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 score for ets modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	1.4333	1.4404	1.4041	1.4105
BottomUp	1.5215	1.5439	1.4849	1.4925
BTTH	2.8341	2.9955	2.8438	2.9970
JPP	2.8697	2.9763	2.8643	2.9545
MinTSam	9400.4672	10293.5555	1.3573	2.1304
MinTShr	1.3713	1.3704	1.3544	1.3622
OLS	1.3699	1.3683	1.3462	1.3536
ScoreOptE	1.3337	1.3355	1.3341	1.3357
ScoreOptEIn	1.4063	1.3921	1.3898	1.3803
ScoreOptV	NA	NA	NA	NA
ScoreOptVIn	NA	NA	NA	NA
WLS	1.3943	1.3916	1.3733	1.3808

independent_bootstrap independent_gaussian ScoreOptE - 3.23 OLS - 3.68 MinTShr - 3.75 ScoreOptEIn - 4.11 WLS - 4.12 ScoreOptE - 3.28 OLS - 3.74 OLS - 3.74 MinTShr - 3.77 WLS - 4.13 ScoreOptEIn - 4.38 Base - 5.22 BottomUp - 5.76 MinTSam - 6.63 BTTH - 8.89 JPP - 9.21 Base - 5.27 BottomUp - 5.99 MinTSam - 6.75 BTTH - 9.03 JPP - 9.07 joint_bootstrap joint_gaussian OLS - 3.78 ScoreOptE - 3.80 ScoreOptE - 3.51 OLS - 3.70 MinTShr - 3.93 ScoreOptEIn - 4.11 WLS - 4.33 MinTShr - 4.04 MinTSam - 4.20 WLS - 4.41ScoreOptEIn - 4.63 BottomUp - 5.46 Base - 5.47 MinTSam - 5.89 JPP - 9.29 BTTH - 9.31 BottomUp – 5.56 Base – 5.59 BTTH – 9.38 JPP – 9.61 ScoreOptEll ScoreOptEll

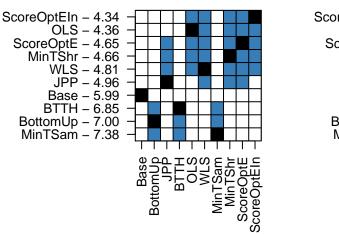
Figure 1: Nemenyi matrix for ets modelling with a nongaussian stationary DGP

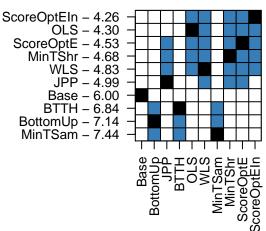
Table 2: Mean score for ets modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	2.664050e+01	2.665790e+01	26.6481	26.6666
BottomUp	2.892380e+01	2.917530e+01	28.0909	28.1669
BTTH	3.083980e+01	3.076780e+01	30.6907	30.9168
JPP	2.659260e+01	2.658630e+01	26.5956	26.6049
MinTSam	2.070934e+11	2.155996e+11	26.2247	62.9175
MinTShr	2.610030e+01	2.607030e+01	26.1815	26.2135
OLS	2.575600e+01	2.572530e+01	25.7954	25.8320
ScoreOptE	2.556640e+01	2.558830e+01	25.4857	25.5465
ScoreOptEIn	2.586070e+01	2.586460e+01	25.7647	25.7809
ScoreOptV	NA	NA	NA	NA
ScoreOptVIn	NA	NA	NA	NA
WLS	2.611930e+01	2.610100e+01	26.1712	26.2166

independent_bootstrap

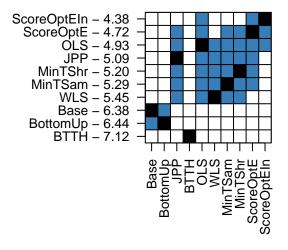
independent_gaussian





joint_bootstrap

joint_gaussian



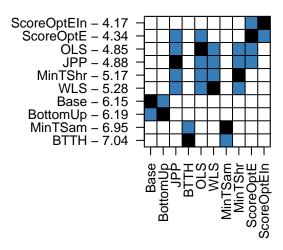


Figure 2: Nemenyi matrix for ets modelling with a nongaussian stationary DGP