Not for publication appendix

“Improved Methods for Combining Point Forecasts for an Asymmetrically Distributed Variable”

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A. Additional Figures for Applications

Figure A1 plots the predictions of recalibrated experts with recursively estimated weights (red solid line), together with the target variable, $FFR_t$ (blue solid line). For each recalibrated expert, the fit to $FFR_t$ is generally improved relative to the corresponding naive expert (shown in Figure 1) in the aftermath of the most recent financial crisis, when the recalibrated experts predict low but positive interest rates. Nevertheless, the forecast errors are typically larger (in absolute value) than for the copula point combination, especially for the Taylor expert.

Figure A2 displays the recursive RMSFE for various combinations and experts for the Federal Funds rate application. It plots the GR regression combination with recursive weights (blue line), the GR regression with equal weights (blue broken line), the copula point combination with recursive weights (red line) and the copula point combination with equal weights (red broken line). The copula combination dominates, although the gap to the GR benchmark narrows during 2008.

Figure A3 displays the recursive RMSFE for various combinations and recalibrated experts for the Federal Funds rate application. It plots the recalibrated Taylor and Bernanke experts (cyan lines, solid and broken, respectively), the GR regression combinations with recalibrated experts with recursive weights (magenta line) and with equal weights (magenta broken line). The copula point combination is displayed again (red line), together with the GR regression benchmark (blue line). The recalibrated combinations perform worse than the copula combination throughout the evaluation, and typically worse than the recalibrated Bernanke expert. For much of the sample performance of the GR combination with recalibrated experts is similar to the benchmark, but after the slump in 2008, the relative performance of the benchmark deteriorates.

Figure A4 displays the recursive RMSFEs for the vulnerable growth application. The
copula point combination (red solid line) and its equally weighted counterpart (red broken line), together with the GR regression benchmark (blue line) and its equal weight counterpart (blue broken line). The recursive copula combination ranks best from 1995 onwards, although the gap between this and the GR benchmark is typically around 1% until the onset of the financial crisis. The equal weight copula combination and benchmark are fairly close for most of the sample, with the copula variant preferred after the GFC. The performance gap in favour of the recursive weight specification over the equal weight specification is slightly larger for the copula combination than for the GR regression.
FIGURE A1: RECALIBRATED EXPERTS AND FFR

- Recalibrated Taylor
- Recalibrated Bernanke
- FFR
FIGURE A2: RECURSIVE RMSFE, CC AND GR COMBINATIONS
FIGURE A3: RECURSIVE RMSFE, RECALIBRATED EXPERTS AND COMBINATIONS
B. Robustness to Kernel Density Smoothing

In our two applications, we use non-parametric kernel-smoothed ECDFs for the marginal distributions, fitted recursively through the expanding window. Throughout the analysis reported in the main text of the paper, non-parametric kernel fitting uses the MATLAB function ksdensity, with a calibrated bandwidth. Higher bandwidths increase the smoothing. The calibrated parameters used in the forecast evaluations reported in the main text are: Federal Funds rate 0.15, Taylor expert 0.15, Bernanke expert 0.15, output growth 0.4, Expert CS 0.4, and Expert AR 0.4.

In figures B1 through B20, we report results based on varying the bandwidth parameter, $kw$, through the range 0.1 to 0.5 in each application. The general pattern of results is that the qualitative nature of the results is fairly robust to the choice of bandwidth parameter. Figures B1 through B10 are for the predicting Federal Funds rate application. Figures B11 through B20 are the corresponding plots for the forecasting output growth application.
FIGURE B1: COMBINATIONS AND FFR, kw=0.1
FIGURE B3: COMBINATIONS AND FFR, kw =0.2
FIGURE B4: RECURSIVE RMSFE, CC AND GR COMBINATIONS, kw=0.2
FIGURE B6: RECURSIVE RMSFE, CC AND GR COMBINATIONS, kw=0.3
FIGURE B7: COMBINATIONS AND FFR, kw = 0.4
FIGURE B8: RECURSIVE RMSFE, CC AND GR COMBINATIONS, kw=0.4
FIGURE B9: COMBINATIONS AND FFR, kw = 0.5
FIGURE B10: RECURSIVE RMSFE, CC AND GR COMBINATIONS, kw=0.5
FIGURE B12: RECURSIVE RMSFE, COMBINATIONS, kw=0.1
FIGURE B13: COMBINATIONS AND OUTTURNS, kw=0.2

Output Growth

CC
GR
Output Growth

FIGURE B14: RECURSIVE RMSFE, COMBINATIONS, kw=0.2
FIGURE B15: COMBINATIONS AND OUTTURNS, kw=0.3
FIGURE B16: RECURSIVE RMSFE, COMBINATIONS, kw=0.3
FIGURE B17: COMBINATIONS AND OUTTURNS, $kw=0.4$
FIGURE B18: RECURSIVE RMSFE, COMBINATIONS, kw=0.4
FIGURE B19: COMBINATIONS AND OUTTURNS, kw=0.5
C. Homogeneous and Heterogeneous Marginals

In the results reported for both applications in the main text the copula point combination uses heterogeneous marginals. We report results for the homogeneous case in figures C1 through C4. The homogeneous marginals results are slightly weaker than the heterogeneous case in terms of RMSFE by the end of the evaluation but slightly better for some samples. Figures C1 and C2 are for the predicting Federal Funds rate application. Figures C3 and C4 are the corresponding plots for the forecasting output growth application.
FIGURE C1: COMBINATIONS AND FFR, homogeneous marginals
FIGURE C2: RECURSIVE RMSFE, CC AND GR COMBINATIONS, Homogeneous marginals

- Red: CC Hetero
- Red dashed: CC Homog
- Blue solid: GR
- Blue dashed: GR EW