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	11.3268	11.9754	21.7864	22.8678	10.8927	11.1325	10.8098
independent	gaussian	11.3225	11.9737	21.7818	22.8923	10.8928	11.1240	10.8303
joint	bootstrap	11.0764	11.6548	21.8468	22.8610	10.7571	10.8503	10.8541
joint	gaussian	11.0489	11.6135	21.8277	22.8513	10.7359	10.8224	10.8370

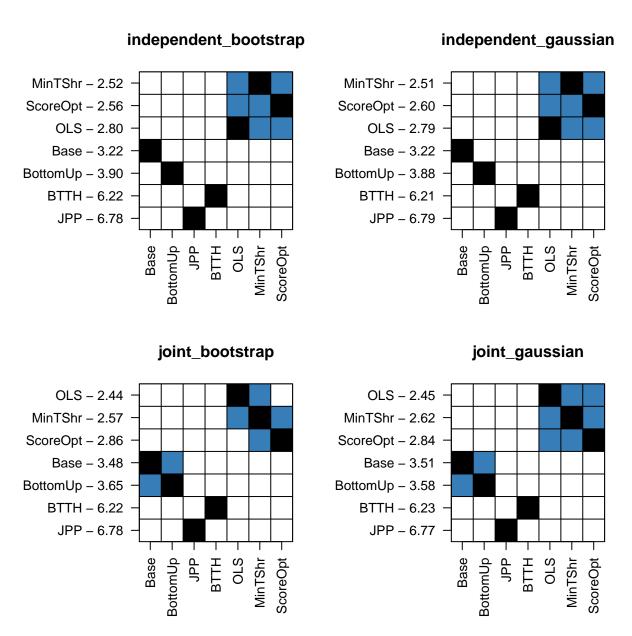


Figure 1: Results for arima modelling with a gaussian stationary DGP

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

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	11.8055	12.4634	23.9093	23.4070	10.9524	11.1822	10.8390
independent	gaussian	11.7943	12.4536	23.9146	23.4426	10.9466	11.1688	10.8361
joint	bootstrap	11.6028	12.2065	23.9898	23.3877	10.7902	10.9307	10.8608
joint	gaussian	11.5791	12.1853	24.0245	23.4111	10.7718	10.9110	10.8353

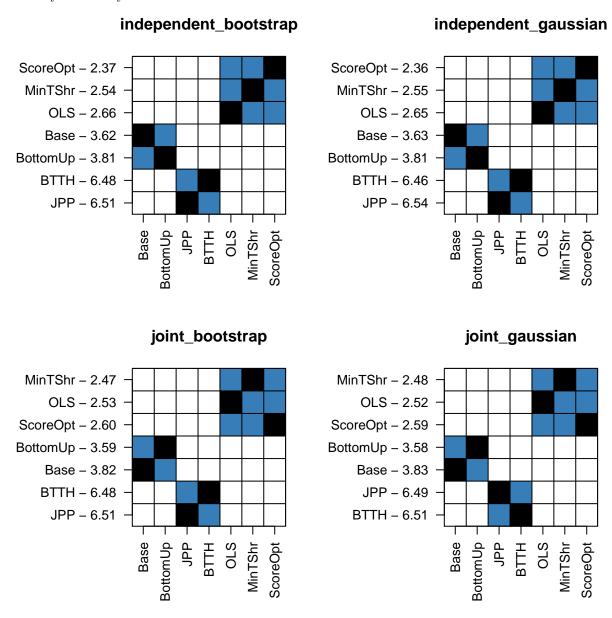


Figure 2: Results for ets modelling with a gaussian stationary DGP

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	1.4163	1.5059	2.7754	2.8797	1.3509	1.3638	1.3382
independent	gaussian	1.4251	1.5312	2.9290	2.9740	1.3513	1.3643	1.3392
joint	bootstrap	1.3841	1.4648	2.7842	2.8779	1.3288	1.3400	1.3376
joint	gaussian	1.3915	1.4727	2.9319	2.9683	1.3370	1.3486	1.3399

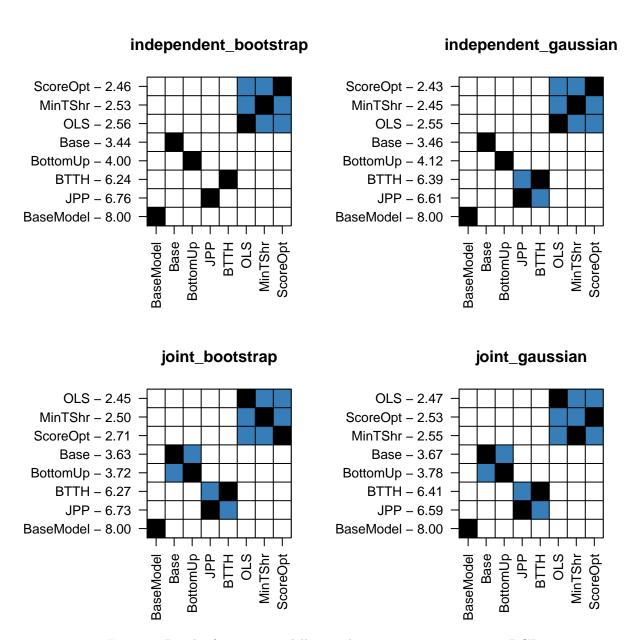


Figure 3: Results for arima modelling with a nongaussian stationary DGP

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

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.4341	1.5213	2.8313	2.8968	1.3716	1.3703	1.3341
independent	gaussian	1.4408	1.5434	3.0036	2.9998	1.3697	1.3683	1.3345
joint	bootstrap	1.4039	1.4845	2.8392	2.8941	1.3544	1.3458	1.3345
joint	gaussian	1.4106	1.4921	2.9986	2.9818	1.3619	1.3536	1.3356

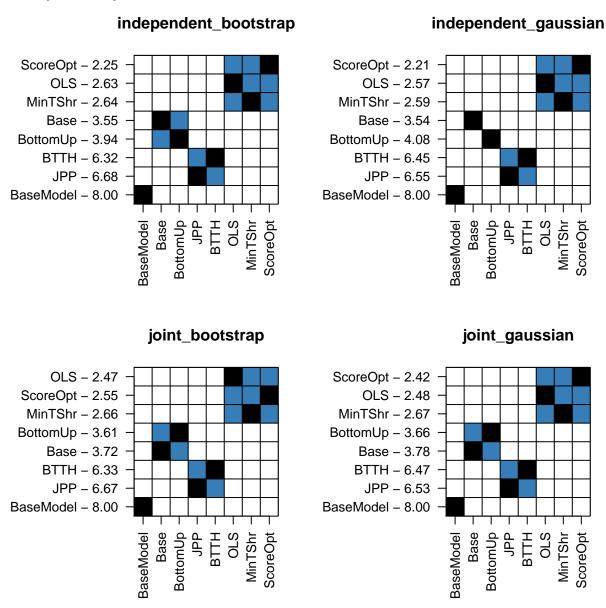


Figure 4: Results for ets modelling with a nongaussian stationary DGP

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	12.9307	14.8360	26.6446	26.0921	11.5736	12.3581	11.9873
independent	gaussian	12.9081	14.7940	26.6645	26.1055	11.5510	12.3342	11.9756
joint	bootstrap	12.6621	14.5803	26.7064	26.0842	11.3557	12.0435	11.8909
joint	gaussian	12.6317	14.5227	26.6555	26.0429	11.3254	12.0173	11.8936

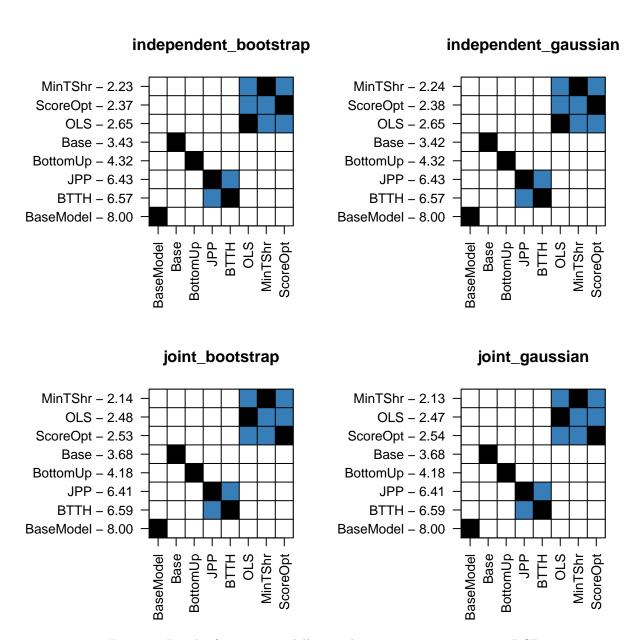


Figure 5: Results for arima modelling with a gaussian nonstationary DGP

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

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	12.8750	15.0345	27.4111	26.0374	11.4840	12.1556	11.9223
independent	gaussian	12.8458	14.9815	27.4013	26.0363	11.4612	12.1212	11.8729
joint	bootstrap	12.6162	14.8164	27.4961	26.0168	11.2488	11.8613	11.7404
joint	gaussian	12.5836	14.7464	27.4402	25.9773	11.2351	11.8351	11.7218

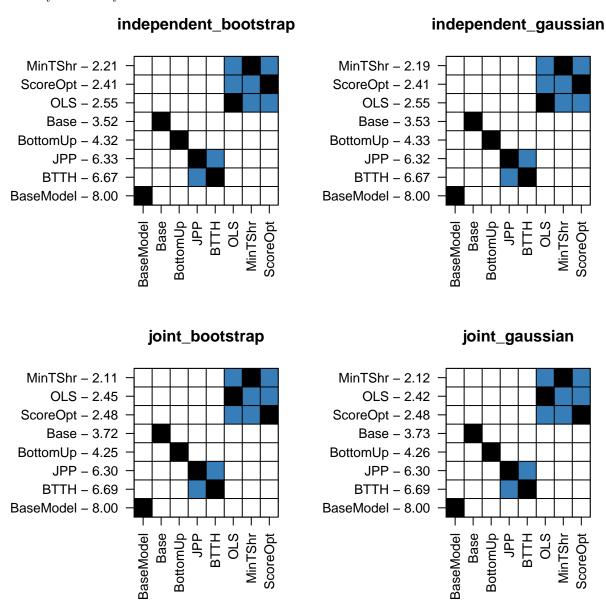


Figure 6: Results for ets modelling with a gaussian nonstationary DGP

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	1.7418	3.2317	3.1987	1.4423	1.4937	1.5230
independent	gaussian	1.5740	1.7466	3.2746	3.2322	1.4443	1.4929	1.5208
joint	bootstrap	1.5332	1.7168	3.2387	3.1947	1.4090	1.4602	1.4967
joint	gaussian	1.5347	1.7186	3.2745	3.2226	1.4107	1.4621	1.4913

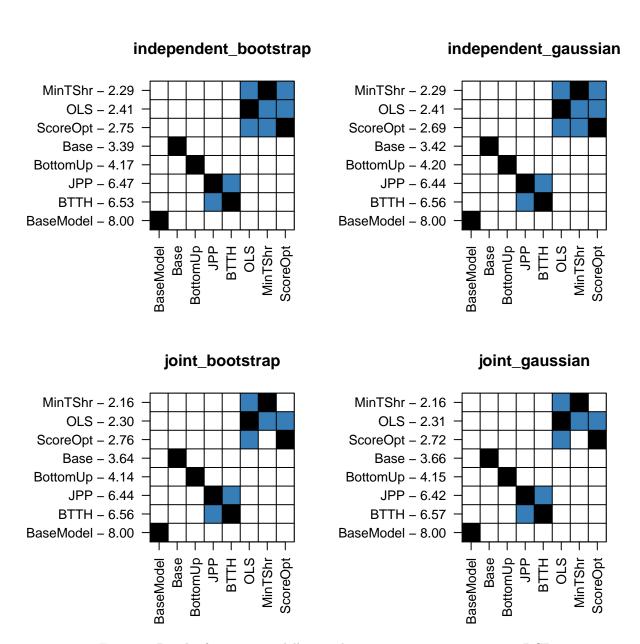


Figure 7: Results for arima modelling with a nongaussian nonstationary DGP

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

BaseDependence	BaseDistribution	Base	BottomUp	BTTH	JPP	MinTShr	OLS	ScoreOpt
independent	bootstrap	1.5834	1.7615	3.2970	3.2020	1.4546	1.4846	1.5376
independent	gaussian	1.5839	1.7642	3.3360	3.2458	1.4564	1.4830	1.5375
joint	bootstrap	1.5469	1.7379	3.3011	3.1986	1.4151	1.4539	1.4764
joint	gaussian	1.5471	1.7387	3.3342	3.2227	1.4158	1.4546	1.4763

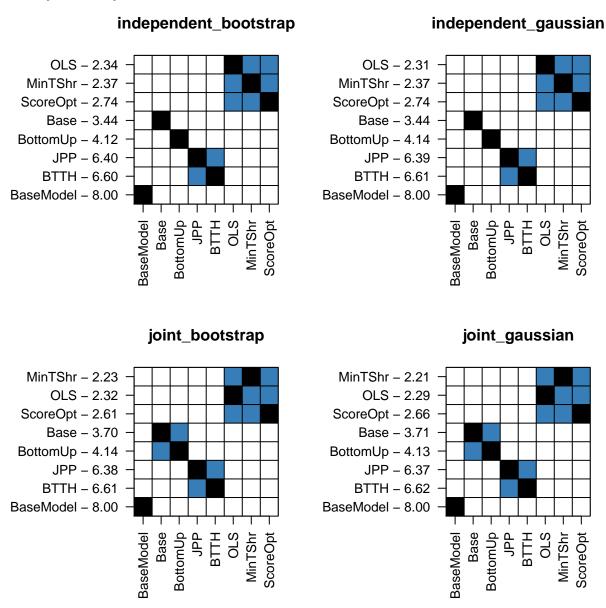


Figure 8: Results for ets modelling with a nongaussian nonstationary DGP