Results Summary

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19 June 2020

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

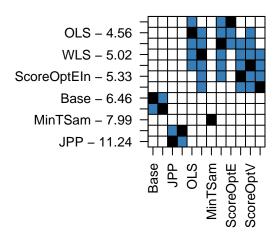
- Base: Not a reconciliation method, just the base forecasts.
- BottomUp: Bottom up
- BTTH: Ben Taieb, Taylor Hyndman (2020). This is like bottom up but reorders a sample from probabilistic forecast to match the empirical copula. Also the mean is adjusted to be the same as that from MinT reconciliation.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

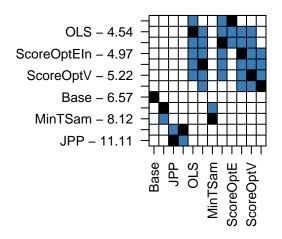
Table 1: Mean energy score for ets modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	1.4338	1.4415	1.4044	1.4102
BottomUp	1.5209	1.5454	1.4851	1.4918
BTTH	2.8329	3.0036	2.8479	2.9964
JPP	2.8966	3.0012	2.8946	2.9812
MinTSam	9549.5512	10361.1522	1.3577	2.1308
MinTShr	1.3717	1.3709	1.3548	1.3617
OLS	1.3702	1.3692	1.3463	1.3532
ScoreOptE	1.3335	1.3362	1.3349	1.3353
ScoreOptEIn	1.4063	1.3928	1.3896	1.3801
ScoreOptV	1.3789	1.3798	1.3769	1.3780
ScoreOptVIn	1.4193	1.4073	1.3976	1.3864
WLS	1.3943	1.3929	1.3733	1.3804

$independent_bootstrap$

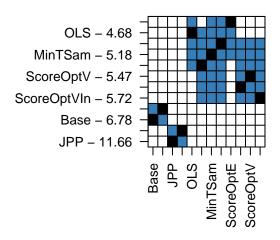
independent_gaussian





joint_bootstrap

joint_gaussian



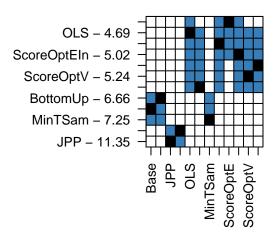


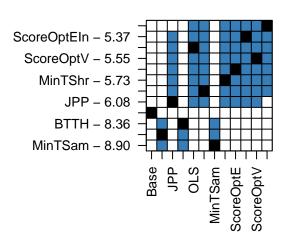
Figure 1: Nemenyi matrix for ets modelling with a nongaussian stationary DGP using energy score

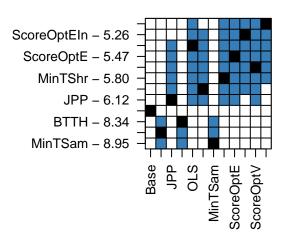
Table 2: Mean variogram score for ets modelling with a nongaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	2.664410e+01	2.664430e+01	26.6378	26.6486
BottomUp	2.886960e+01	2.915230e+01	28.0786	28.1394
BTTH	3.078800e+01	3.081620e+01	30.8897	30.7478
JPP	2.658730e+01	2.658310e+01	26.5765	26.5836
MinTSam	2.086405e+11	2.238422e+11	26.2167	62.9463
MinTShr	2.609710e+01	2.606120e+01	26.1742	26.1943
OLS	2.575310e+01	2.572330e+01	25.7866	25.8106
ScoreOptE	2.554990e+01	2.559720e+01	25.4823	25.5340
ScoreOptEIn	2.585230e+01	2.586310e+01	25.7588	25.7755
ScoreOptV	2.549810e+01	2.548800e+01	25.3794	25.3635
ScoreOptVIn	2.579940e+01	2.577680e+01	25.8063	25.8064
WLS	2.611100e+01	2.609450e+01	26.1605	26.1931

independent_bootstrap

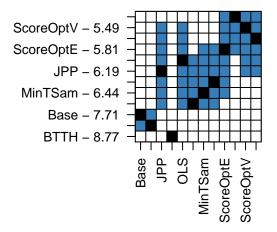
independent_gaussian





joint_bootstrap

joint_gaussian



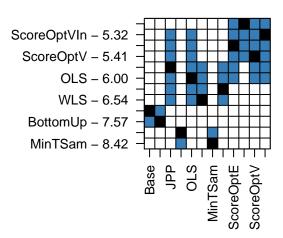


Figure 2: Nemenyi matrix for ets modelling with a nongaussian stationary DGP using variogram score