Results Summary

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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

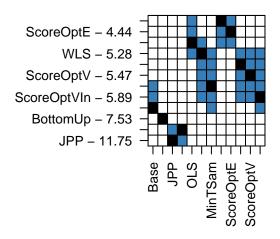
- Base: Not a reconciliation method, just the base forecasts.
- BottomUp: Bottom up
- BTTH: Ben Taieb, Taylor Hyndman (2020). This is like bottom up but reorders a sample from probabilistic forecast to match the empirical copula. Also the mean is adjusted to be the same as that from MinT reconciliation.
- 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
- ScoreOptE: Energy score Optimisation by stochastic gradient descent.
- ScoreOptEIn: Energy score Optimisation by stochastic gradient descent but with predicted values (in-sample) used instead of rolling window forecasts.
- ScoreOptV: Variogram score Optimisation by stochastic gradient descent.
- ScoreOptVIn: Variogram score Optimisation by stochastic gradient descent but with predicted values (in-sample) used instead of rolling window forecasts.
- WLS: Weighted least squares using structural scaling.

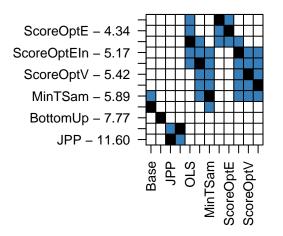
Table 1: Mean energy score for arima modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	1.4169	1.4246	1.3850	1.3912
BottomUp	1.5071	1.5305	1.4658	1.4731
BTTH	2.7704	2.9271	2.7817	2.9335
JPP	2.8805	2.9737	2.8788	2.9672
MinTSam	1.3909	1.4050	1.3311	1.3379
MinTShr	1.3514	1.3504	1.3297	1.3367
OLS	1.3643	1.3638	1.3409	1.3483
ScoreOptE	1.3391	1.3379	1.3384	1.3391
ScoreOptEIn	1.3914	1.3860	1.3771	1.3668
ScoreOptV	1.3772	1.3772	1.3746	1.3738
ScoreOptVIn	1.4088	1.4035	1.3860	1.3745
WLS	1.3849	1.3848	1.3645	1.3720

independent_bootstrap

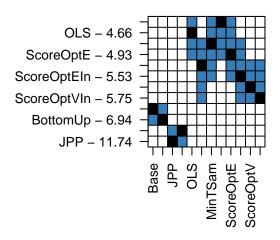
independent_gaussian





joint_bootstrap

joint_gaussian



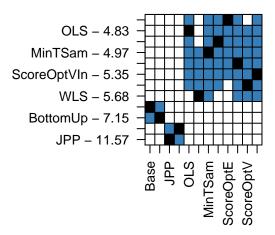


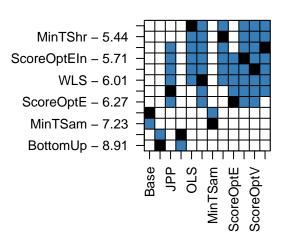
Figure 1: Nemenyi matrix for arima modelling with a nongaussian stationary DGP using energy score

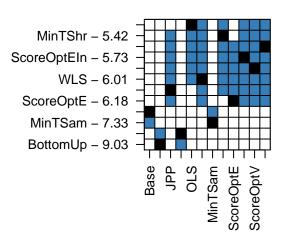
Table 2: Mean variogram score for arima modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	26.2480	26.2638	26.2339	26.2643
BottomUp	28.5977	28.7956	27.6925	27.7625
BTTH	29.2544	29.1507	29.0767	29.0854
JPP	26.3968	26.3993	26.3833	26.4030
MinTSam	26.5895	26.7292	25.5373	25.5796
MinTShr	25.4412	25.4215	25.4799	25.5248
OLS	25.6498	25.6362	25.6860	25.7348
ScoreOptE	25.6992	25.6954	25.5763	25.6889
ScoreOptEIn	25.6897	25.7068	25.5615	25.5700
ScoreOptV	25.5433	25.5325	25.4541	25.4798
ScoreOptVIn	25.6161	25.6009	25.6357	25.6354
WLS	25.9648	25.9563	26.0088	26.0644

independent_bootstrap

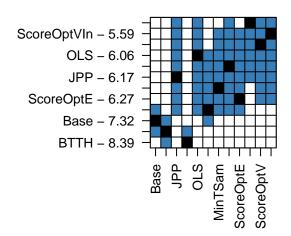
independent_gaussian





joint_bootstrap

joint_gaussian



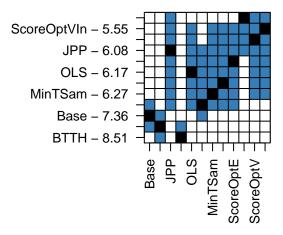


Figure 2: Nemenyi matrix for arima modelling with a nongaussian stationary DGP using variogram score