# Results Summary

#### Anastasios Panagiotelis

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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

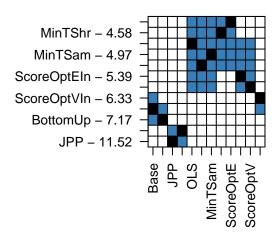
- Base: Not a reconciliation method, just the base forecasts.
- BottomUp: Bottom up
- BTTH: Ben Taieb, Taylor Hyndman (2020). This is like bottom up but reorders a sample from probabilistic forecast to match the empirical copula. Also the mean is adjusted to be the same as that from MinT reconciliation.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

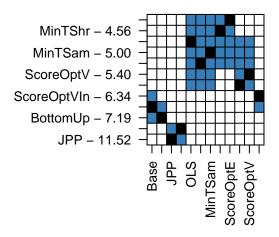
Table 1: Mean energy score for ets modelling with a gaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	11.8029	11.7944	11.6020	11.5894
BottomUp	12.4636	12.4589	12.2062	12.1913
BTTH	23.9131	23.9062	23.9773	23.9974
JPP	23.4044	23.4454	23.3905	23.4225
MinTSam	11.0003	10.9941	10.8019	10.7919
MinTShr	10.9546	10.9480	10.7904	10.7810
OLS	11.1773	11.1669	10.9297	10.9228
ScoreOptE	10.8394	10.8326	10.8630	10.8403
ScoreOptEIn	11.2965	11.2917	11.2078	11.2050
ScoreOptV	11.2269	11.2238	11.0378	11.0269
ScoreOptVIn	11.6515	11.6505	11.4468	11.4476
WLS	11.2180	11.2106	11.0179	11.0107

#### independent\_bootstrap

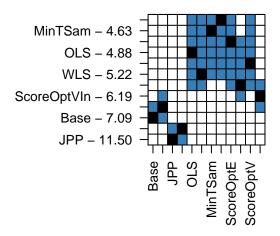
# independent\_gaussian





#### joint\_bootstrap

### joint\_gaussian



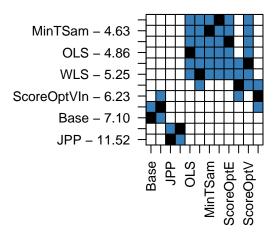


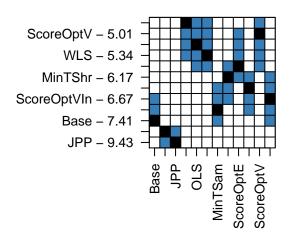
Figure 1: Nemenyi matrix for ets modelling with a gaussian stationary DGP using energy score

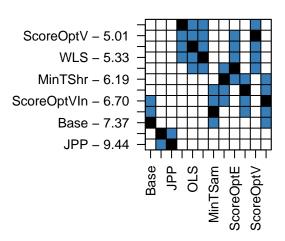
Table 2: Mean variogram score for ets modelling with a gaussian stationary DGP

Method	independent_bootstrap	independent_gaussian	joint_bootstrap	joint_gaussian
Base	781.5098	780.9110	781.1336	781.0773
BottomUp	908.9779	910.2198	716.6146	716.4197
BTTH	643.3761	643.1271	643.4658	643.8445
JPP	1071.0689	1076.1639	1070.4064	1076.2384
MinTSam	732.2974	732.2618	684.1331	684.1004
MinTShr	711.4874	711.3019	684.2597	684.2609
OLS	706.8968	706.3115	691.2450	691.4008
ScoreOptE	690.5846	690.8687	686.4487	686.0868
ScoreOptEIn	783.6844	783.2156	797.4270	797.4903
ScoreOptV	680.4307	680.0718	680.4983	679.8902
ScoreOptVIn	802.2754	801.6217	814.9090	815.0333
WLS	706.3804	705.9445	689.0093	689.3052

#### independent\_bootstrap

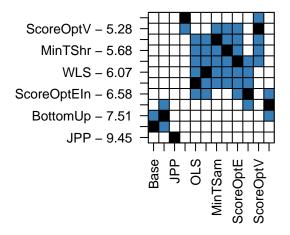
#### independent\_gaussian





## joint\_bootstrap

# joint\_gaussian



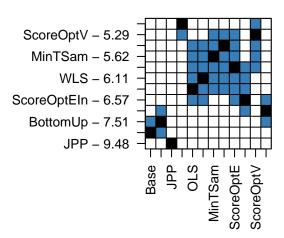


Figure 2: Nemenyi matrix for ets modelling with a gaussian stationary DGP using variogram score