# 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

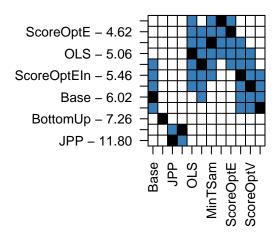
- Base: Not a reconciliation method, just the base forecasts.
- BottomUp: Bottom up
- BTTH: Ben Taieb, Taylor Hyndman (2020). This is like bottom up but reorders a sample from probabilistic forecast to match the empirical copula. Also the mean is adjusted to be the same as that from MinT reconciliation.
- 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.

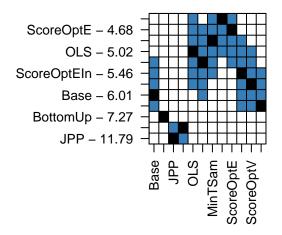
Table 1: Mean energy score for arima modelling with a gaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	11.3256	11.3247	11.0662	11.0556
BottomUp	11.9759	11.9705	11.6429	11.6203
BTTH	21.7508	21.8051	21.8542	21.8826
JPP	22.8651	22.8986	22.8573	22.8599
MinTSam	10.9020	10.9066	10.7633	10.7590
MinTShr	10.8865	10.8905	10.7475	10.7428
OLS	11.1284	11.1264	10.8396	10.8292
ScoreOptE	10.8053	10.8297	10.8433	10.8406
ScoreOptEIn	11.2462	11.2484	11.1393	11.1360
ScoreOptV	11.2066	11.2074	11.0413	11.0262
ScoreOptVIn	11.4680	11.4703	11.3432	11.3439
WLS	11.2294	11.2254	10.9995	10.9873

### independent\_bootstrap

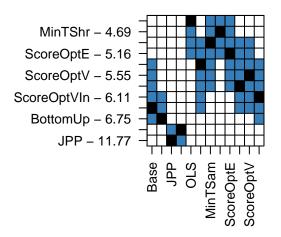
### independent\_gaussian





### joint\_bootstrap

## joint\_gaussian



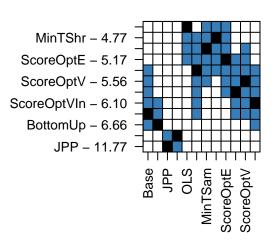


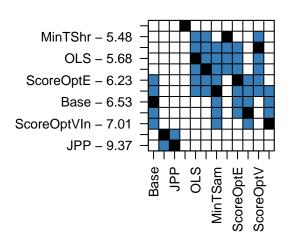
Figure 1: Nemenyi matrix for arima modelling with a gaussian stationary DGP using energy score

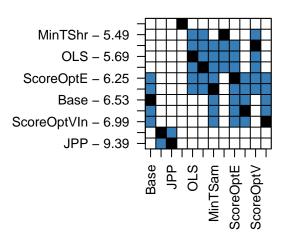
Table 2: Mean variogram score for arima modelling with a gaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	694.5012	694.6362	694.7861	694.5443
BottomUp	888.7264	891.1163	697.9468	697.7384
BTTH	630.8518	632.3063	632.7646	631.8727
JPP	1032.9742	1039.0791	1033.3112	1038.1928
MinTSam	690.5337	690.7602	677.8265	677.4925
MinTShr	683.3065	683.0490	677.8987	677.4923
OLS	713.4531	713.5246	680.3692	680.1407
ScoreOptE	686.0447	686.8067	683.5021	684.2645
ScoreOptEIn	766.1230	764.7783	791.9662	791.6630
ScoreOptV	675.1864	675.2327	673.5918	672.3905
ScoreOptVIn	793.8187	793.3693	808.9654	809.1151
WLS	707.2066	707.3780	683.7460	683.6068

### independent\_bootstrap

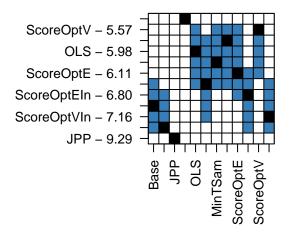
### independent\_gaussian





### joint\_bootstrap

## joint\_gaussian



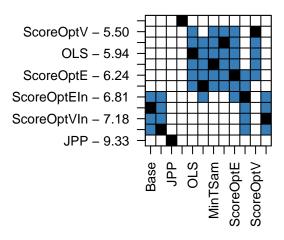


Figure 2: Nemenyi matrix for arima modelling with a gaussian stationary DGP using variogram score