Summary of Results

In all cases four methods are used to generate base forecasts. Either base forecasts are drawn from an independent distribution or dependent distribution (all DGPs actually have dependence). Also base forecasts are Gaussian or use bootstrapping (the DGPs may be Gaussian or non-Gaussian). The following reconciliation methods are considered

- Base: Not a reconciliation method, just the base forecasts.
- BottomUp: Bottom up
- BTTH: Ben Taieb, Taylor Hyndman (2020). This is like bottom up but reorders a sample from probabilistic forecast to match the empirical copula. Also the mean is adjusted to be the same as that from MinT reconciliation.
- JPP: Jeon Panagiotelis Petropoulos (2019). This reorders a sample from the probabilistic forecast to be perfectly dependent, i.e. it reconciles quantiles. Reconciliation is done by WLS (structural)
- MinTSam: MinT with the usual sample covariance estimator
- MinTShr: MinT with shrinkage covariance estimator
- OLS: OLS reconciliation
- ScoreOpt: Score Optimisation by stochastic gradient descent.
- WLS: Weighted least squares using structural scaling.

Gaussian and Stationary DGP

The DGP has Gaussian residuals and all series are forced to be stationary.

ARIMA model

Recall that the true DGP is ARIMA

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	11.3256	11.9802	21.7502	22.8683	10.8959	11.1309	10.8041
independent	gaussian	11.3176	11.9620	21.7620	22.8895	10.8916	11.1198	10.8231
joint	bootstrap	11.0652	11.6430	21.8745	22.8528	10.7468	10.8388	10.8429
joint	gaussian	11.0542	11.6190	21.8842	22.8575	10.7410	10.8280	10.8420

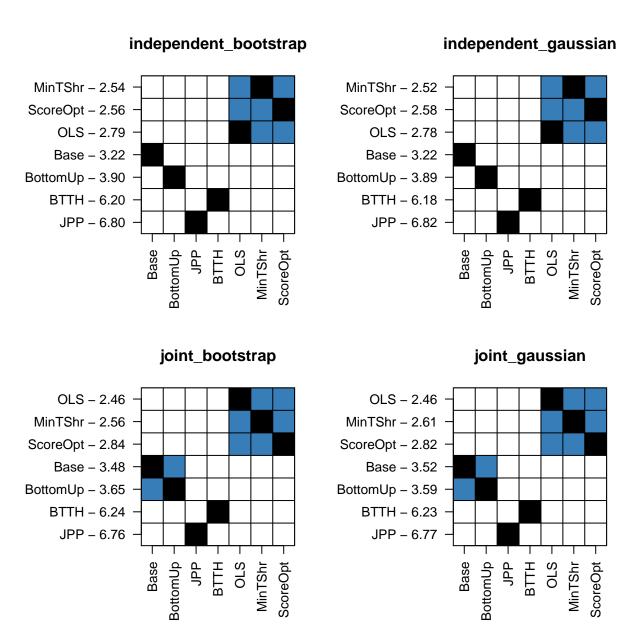


Figure 1: Results for arima modelling with a gaussian stationary DGP

Recall that the true DGP is ARIMA so there is model misspecification here.

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	11.8019	12.4569	23.9076	23.4051	10.9495	11.1776	10.8344
independent	gaussian	11.7927	12.4548	23.9336	23.4421	10.9446	11.1667	10.8290
joint	bootstrap	11.6016	12.2067	24.0121	23.3864	10.7910	10.9302	10.8637
joint	gaussian	11.5891	12.1918	24.0381	23.4158	10.7844	10.9224	10.8471

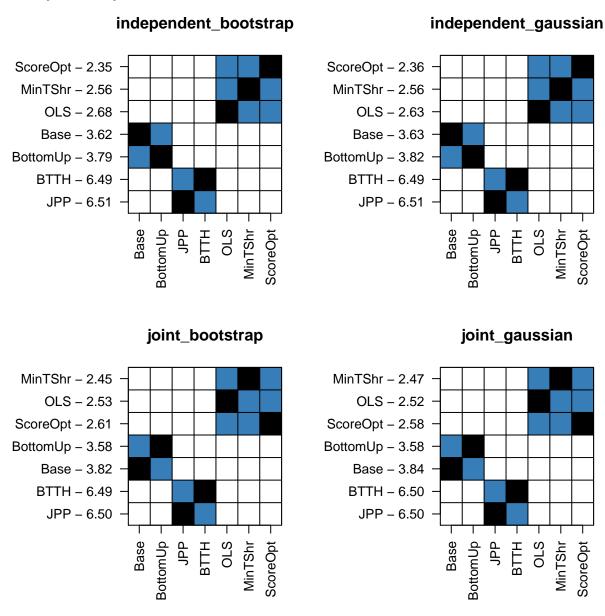


Figure 2: Results for ets modelling with a gaussian stationary DGP

Non Gaussian and Stationary DGP

The DGP has non-Gaussian residuals and all series are forced to be stationary.

ARIMA model

Recall that the true DGP is ARIMA

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.4161	1.5055	2.7647	2.8793	1.3505	1.3635	1.3383
independent	gaussian	1.4250	1.5312	2.9205	2.9740	1.3510	1.3641	1.3385
joint	bootstrap	1.3854	1.4658	2.7867	2.8795	1.3301	1.3412	1.3390
joint	gaussian	1.3910	1.4728	2.9337	2.9674	1.3364	1.3480	1.3391

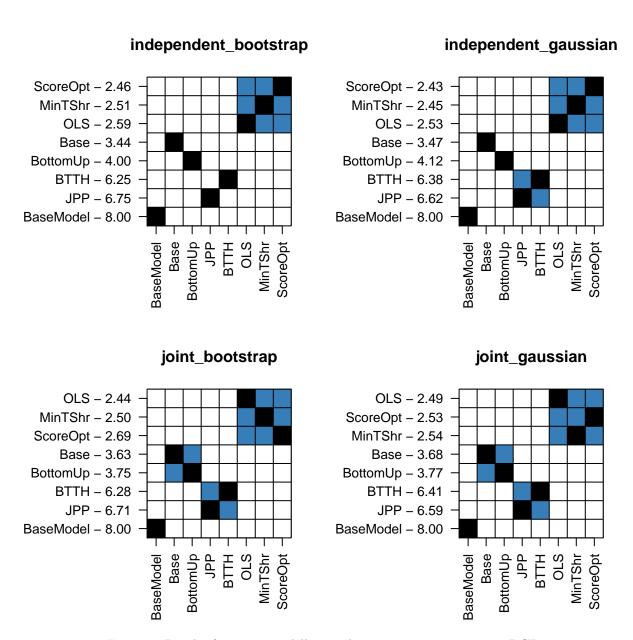


Figure 3: Results for arima modelling with a nongaussian stationary DGP

Recall that the true DGP is ARIMA so there is model misspecification here.

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.4344	1.5221	2.8345	2.8969	1.3721	1.3707	1.3343
independent	gaussian	1.4405	1.5442	2.9977	2.9997	1.3697	1.3679	1.3347
joint	bootstrap	1.4048	1.4854	2.8412	2.8951	1.3552	1.3466	1.3354
joint	gaussian	1.4105	1.4919	2.9981	2.9813	1.3620	1.3535	1.3356

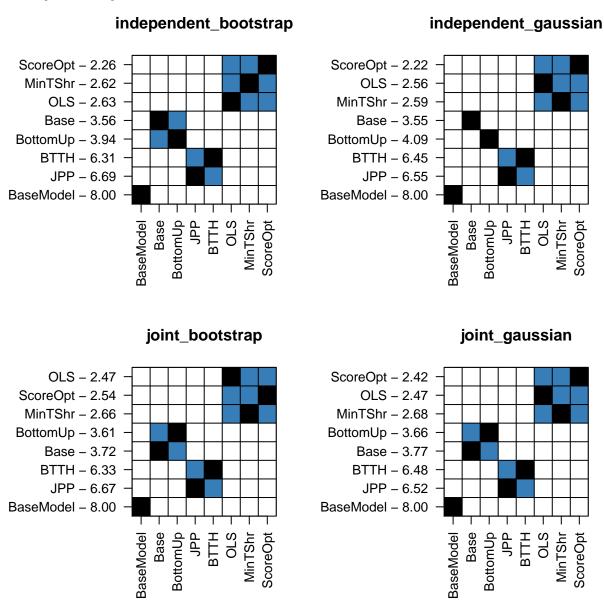


Figure 4: Results for ets modelling with a nongaussian stationary DGP

Gaussian and non-Stationary DGP

The DGP has Gaussian residuals and some series are non stationary.

ARIMA model

Recall that the true DGP is ARIMA

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	12.9297	14.8344	26.6316	26.0958	11.5767	12.3595	11.9863
independent	gaussian	12.9078	14.7851	26.6309	26.1032	11.5521	12.3339	11.9738
joint	bootstrap	12.6512	14.5738	26.7287	26.0713	11.3431	12.0316	11.8789
joint	gaussian	12.6372	14.5220	26.6920	26.0405	11.3328	12.0235	11.8985

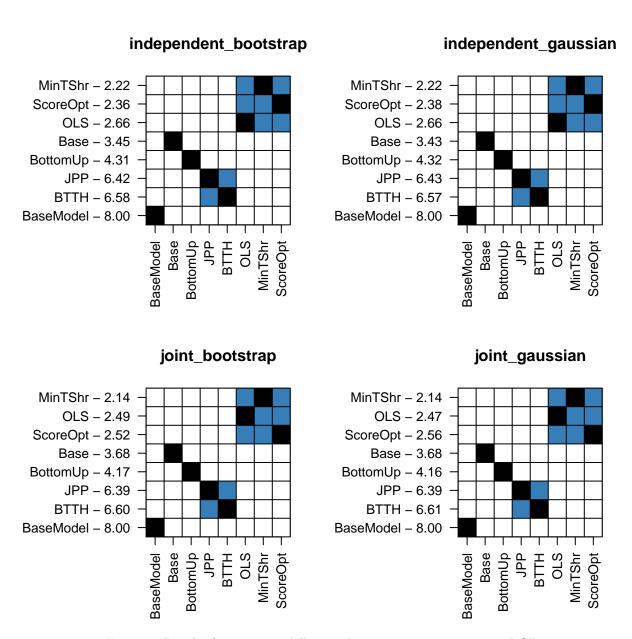


Figure 5: Results for arima modelling with a gaussian nonstationary DGP

Recall that the true DGP is ARIMA so there is model misspecification here.

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	12.8746	15.0455	27.4547	26.0359	11.4797	12.1518	11.9216
independent	gaussian	12.8439	14.9823	27.4171	26.0300	11.4598	12.1172	11.8692
joint	bootstrap	12.6206	14.8212	27.4981	26.0168	11.2542	11.8645	11.7445
joint	gaussian	12.5919	14.7508	27.4786	25.9833	11.2416	11.8443	11.7298

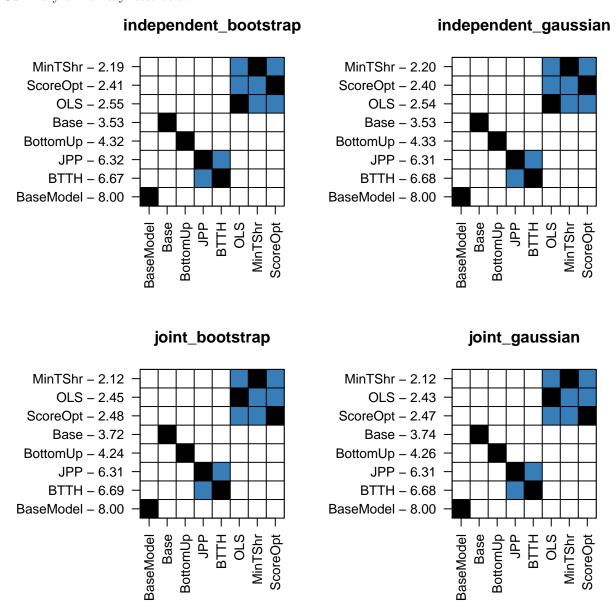


Figure 6: Results for ets modelling with a gaussian nonstationary DGP

Non Gaussian and non Stationary DGP

The DGP has non-Gaussian residuals and some series are non-stationary.

ARIMA model

Recall that the true DGP is ARIMA

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.5724	1.7422	3.2335	3.1984	1.4424	1.4934	1.5226
independent	gaussian	1.5739	1.7467	3.2723	3.2321	1.4423	1.4924	1.5203
joint	bootstrap	1.5342	1.7177	3.2395	3.1951	1.4105	1.4613	1.4979
joint	gaussian	1.5357	1.7196	3.2725	3.2231	1.4113	1.4631	1.4925

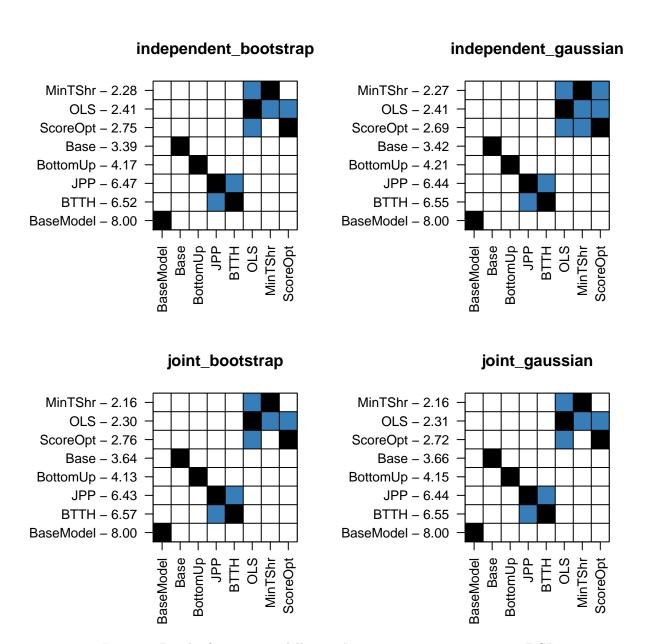


Figure 7: Results for arima modelling with a nongaussian nonstationary DGP

Recall that the true DGP is ARIMA so there is model misspecification here.

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.5831	1.7609	3.2929	3.2022	1.4548	1.4845	1.5375
independent	gaussian	1.5842	1.7632	3.3358	3.2458	1.4553	1.4831	1.5377
joint	bootstrap	1.5485	1.7395	3.3013	3.2009	1.4165	1.4554	1.4779
joint	gaussian	1.5479	1.7388	3.3410	3.2232	1.4170	1.4556	1.4773

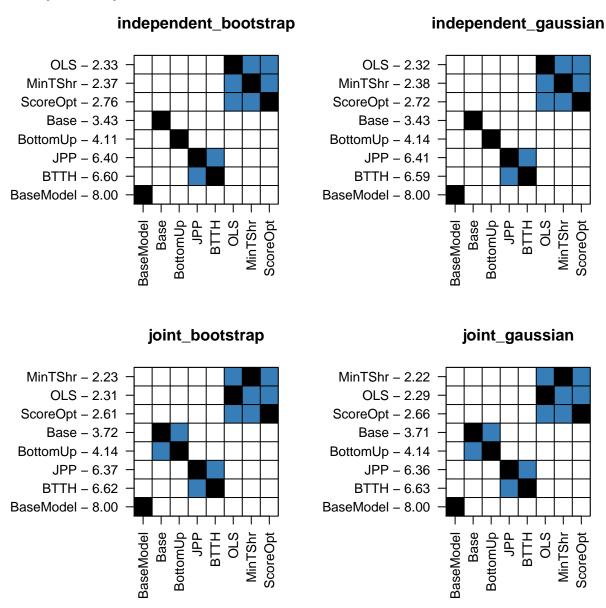


Figure 8: Results for ets modelling with a nongaussian nonstationary DGP