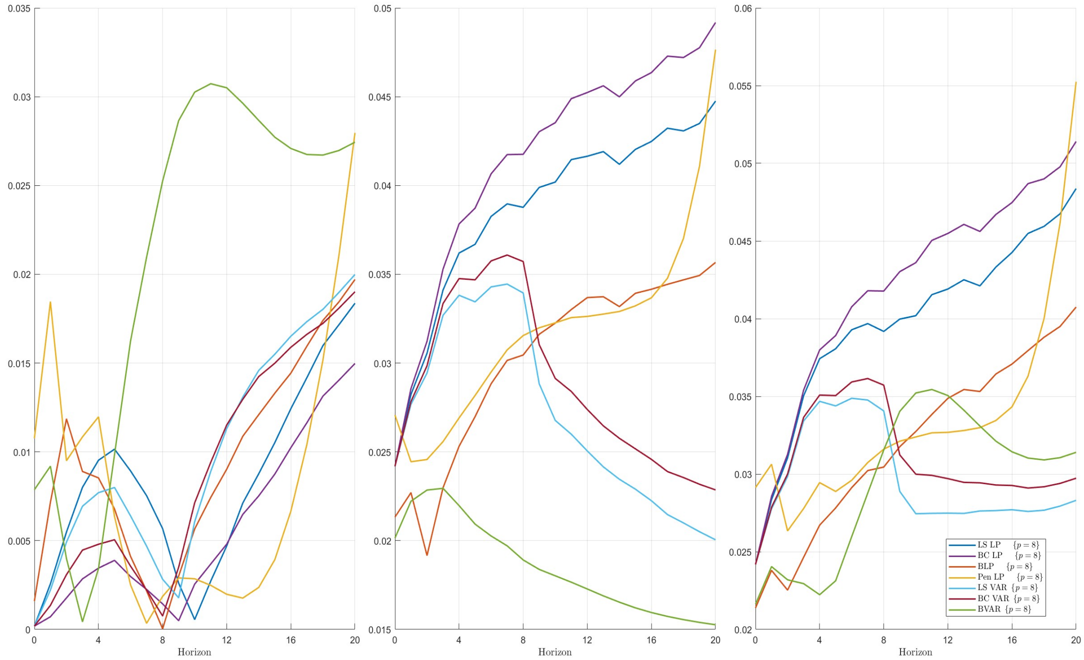
Figures F.12 to F.15 compare model-averaging groups with selected single estimators. For fiscal shocks, the MAVG_{LP} group outperforms BVAR in terms of bias from the intermediate horizon onward, while the MAVG_{VAR} group outperforms BC LP in terms of variance across all horizons. For monetary shocks, the same dominance of MAVG_{LP} in bias and MAVG_{VAR} in variance is clearly observable for $h < 12$. Overall, α_{LP} estimators continue to reduce MSE, consistent with the main results despite the change in lag length.

Figures F.16 to F.17 compare the four MAVG_{ALL} estimators that incorporate α_{LP}. In both fiscal and monetary cases, at least one α_{LP} estimator exhibits lower bias than the MAVG_{VAR} group and lower variance than the MAVG_{LP} group, thereby offering a lower overall loss when both error components are weighted equally.

Figure F.18 compares the four α_{LP} schemes that combine LP- and VAR-based estimators. Results remain consistent with those obtained using four lags. Schemes that incorporate both model fit and predictive accuracy—specifically $\alpha_{\text{LP,MSPE}}$-GMA and $\alpha_{\text{LP,RS}}$—CVA—outperform or closely match the alternatives in at least one evaluation metric for fiscal shocks. For monetary shocks, their advantage is somewhat reduced but still evident at selected horizons.

Observed Identification, 8 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**



Observed Identification, 8 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

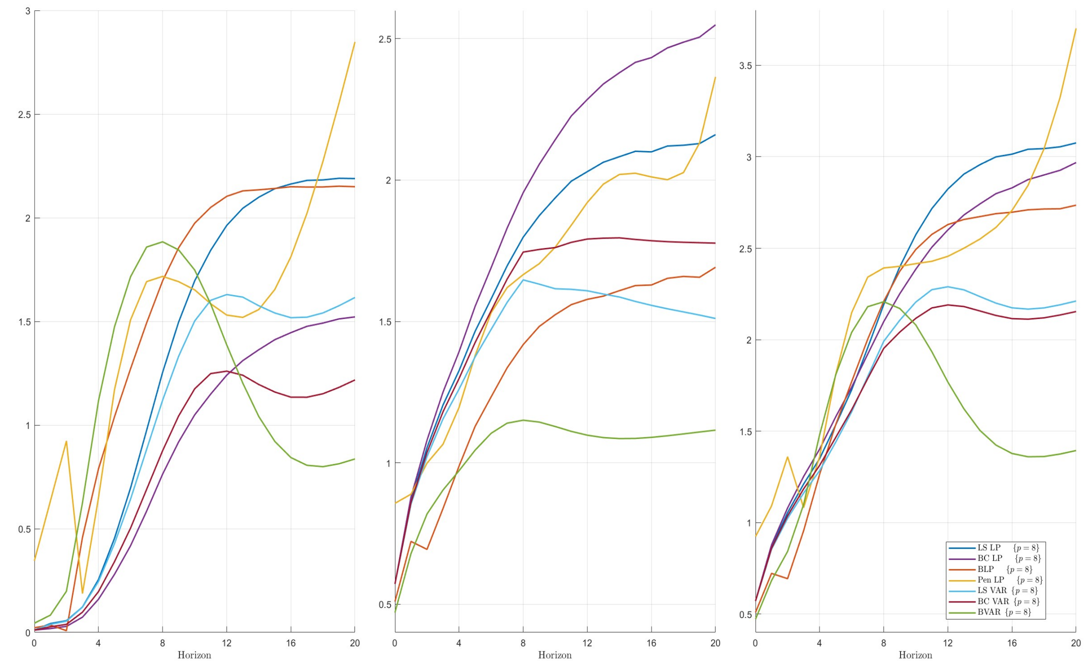
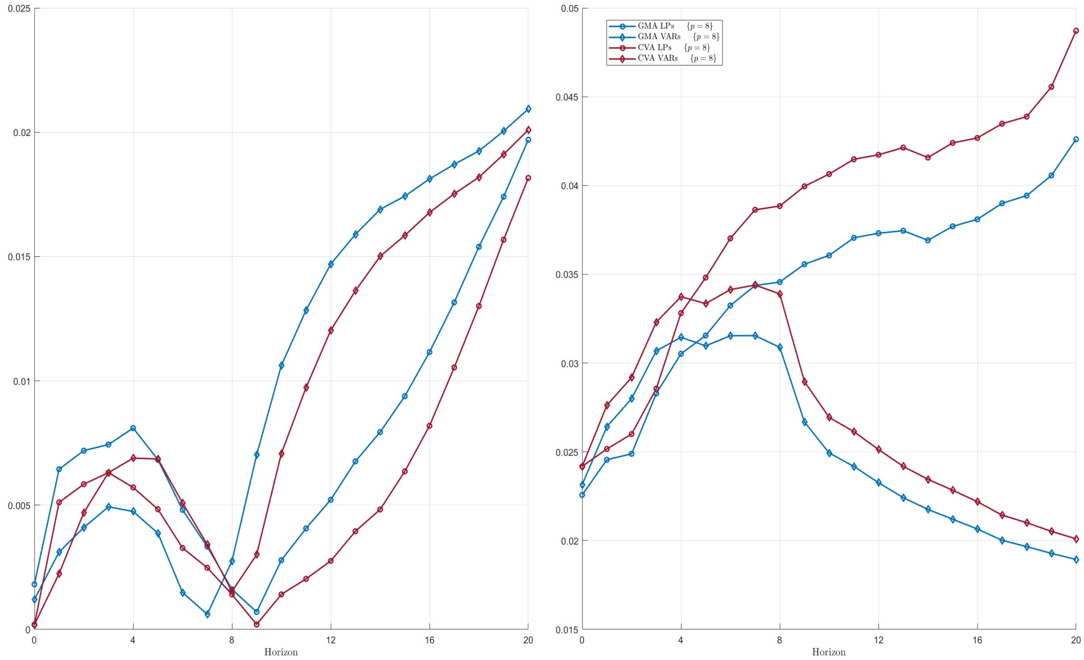


Figure F.10: Average absolute bias, standard deviation and MSE when a shock is observed.

Observed Identification, 8 lags: Fiscal Shock

$aBias$ (Left) and SD (Right) of Estimators



Observed Identification, 8 lags: Monetary Shock

$aBias$ (Left) and SD (Right) of Estimators

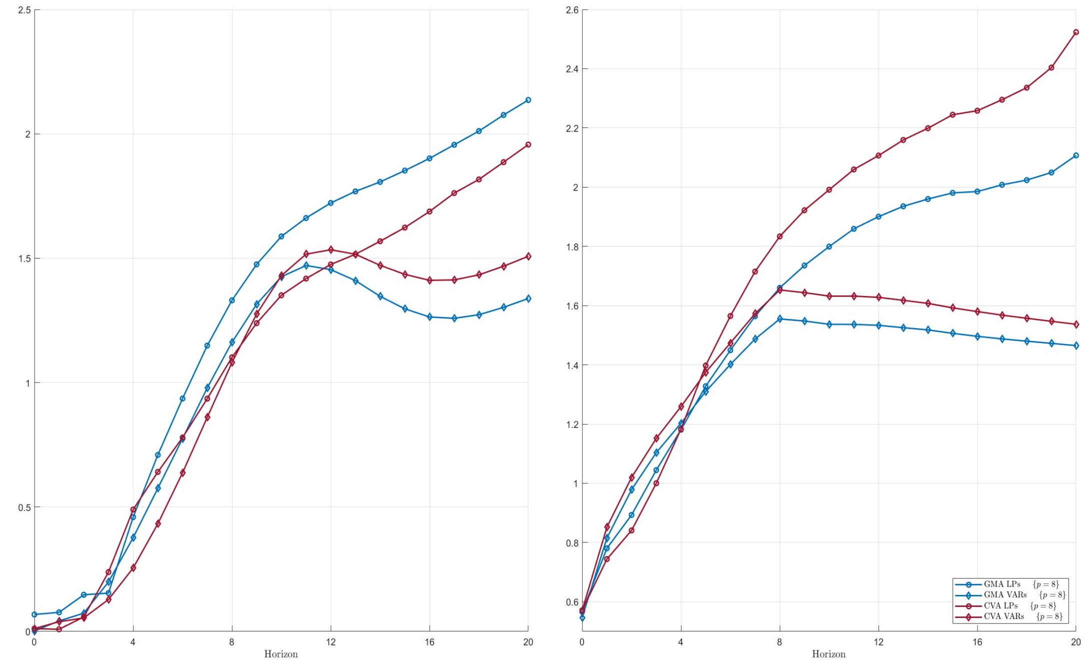


Figure F.11: Average absolute bias and standard deviation when a shock is observed.

Observed Identification, 8 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

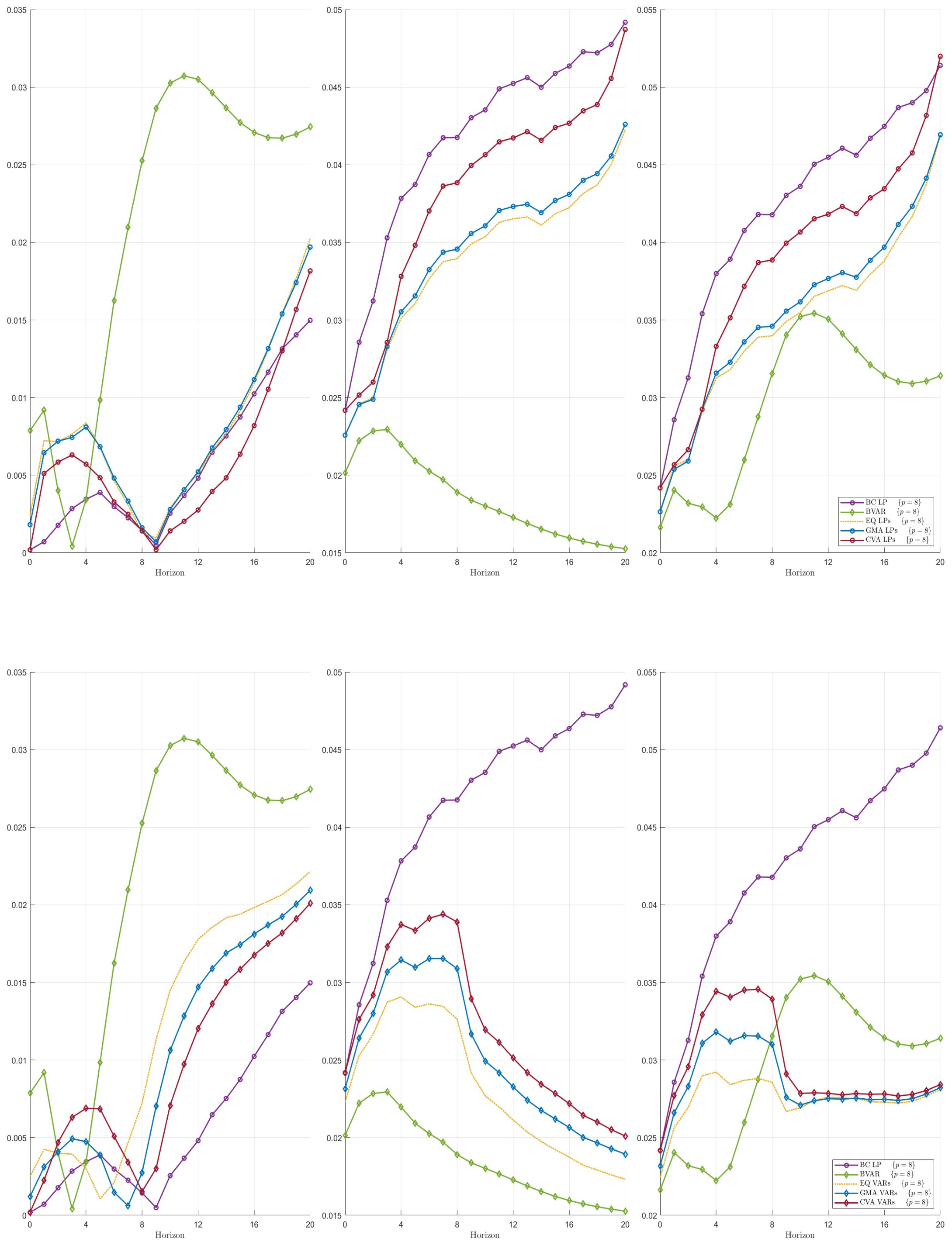


Figure F.12: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, 8 lags: Fiscal Shock
$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

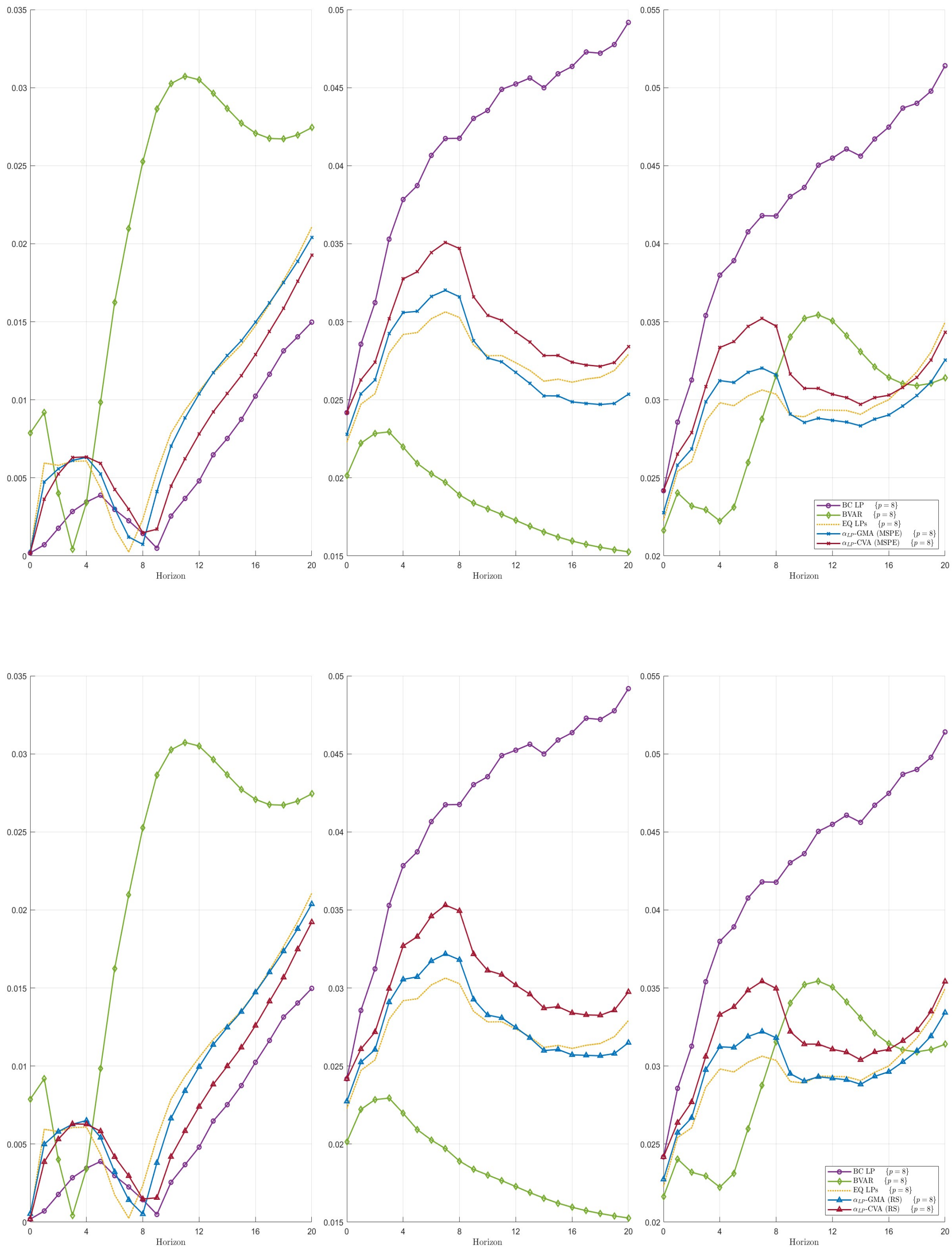


Figure F.13: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{ALL} group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG_{ALL} group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, 8 lags: Monetary Shock
$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

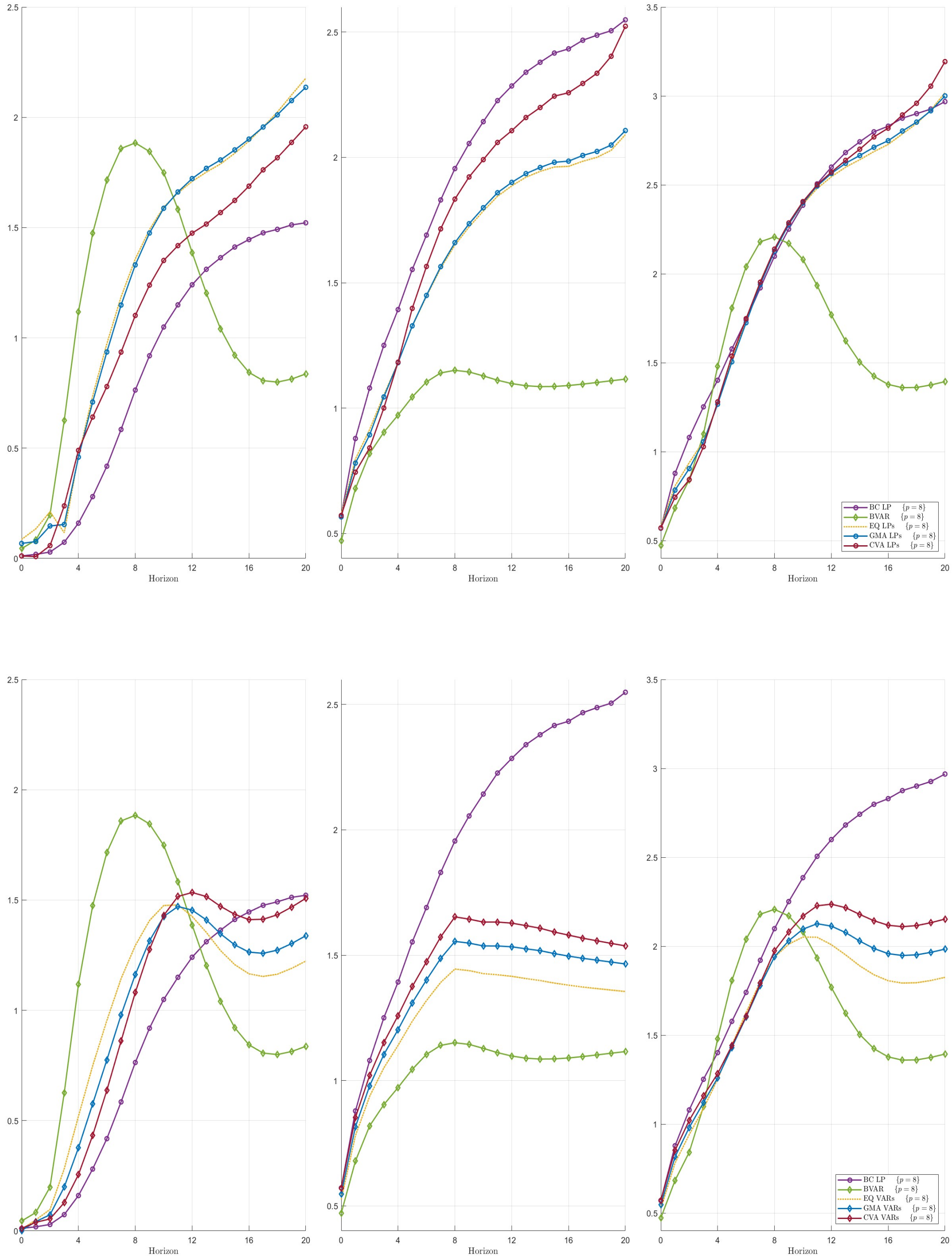


Figure F.14: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} group with BC LP and BVAR, while the **bottom panel** compares estimators in MAVG_{VAR} group with the same benchmarks.

Observed Identification, 8 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

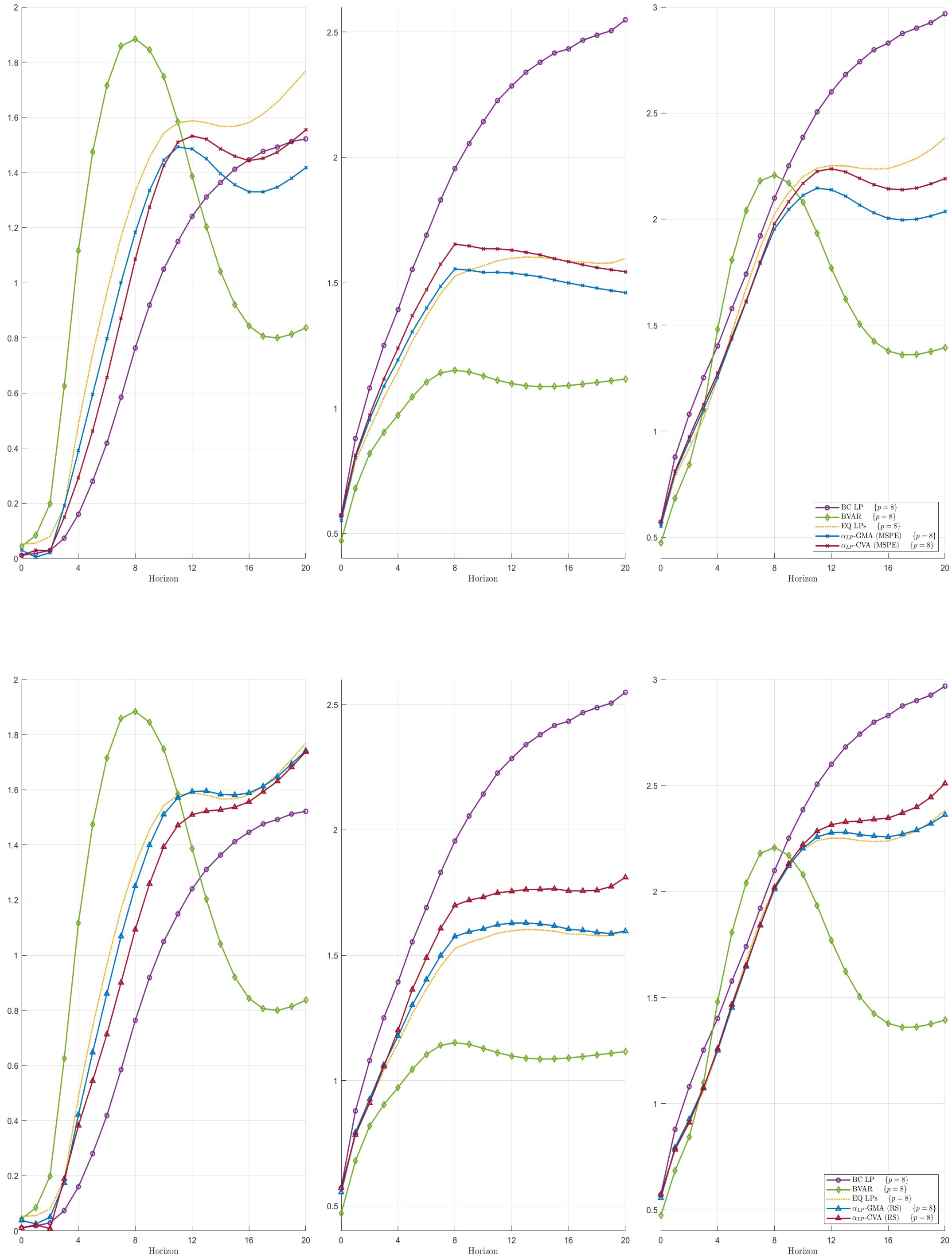


Figure F.15: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG$_{\text{ALL}}$ group using MSPE-guided α_{LP} values with BC LP and BVAR. The **bottom panel** compares estimators in the MAVG$_{\text{ALL}}$ group using R^2-guided α_{LP} values with the same benchmarks.

Observed Identification, 8 lags: Fiscal Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

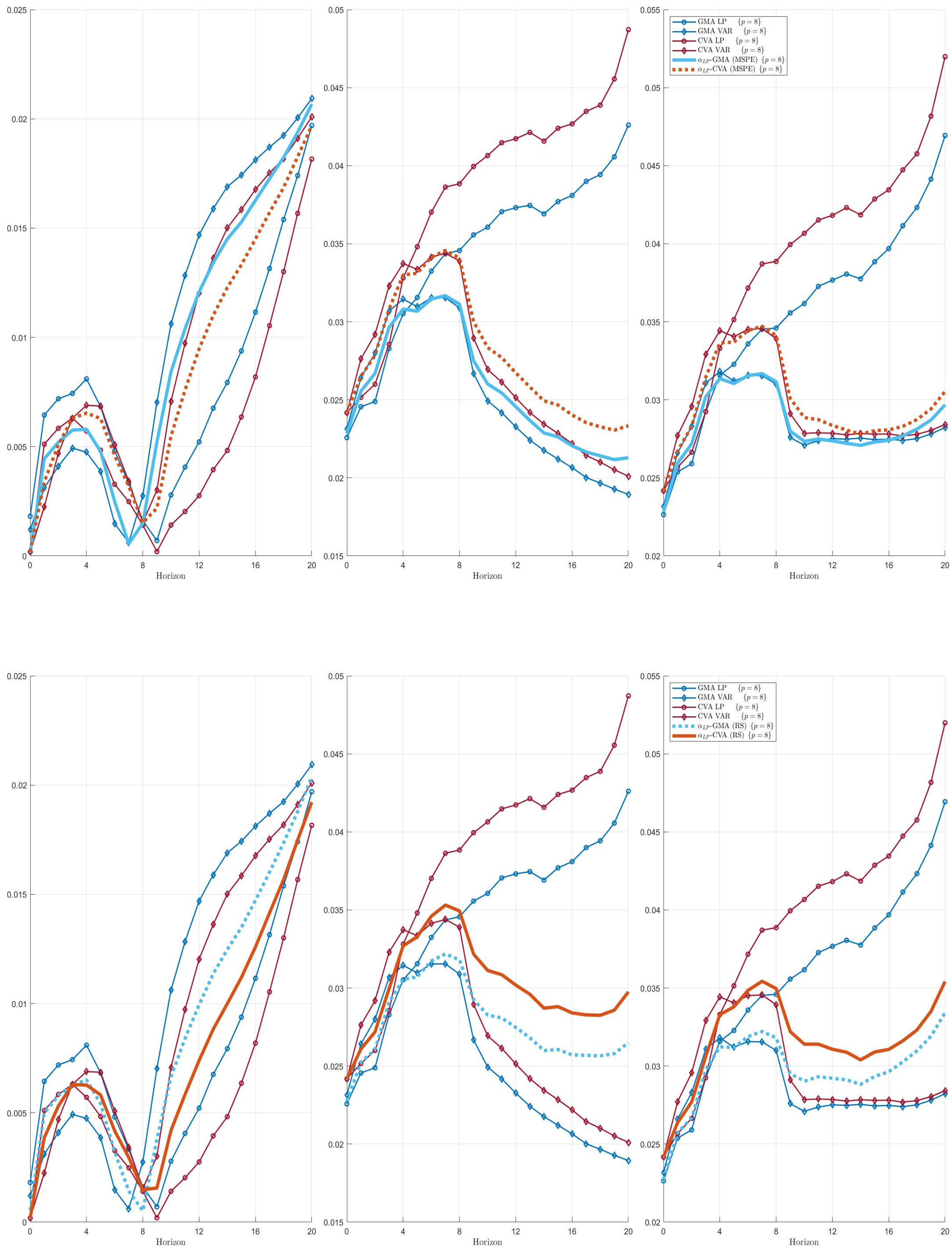


Figure F.16: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, 8 lags: Monetary Shock

$aBias$ **(Left)** SD **(Middle) and MSE (Right) of Estimators**

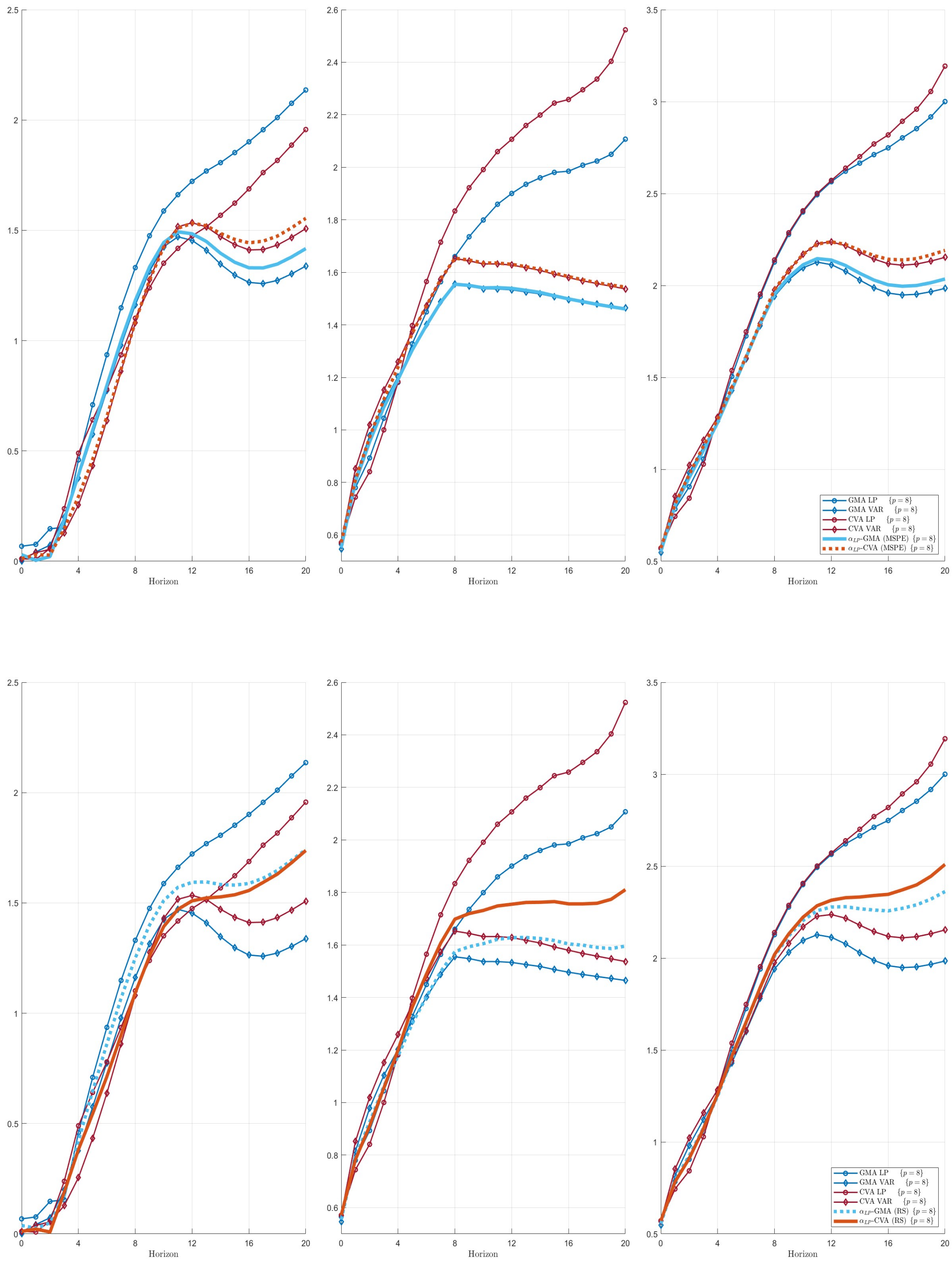
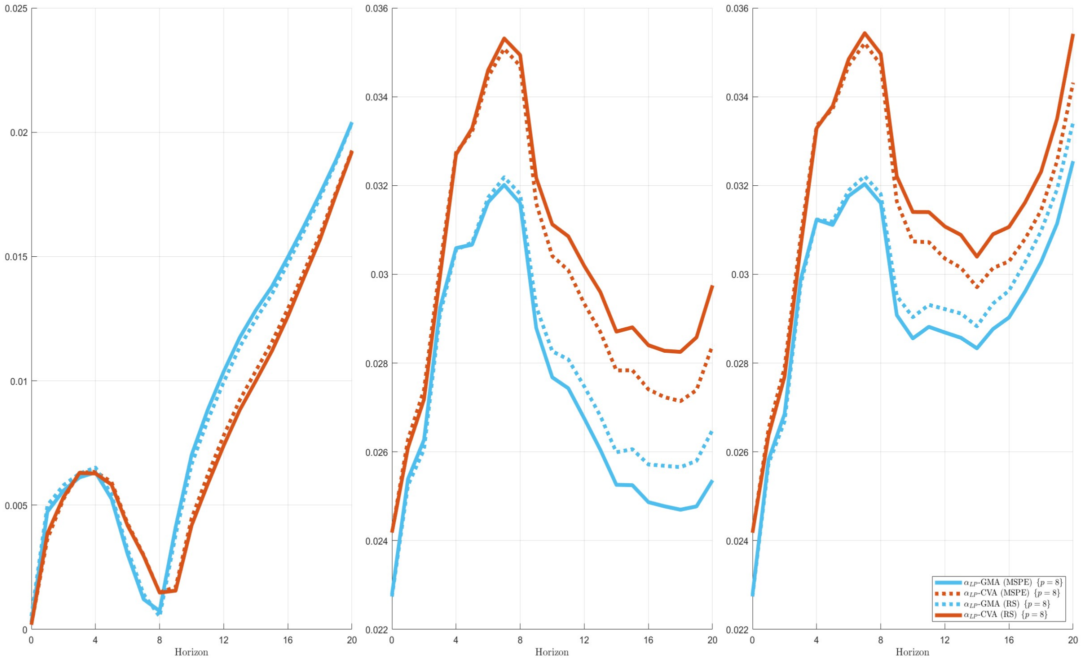


Figure F.17: Average absolute bias, standard deviation and MSE when a shock is observed. The **top panel** compares estimators in the MAVG_{LP} and MAVG_{VAR} groups with those in the MAVG_{ALL} group using MSPE-guided α_{LP} values. The **bottom panel** compares the same groups using R^2-guided α_{LP} values. All MAVG groups exclude EQ-based estimators.

Observed Identification, 8 lags: Fiscal Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators



Observed Identification, 8 lags: Monetary Shock

$aBias$ (Left) SD (Middle) and MSE (Right) of Estimators

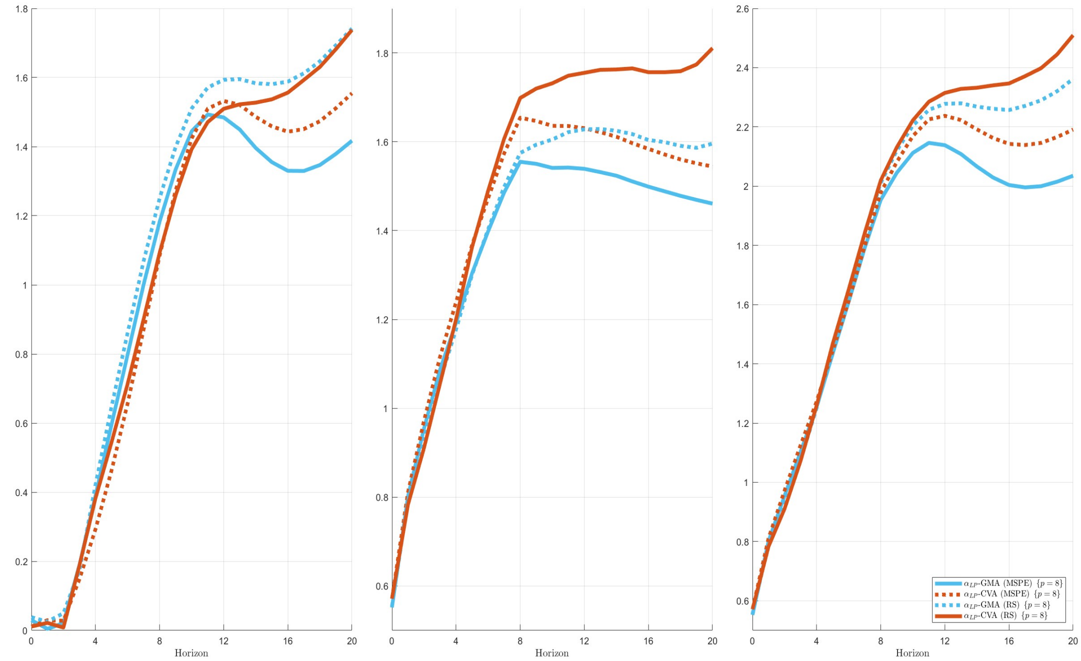


Figure F.18: Average absolute bias, standard deviation and MSE when a shock is observed.