TASCT: TEMPORAL–SPECTRAL ADAPTATION AND SHAPE CALIBRATION FOR TIME SERIES FORECASTING

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Paper under double-blind review

ABSTRACT

We introduce Temporal–Spectral Adaptation and Shape Calibration for Time Series Forecasting (TASCT), which combines temporal–spectral input adaptation with level-preserving forecast calibration. Its Temporal–Spectral Adapter (TSA) combines centered temporal and spectral corrections, preserving the historical mean. Its Level-Preserving Calibrator (LPC) combines centered contextual and consistency corrections, preserving the pre-calibration forecast mean. Across five backbones, seven datasets, and four forecasting horizons, TASCT improves three-seed mean MSE in 130 of 140 settings, with an average relative reduction of 4.17%. Experiments with LIFT and CCM further show that TASCT can provide additional gains on top of existing forecasting plugins. These results demonstrate individual and combined gains from input adaptation and output calibration.

1 INTRODUCTION

Multivariate time-series forecasting is a fundamental problem in a wide range of real-world applications, including energy systems, weather monitoring, and financial analysis. Recent years have witnessed substantial progress in forecasting architectures through more efficient attention, series decomposition, and patch-based temporal representations (Zhou et al., 2021; Wu et al., 2021; Nie et al., 2023; Zeng et al., 2023). Subsequent work has further advanced forecasting through multi-scale modeling, channel dependency modeling, adaptive filtering, and non-stationarity-aware representations (Wang et al., 2024; Hu et al., 2025; Qiu et al., 2025; Liu et al., 2025a).

A complementary direction enhances existing forecasters through plug-and-play modules that exploit lead–lag relationships, channel clustering, and graph-spectral dependency routing (Zhao & Shen, 2024; Chen et al., 2024; Li et al., 2026). These approaches primarily improve forecasting by exploiting dependencies across channels. Beyond these dependencies, we investigate how adapting historical temporal patterns and correcting forecast trajectories can enhance existing backbones.

Weather–MixLinear diagnostics associate local input variability with error and identify probe-correctable residual shape information, providing observational motivation (Section 4.1). We propose **TASCT**, which organizes forecast correction around complementary temporal views and mean-preserving residual updates. Its **Temporal–Spectral Adapter (TSA)** combines multi-scale temporal and frequency-grouped corrections to adapt historical inputs while preserving their mean. Its **Level-Preserving Calibrator (LPC)** uses context and cross-origin consistency to refine forecast shape through zero-mean corrections, preserving each channel's forecast mean. The modules integrate with existing backbone architectures, with TSA trained jointly with the backbone and LPC fitted afterward.

Across five backbones and seven datasets, TSA and LPC each improve forecasting accuracy on average, and their combination yields larger average gains than either module alone.

Our main contributions are summarized as follows:

- We develop multi-scale temporal and frequency-grouped input corrections with contextual and consistency-based forecast calibration, preserving historical and forecast means through centered residual updates.

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- Single-branch advantages vary by backbone, while their combination outperforms either branch in all nine evaluated backbone–dataset groups by four-horizon mean MSE. Level-preserving calibration adds further gains.
- Three-seed experiments across five backbones, seven datasets, and four horizons quantify accuracy and cost, with further MSE reductions on top of both LIFT and CCM.

2 Related Work

Input Adaptation and Forecast Revision. Prior work enhances forecasters through adaptive normalization (Fan et al., 2023; Liu et al., 2023; Ye et al., 2024), context-based post-hoc revision (Liu et al., 2025b), and output alignment (Park et al., 2025); δ-Adapter (Liang et al., 2026) learns input and output adjustments around a frozen forecaster. Within this line of work, TASCT combines multiscale temporal and grouped spectral input corrections with centered contextual and consistency-based output corrections, preserving historical and forecast means, respectively. This design links temporal–spectral input adaptation to level-preserving trajectory correction. Appendix G includes a supplementary comparison with δ-Adapter.

Channel Modeling in Multivariate Forecasting. Channel-independent (CI) models predict each variate from its own history, optionally with covariates, without directly mixing target channels: DLinear uses decomposition-based linear mappings (Zeng et al., 2023), PatchTST learns patch-based temporal representations (Nie et al., 2023), and TiDE employs a dense encoder–decoder (Das et al., 2023). MixLinear combines segment-based temporal modeling with low-rank spectral filtering in a compact channel-independent architecture (Ma et al., 2026). Model parameters may still be shared across channels. Channel-dependent (CD) models instead exploit interactions among variates. Crossformer couples cross-time and cross-dimension attention (Zhang & Yan, 2023), iTransformer attends over variate tokens (Liu et al., 2024), and TimeBridge combines short-term intra-variate modeling with long-term cross-variate cointegration (Liu et al., 2025a).

Beyond a fixed choice between CI and CD, other approaches make channel processing configurable or selectively determine which dependencies to retain. TimeMixer supports both channel-independent and channel-dependent configurations within its multiscale mixing framework (Wang et al., 2024). DUET combines temporal clustering with channel soft clustering (Qiu et al., 2025), while TimeFilter selects patch-specific spatial–temporal dependencies through graph filtration (Hu et al., 2025). Crisp uses spectral priors and sparse attention to restrict interactions between variables with incompatible oscillatory patterns (Wang et al., 2026).

Forecasting Enhancement Strategies. LIFT (Zhao & Shen, 2024) captures time-varying cross-channel lead–lag relationships by dynamically selecting leading indicators and aligning them with the target channel to refine backbone predictions. CCM (Chen et al., 2024) learns similarity-guided channel assignments and cluster prototypes, and employs cluster-aware feed-forward layers to balance shared patterns and channel heterogeneity. PCD (Lee et al., 2026) modulates Transformer attention with channel masks that combine inter-channel similarity and learnable dataset-specific parameters. xCPD (Li et al., 2026) constructs a graph over channel–patch representations derived from backbone predictions, and uses a shared graph Fourier basis to guide spectral grouping and frequency-specific expert routing. TASCT complements these channel-focused approaches through within-channel temporal adaptation.

3 Preliminaries

Problem Formulation. Given a multivariate historical window $\mathbf{X} \in \mathbb{R}^{L \times C}$, where L denotes the lookback length and C the number of channels, multivariate time-series forecasting aims to predict the subsequent H observations $\mathbf{Y} \in \mathbb{R}^{H \times C}$. A forecasting backbone f_θ, parameterized by θ, maps the historical window to a forecast:

$$\widehat{\mathbf{Y}} = f_\theta(\mathbf{X}). \tag{1}$$

We denote the historical observations and future targets of channel c by $\mathbf{x}_c \in \mathbb{R}^L$ and $\mathbf{y}_c \in \mathbb{R}^H$, respectively. For clarity, we omit the batch dimension throughout.

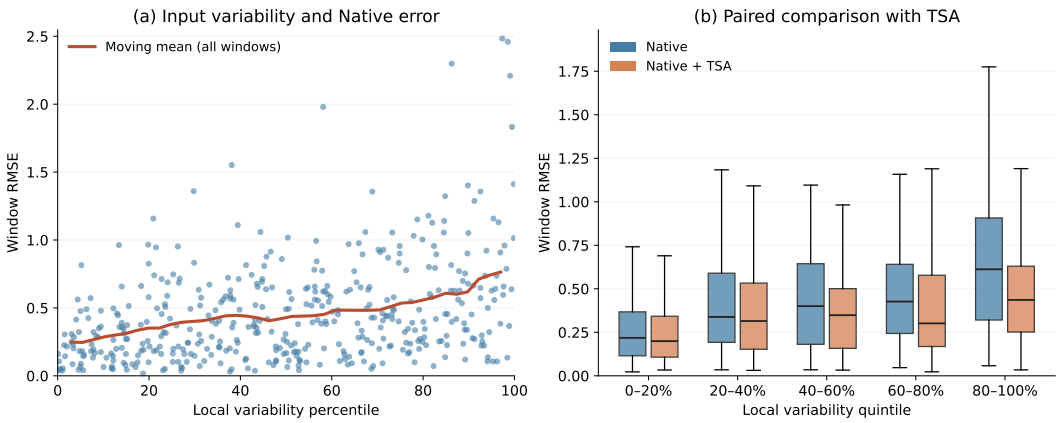

Figure 1: Local input variability and forecasting error on Weather's pressure channel (MixLinear, $L = 192$, $H = 96$). Left: native RMSE with a moving-average trend. Right: RMSE distributions before and after TSA across variability quintiles.

4 METHOD

4.1 MOTIVATION

We examine how local temporal structure relates to forecasting errors at two stages: the historical context presented to a backbone and the forecast trajectory it produces. For the diagnostics, we use MixLinear (Ma et al., 2026), whose compact architecture and computational efficiency make it a practical backbone for a series of controlled analyses.

4.1.1 LOCAL INPUT VARIABILITY AND FORECASTING ERROR

Historical windows of the same length can differ substantially in local variability. To examine how this variation relates to forecasting error, we analyze MixLinear on Weather with $L = 192$ and $H = 96$. After channel-wise standardization using training-set statistics, we quantify each window's local variability as the square root of the mean variance of two overlapping 128-step segments:

$$v_{i,c} = \sqrt{\frac{\mathrm{Var}_0(\mathbf{x}_{i,c}[1{:}128]) + \mathrm{Var}_0(\mathbf{x}_{i,c}[65{:}192])}{2}}, \tag{2}$$

where i indexes windows, c indexes channels, and Var_0 denotes population variance. We rank test windows by this measure within each channel and evaluate their forecast RMSE, both continuously and across five equal-percentile groups.

Figure 1(a) shows that average forecasting error increases with local input variability for the pressure channel. The Native distributions in Figure 1(b) further reveal higher median errors and a wider spread in the highest-variability group. This descriptive association motivates adapting historical inputs before forecasting. Figure 1(b) compares Native and TSA on the same test windows within each variability group, providing a paired view of their error distributions. Appendix D extends this comparison to all 21 Weather channels.

Table 1: Weather test shape error (MixLinear, $L = 192$, $H = 96$); gains over Native.

Seed	Native	Intercept only	Linear probe	Probe gain
2027	0.096891	0.096901	0.094320	2.65%
2026	0.096707	0.096717	0.094340	2.45%
2025	0.096369	0.096379	0.094372	2.07%
Mean	0.096656	0.096666	0.094344	2.39%

4.1.2 STRUCTURED RESIDUAL ERRORS IN FORECASTS

Do forecast residuals retain temporal structure that can be corrected after prediction? To isolate trajectory errors from level offsets, we decompose MSE over N windows and C channels into

$$E_{\text{level}} = \frac{1}{NC}\sum_{i,c}(\bar{\hat{Y}}_{i,c} - \bar{Y}_{i,c})^2,$$
$$E_{\text{shape}} = \frac{1}{NCH}\sum_{i,c,h}\left[(\hat{Y}_{i,h,c} - \bar{\hat{Y}}_{i,c}) - (Y_{i,h,c} - \bar{Y}_{i,c})\right]^2, \tag{3}$$

where bars denote temporal means and $\text{MSE} = E_{\text{level}} + E_{\text{shape}}$.

Using frozen MixLinear forecasts on Weather, we fit a shared linear probe on validation data to predict mean-centered residuals from 16 pooled forecast features. An intercept-only control instead applies a shared, lead-dependent correction estimated from mean validation residuals. Across three seeds, the probe reduces test shape error by 2.39% on average, while the control leaves it virtually unchanged (Table 1). The probe provides setting-specific motivation for shape calibration, rather than a direct test of LPC; its gains vary across temporal segments (Appendix C).

4.2 FRAMEWORK OVERVIEW

TASCT consists of two complementary components around a forecasting backbone (Figure 2): a Temporal–Spectral Adapter (TSA), which adapts historical inputs through temporal and spectral corrections, and a Level-Preserving Calibrator (LPC), which refines the resulting forecast shape while preserving its temporal mean. Given a historical window $\mathbf{X}$, the prediction process is

$$\widetilde{\mathbf{X}} = \mathbf{X} + \Delta_{\text{TSA}}(\mathbf{X}), \qquad \widehat{\mathbf{Y}} = f_\theta(\widetilde{\mathbf{X}}), \qquad \widetilde{\mathbf{Y}} = \widehat{\mathbf{Y}} + \Delta_{\text{LPC}}. \tag{4}$$

TSA preserves the mean of $\mathbf{X}$; LPC preserves that of $\widehat{\mathbf{Y}}$. The backbone's predicted level can still respond to adapted inputs.

4.3 TEMPORAL–SPECTRAL ADAPTER

TSA adapts historical inputs through multi-scale temporal correction (the temporal branch) and frequency-grouped correction (the spectral branch). For each channel, we first normalize the histor-

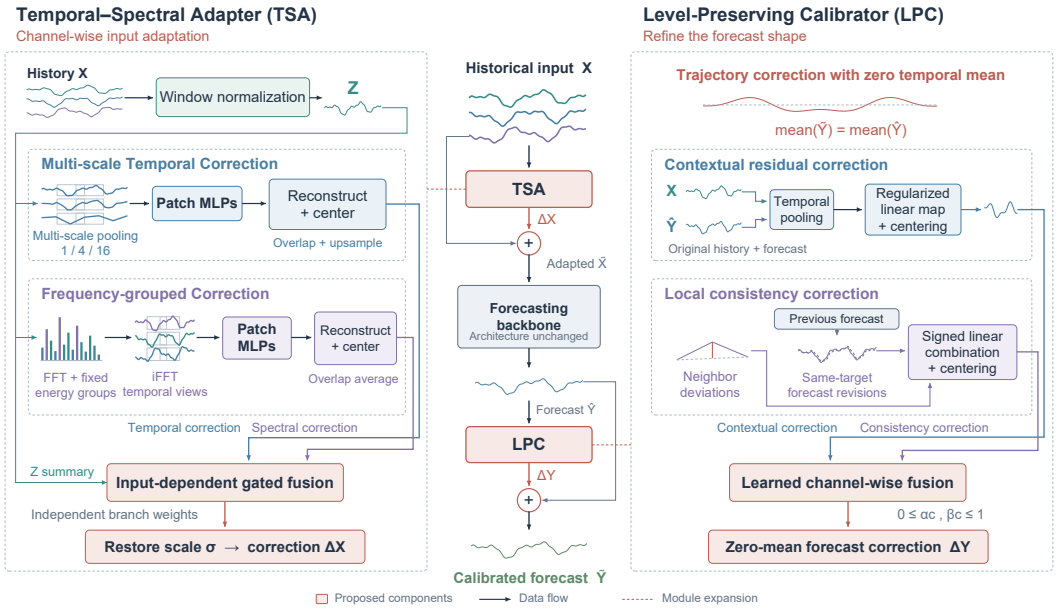

Figure 2: TASCT overview: TSA adapts inputs; LPC calibrates forecasts.

ical window using its temporal mean μ_c and stabilized standard deviation σ_c:

$$\mathbf{Z}_{:,c} = \frac{\mathbf{X}_{:,c} - \mu_c}{\sigma_c}, \qquad \sigma_c = \sqrt{\mathrm{Var}(\mathbf{X}_{:,c}) + \epsilon}. \tag{5}$$

Two parallel branches map $\mathbf{Z}$ to temporal correction $\mathbf{D}^{\mathrm{loc}}$ and spectral correction $\mathbf{D}^{\mathrm{freq}} \in \mathbb{R}^{L\times C}$. Each correction is centered along the temporal dimension before fusion. The adapted input is

$$\widetilde{\mathbf{X}}_{:,c} = \mathbf{X}_{:,c} + \sigma_c \left(g_c^{\mathrm{loc}} \mathbf{D}^{\mathrm{loc}}_{:,c} + g_c^{\mathrm{freq}} \mathbf{D}^{\mathrm{freq}}_{:,c} \right), \tag{6}$$

where the two gate weights depend on the current window and channel. This residual formulation preserves the historical mean and restores corrections to the original input scale. Window standardization is internal to the correction branches: the backbone receives $\widetilde{\mathbf{X}}$, not $\mathbf{Z}$, and zero correction recovers its original input exactly. The backbone's own normalization remains unchanged.

Multi-scale Temporal Correction. We average-pool $\mathbf{Z}$ at multiple temporal scales and divide each pooled sequence into overlapping patches. A scale-specific two-layer MLP transforms each patch into a local correction, with parameters shared across channels and patch positions. We average overlapping outputs and linearly upsample each scale to length L before aggregation:

$$\mathbf{D}^{\mathrm{loc}} = \mathcal{C}\left[\frac{1}{\sqrt{|\mathcal{S}|}} \sum_{s\in\mathcal{S}} \mathcal{U}_s \mathcal{O}_s \phi_s \big(\mathcal{P}_s \mathcal{A}_s(\mathbf{Z}) \big) \right], \tag{7}$$

where $\mathcal{A}$, $\mathcal{P}$, $\mathcal{O}$, and $\mathcal{U}$ denote average pooling, patch extraction, overlap averaging, and upsampling, respectively; $\mathcal{C}$ removes the temporal mean. Pooling changes the temporal span covered by a patch, allowing the branch to adjust both fine and coarse local patterns.

Frequency-grouped Correction. We partition Fourier bins into K disjoint groups using training-set spectral energy and hold the partition fixed. For each binary mask $\mathbf{M}_k$, we reconstruct a temporal view $\mathbf{V}_k = \mathcal{F}^{-1}(\mathbf{M}_k \odot \mathcal{F}(\mathbf{Z}))$, where the transform acts along time and the masks are shared across channels. A group-specific patch MLP ψ_k learns corrections from each reconstructed view:

$$\mathbf{D}^{\mathrm{freq}} = \mathcal{C}\left[\frac{1}{\sqrt{K}} \sum_{k=1}^{K} \mathcal{O}_{\mathrm{f}} \psi_k \big(\mathcal{P}_{\mathrm{f}} \mathbf{V}_k \big) \right]. \tag{8}$$

The learned transformations operate on reconstructed time-domain patches at the original temporal resolution. Together, the two branches organize historical variation by temporal span and oscillatory component, providing complementary views for input adaptation.

Gated fusion. For each channel, we concatenate pooled summaries of the normalized history and both corrections into $\mathbf{u}_c$. A shared MLP predicts bounded adjustments to a learned static anchor $\mathbf{a}_c$:

$$\mathbf{g}_c = \mathrm{clip}_{[\ell,u]} \left(\mathbf{a}_c + \rho \tanh\big(h_\eta(\mathbf{u}_c)\big) \right). \tag{9}$$

Here ρ bounds the window-dependent offset from the static anchor, and $[\ell, u]$ bounds each weight; the weights need not sum to one. We first learn zero-initialized branch corrections jointly with the backbone under equal mixing, then freeze both to fit static anchors followed by the dynamic gate with an energy-weighted penalty. This separates correction learning from learning how to weight the fixed corrections for each window. Implementation details, including branch configurations, backbone normalization, and gate fitting, are provided in Appendix A.

4.4 Level-Preserving Calibrator

LPC corrects forecast trajectories after the backbone has been trained. It combines a contextual residual correction $\mathbf{D}^{\mathrm{ctx}}$ with a local consistency correction $\mathbf{D}^{\mathrm{con}}$:

$$\widetilde{\mathbf{Y}}_{:,c} = \widehat{\mathbf{Y}}_{:,c} + \alpha_c \mathbf{D}^{\mathrm{ctx}}_{:,c} + \beta_c \mathbf{D}^{\mathrm{con}}_{:,c}, \tag{10}$$

where $\alpha_c, \beta_c \in [0, 1]$ are channel-wise fusion parameters learned from calibration data. Both corrections have zero temporal mean, ensuring that LPC preserves the overall prediction level.

Contextual residual correction. We pool the original historical window $\mathbf{X}$ and current backbone forecast $\widehat{\mathbf{Y}}$ into compact temporal representations and fit a regularized linear mapping to the mean-centered forecast residual. Four chronological block fits determine direction-wise shrinkage from their disagreement with the pooled ridge fit (Appendix A), yielding an input-dependent trajectory correction.

Local consistency correction. Let $\widehat{Y}_{h,c}^{(t)}$ denote the backbone forecast at origin t, with consecutive origins one time step apart. For interior leads $h = 5, \ldots, H-4$, we define a neighborhood deviation and a same-target revision:

$$U_{h,c}^{(t)} = \frac{1}{2}\left(\frac{\widehat{Y}_{h-1,c}^{(t)} + \widehat{Y}_{h+1,c}^{(t)}}{2} - \widehat{Y}_{h,c}^{(t)}\right), \qquad V_{h,c}^{(t)} = \frac{1}{2}\left(\widehat{Y}_{h+1,c}^{(t-1)} - \widehat{Y}_{h,c}^{(t)}\right). \tag{11}$$

The fixed four-lead boundary margin is shared by both signals; their raw corrections are zero there before temporal centering. Signed channel-wise coefficients combine them into $\mathbf{D}_{:,c}^{\mathrm{con}} = \mathcal{C}\big(\gamma_c \mathbf{U}_{:,c} + \delta_c \mathbf{V}_{:,c}\big)$, allowing local variation to be strengthened or attenuated according to calibration evidence. The rolling state stores the preceding backbone forecast before LPC calibration, so the revision compares predictions for the same target time. Unlike AliO's training-time alignment loss (Park et al., 2025), this difference is a signed calibration feature, not an agreement penalty on the backbone. At the first origin, $\mathbf{V}$ is initialized to zero; subsequent origins use the stored forecast.

Calibration. With the forecasting pipeline fixed, we fit the correction branches on validation data and estimate their fusion weights using predictions from chronological held-out calibration blocks. The fitted calibrator is then fixed for test evaluation. This separates output calibration from backbone training and allows LPC to operate on either native or TSA-adapted forecasts.

5 Experiments

5.1 Experimental Setup

Datasets and evaluation. Our evaluation protocol covers seven multivariate forecasting benchmarks: ETTh1, ETTh2, ETTm1, ETTm2, Weather, Solar, and Electricity. We use chronological training/validation/test splits of 12/4/4 months for ETT and 70%/10%/20% for the remaining datasets. Each channel is standardized using training-set statistics. We fix the lookback length to $L = 192$ and consider forecasting horizons $H \in \{96, 192, 336, 720\}$. Performance is measured by MSE and MAE in standardized units, averaged over test windows, forecast steps, and channels. The protocol uses three random seeds: 2025, 2026, and 2027.

Backbones and comparisons. We consider five backbones spanning linear, MLP-based, and Transformer-based architectures: DLinear (Zeng et al., 2023), MixLinear (Ma et al., 2026), PatchTST (Nie et al., 2023), TimeMixer (Wang et al., 2024), and TimeBridge (Liu et al., 2025a). For each backbone, we compare four variants: Native, Native + TSA, Native + LPC, and the complete TASCT framework. Our evaluation focuses on plugin gains within each backbone under a shared input budget, using matched configurations for each comparison. Lookback length affects performance and model rankings (Abdelmalak et al., 2026), while published protocols differ: TimeMixer uses $L = 96$ (Wang et al., 2024) and MixLinear $L = 720$ (Ma et al., 2026). We therefore retrain Native at $L = 192$ with the same predictive objective as its TSA-augmented counterpart and use the resulting matched baseline as the reference for measuring gains.

We evaluate complementarity with LIFT (Zhao & Shen, 2024) and CCM (Chen et al., 2024) on DLinear and PatchTST. We apply TSA, LPC, and their combination to each enhanced forecaster and measure the additional gains. Implementation details are provided in Appendix B. We also considered xCPD (Li et al., 2026), but its complete official implementation was unavailable at the time of writing.

Training and calibration. Native and TSA-augmented models share the predictive objective $0.5\,\mathrm{MSE} + 0.5\,\mathrm{MAE}$, with an additional correction-energy regularizer for TSA. Within each pair, backbone configurations and random seeds are matched, while TSA uses a separate optimizer parameter group. Training budgets, learning-rate schedules, and checkpoint criteria follow backbone- and dataset-specific recipes. Following joint training, the static and dynamic gates are fitted sequentially for eight epochs each with the backbone and TSA branches frozen. LPC is subsequently fitted using the final 75% of the validation interval. Validation data support checkpoint selection and calibration, and the resulting models are fixed for test evaluation.

5.2 Main Results

Table 2 summarizes results across five backbones, seven datasets, and four forecasting horizons. TASCT reduces MSE in 130 of 140 settings and MAE in 123, with average reductions of 4.17% and 2.34%, respectively. Each setting uses the mean over three seeds, and relative reductions are averaged equally across settings. Appendix H provides detailed per-seed results.

The largest gains occur on MixLinear and DLinear. Their average MSE reductions reach 8.40% and 6.15%, alongside MAE reductions of 4.86% and 3.19%. Solar shows particularly strong gains, averaging 13.09% in MSE across the five backbones and four horizons. On Electricity, TASCT improves both metrics in all 20 backbone–horizon combinations. The benefits also extend to PatchTST, TimeMixer, and TimeBridge, with MSE improvements in 27, 25, and 24 of their 28 settings, respectively. Native PatchTST already uses RevIN (Kim et al., 2022), unchanged with TSA (Appendix A); these gains are additional to its existing normalization.

Table 2: Forecasting results: three-seed means; bold indicates the better result in each pair.

Backbone		DLinear				MixLinear				PatchTST				TimeMixer				TimeBridge			
Variant		Native		+TASCT		Native		+TASCT		Native		+TASCT		Native		+TASCT		Native		+TASCT	
Data	H	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	0.386	0.402	**0.375**	**0.397**	0.376	**0.388**	**0.369**	0.390	0.388	0.405	**0.382**	**0.403**	0.380	0.398	**0.374**	**0.393**	0.374	0.397	**0.365**	**0.392**
	192	0.442	0.441	**0.430**	**0.437**	0.424	**0.417**	**0.420**	0.418	0.433	0.429	**0.429**	**0.428**	0.430	0.425	**0.427**	**0.423**	0.451	0.444	**0.428**	**0.433**
	336	0.470	0.457	**0.462**	**0.454**	0.458	0.436	**0.451**	**0.435**	0.462	0.444	**0.454**	**0.442**	0.477	0.455	**0.467**	**0.448**	0.493	0.467	**0.472**	**0.456**
	720	0.516	0.515	**0.511**	**0.514**	**0.432**	**0.443**	0.441	0.448	0.460	0.466	**0.457**	**0.466**	**0.488**	**0.483**	0.507	0.494	0.590	0.527	**0.545**	**0.508**
ETTh2	96	0.312	0.365	**0.293**	**0.349**	0.301	0.345	**0.284**	**0.337**	0.286	0.340	**0.285**	**0.338**	0.293	0.347	**0.289**	**0.344**	0.302	0.351	**0.298**	**0.347**
	192	0.378	0.406	**0.365**	**0.397**	0.370	0.390	**0.357**	**0.383**	0.360	0.387	**0.357**	**0.385**	0.365	0.392	**0.362**	**0.389**	0.362	0.394	**0.362**	**0.390**
	336	0.445	0.455	**0.438**	**0.454**	0.396	0.415	**0.391**	**0.414**	0.390	**0.414**	**0.390**	0.414	0.394	0.417	**0.392**	**0.416**	**0.394**	0.419	0.395	**0.417**
	720	0.589	0.540	**0.586**	**0.540**	0.407	**0.431**	**0.405**	0.432	0.407	0.434	**0.406**	**0.434**	0.422	0.443	**0.416**	**0.439**	**0.410**	0.436	0.410	**0.436**
ETTm1	96	0.304	0.342	**0.300**	**0.341**	0.314	0.350	**0.300**	**0.344**	0.304	0.343	**0.295**	**0.342**	0.292	0.341	**0.286**	**0.336**	0.291	0.337	**0.291**	**0.335**
	192	0.341	**0.365**	**0.338**	0.366	0.351	0.370	**0.337**	**0.367**	0.343	0.366	**0.333**	**0.364**	0.340	0.371	**0.333**	**0.366**	0.339	0.366	**0.333**	**0.364**
	336	0.376	**0.386**	**0.373**	0.388	0.393	0.397	**0.367**	**0.388**	0.379	0.387	**0.364**	**0.386**	0.365	0.388	**0.364**	**0.388**	0.373	**0.390**	**0.366**	0.390
	720	**0.437**	**0.427**	0.440	0.432	0.452	0.431	**0.426**	**0.425**	0.438	0.422	**0.424**	**0.421**	**0.427**	**0.426**	0.427	0.427	0.432	0.425	**0.427**	**0.425**
ETTm2	96	0.172	0.261	**0.169**	**0.257**	0.182	0.266	**0.170**	**0.254**	0.167	0.251	**0.167**	**0.251**	0.172	0.254	**0.168**	**0.251**	0.170	0.252	**0.168**	**0.250**
	192	0.235	0.305	**0.229**	**0.300**	0.242	0.305	**0.231**	**0.295**	**0.228**	**0.291**	0.228	0.292	0.232	0.294	**0.227**	**0.291**	0.235	0.296	**0.232**	**0.293**
	336	0.318	0.370	**0.300**	**0.360**	0.297	0.341	**0.283**	**0.331**	0.283	0.329	**0.280**	**0.328**	0.280	0.328	**0.278**	**0.326**	0.288	0.334	**0.284**	**0.330**
	720	0.430	0.439	**0.414**	**0.431**	0.395	0.397	**0.375**	**0.387**	0.378	0.384	**0.371**	**0.384**	0.376	0.389	**0.368**	**0.383**	**0.382**	**0.393**	0.383	0.393
Solar	96	0.223	0.240	**0.179**	**0.221**	0.274	0.316	**0.193**	**0.245**	0.221	0.263	**0.187**	**0.241**	0.176	0.222	**0.173**	**0.214**	**0.174**	**0.213**	0.176	0.214
	192	0.263	0.260	**0.208**	**0.238**	0.306	0.292	**0.232**	**0.262**	0.253	0.284	**0.221**	**0.265**	0.201	0.239	**0.197**	**0.235**	0.200	0.236	**0.198**	**0.234**
	336	0.303	0.287	**0.228**	**0.253**	0.366	0.360	**0.262**	**0.301**	0.280	0.306	**0.243**	**0.276**	0.219	0.255	**0.211**	**0.248**	0.213	0.245	**0.208**	**0.243**
	720	0.305	0.291	**0.233**	**0.256**	0.382	0.376	**0.281**	**0.323**	0.276	0.298	**0.249**	**0.279**	0.222	0.257	**0.217**	**0.253**	0.217	0.248	**0.213**	**0.246**
Weather	96	0.182	0.232	**0.163**	**0.215**	0.192	0.235	**0.167**	**0.210**	0.178	0.219	**0.170**	**0.212**	0.152	0.195	**0.150**	**0.192**	0.156	**0.197**	**0.156**	0.197
	192	0.223	0.274	**0.205**	**0.258**	0.236	0.272	**0.210**	**0.249**	0.222	0.256	**0.214**	**0.251**	0.194	0.236	**0.193**	**0.234**	0.201	**0.238**	**0.200**	0.239
	336	0.270	0.317	**0.252**	**0.296**	0.286	0.308	**0.263**	**0.289**	0.273	0.293	**0.266**	**0.289**	0.249	0.278	**0.247**	**0.276**	0.256	0.279	**0.254**	**0.278**
	720	0.334	0.369	**0.322**	**0.355**	0.357	0.355	**0.339**	**0.341**	0.345	0.342	**0.339**	**0.339**	**0.327**	**0.331**	0.327	0.331	0.336	0.334	**0.334**	**0.334**
Electricity	96	0.152	0.246	**0.142**	**0.236**	0.161	0.251	**0.145**	**0.238**	0.178	0.281	**0.166**	**0.268**	0.137	0.230	**0.136**	**0.228**	0.140	0.230	**0.138**	**0.228**
	192	0.164	0.256	**0.157**	**0.250**	0.180	0.269	**0.161**	**0.251**	0.190	0.290	**0.180**	**0.280**	0.155	0.246	**0.154**	**0.245**	0.156	0.245	**0.154**	**0.244**
	336	0.180	0.275	**0.173**	**0.268**	0.197	0.286	**0.178**	**0.269**	0.207	0.305	**0.197**	**0.296**	0.173	0.264	**0.172**	**0.263**	0.174	0.263	**0.172**	**0.261**
	720	0.214	0.305	**0.207**	**0.300**	0.228	0.311	**0.216**	**0.300**	0.246	0.335	**0.238**	**0.328**	0.212	0.298	**0.210**	**0.296**	0.213	0.296	**0.211**	**0.295**

5.3 Ablation Study

Overall component ablation. Table 3 compares Native, TSA, LPC, and TSA+LPC across 140 equally weighted three-seed means. MSE/MAE reductions are 3.49%/1.94% for TSA, 1.15%/0.73% for LPC, and 4.17%/2.34% for TSA+LPC. TSA/LPC improve MSE in 120/140 and 139/140 settings, respectively. Each module contributes, with the combination achieving the largest average gains.

Input adaptation ablation. We compare TSA branches, gates, and a residual MLP on MixLinear, DLinear, and PatchTST across Weather, Solar, and Electricity at four horizons. By four-horizon MSE, temporal correction leads on linear backbones and spectral correction on PatchTST; full TSA beats both in all nine groups. By three-seed MSE, full TSA beats MLP/Temporal only in 36/36 settings and Spectral only in 35/36. Before gate fitting, TSA beats the approximately parameter-matched MLP in all nine groups with the same 16-epoch joint training. Gate fitting and subsequent LPC each improve MSE in all 36 settings. Together, the branches capture backbone-dependent strengths; gate fitting adds further gains (Appendix E).

Output calibration ablation. We compare LPC with and without its zero-mean constraint in 140 settings. Removing it lowers average MSE reduction from 1.15% to 1.05% and improvements over Native from 139/140 to 119/140 in MSE and 124/140 to 102/140 in MAE. Mean absolute forecast-level shift reaches 0.025 in standardized units. The constraint therefore preserves channel-wise forecast means and reduces degradation relative to Native, with accuracy gains varying across settings (Appendix F).

Table 3: Four-horizon ablations: three-seed mean$_{\pm \mathrm{SD}}$; bold: best mean per row.

Dataset	Backbone	Native		+TSA		+LPC		TSA+LPC	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	DLinear	$0.453_{\pm.013}$	$0.454_{\pm.010}$	$0.448_{\pm.014}$	$0.451_{\pm.011}$	$0.447_{\pm.012}$	$0.452_{\pm.009}$	$\mathbf{0.444}_{\pm.013}$	$\mathbf{0.450}_{\pm.010}$
	MixLinear	$0.422_{\pm.003}$	$0.421_{\pm.003}$	$0.422_{\pm.001}$	$\mathbf{0.421}_{\pm.001}$	$0.421_{\pm.002}$	$0.422_{\pm.002}$	$\mathbf{0.420}_{\pm.001}$	$0.423_{\pm.000}$
	PatchTST	$0.436_{\pm.003}$	$0.436_{\pm.002}$	$0.433_{\pm.004}$	$0.435_{\pm.003}$	$0.433_{\pm.002}$	$0.435_{\pm.002}$	$\mathbf{0.431}_{\pm.003}$	$\mathbf{0.435}_{\pm.002}$
	TimeMixer	$0.444_{\pm.002}$	$0.440_{\pm.001}$	$0.449_{\pm.015}$	$0.442_{\pm.008}$	$\mathbf{0.438}_{\pm.002}$	$\mathbf{0.437}_{\pm.001}$	$0.444_{\pm.016}$	$0.440_{\pm.009}$
	TimeBridge	$0.477_{\pm.018}$	$0.459_{\pm.008}$	$0.457_{\pm.011}$	$\mathbf{0.447}_{\pm.003}$	$0.473_{\pm.017}$	$0.459_{\pm.008}$	$\mathbf{0.452}_{\pm.012}$	$0.447_{\pm.003}$
ETTh2	DLinear	$0.431_{\pm.011}$	$0.442_{\pm.007}$	$0.429_{\pm.012}$	$0.441_{\pm.006}$	$0.424_{\pm.010}$	$0.437_{\pm.005}$	$\mathbf{0.420}_{\pm.009}$	$\mathbf{0.435}_{\pm.003}$
	MixLinear	$0.369_{\pm.001}$	$0.395_{\pm.000}$	$0.360_{\pm.001}$	$0.392_{\pm.001}$	$0.366_{\pm.001}$	$0.394_{\pm.000}$	$\mathbf{0.359}_{\pm.001}$	$\mathbf{0.391}_{\pm.001}$
	PatchTST	$0.361_{\pm.001}$	$0.394_{\pm.001}$	$0.360_{\pm.001}$	$0.393_{\pm.001}$	$\mathbf{0.359}_{\pm.001}$	$\mathbf{0.392}_{\pm.001}$	$0.359_{\pm.001}$	$0.393_{\pm.001}$
	TimeMixer	$0.368_{\pm.001}$	$0.400_{\pm.000}$	$0.367_{\pm.001}$	$0.399_{\pm.002}$	$0.366_{\pm.001}$	$0.398_{\pm.001}$	$\mathbf{0.365}_{\pm.001}$	$\mathbf{0.397}_{\pm.002}$
	TimeBridge	$0.367_{\pm.002}$	$0.400_{\pm.003}$	$0.369_{\pm.003}$	$0.400_{\pm.002}$	$\mathbf{0.364}_{\pm.002}$	$0.398_{\pm.003}$	$0.366_{\pm.003}$	$\mathbf{0.398}_{\pm.002}$
ETTm1	DLinear	$0.365_{\pm.000}$	$0.380_{\pm.001}$	$0.365_{\pm.001}$	$0.382_{\pm.001}$	$\mathbf{0.362}_{\pm.000}$	$\mathbf{0.380}_{\pm.001}$	$0.363_{\pm.001}$	$0.382_{\pm.001}$
	MixLinear	$0.378_{\pm.001}$	$0.387_{\pm.000}$	$0.363_{\pm.001}$	$0.384_{\pm.001}$	$0.371_{\pm.000}$	$0.383_{\pm.000}$	$\mathbf{0.357}_{\pm.001}$	$\mathbf{0.381}_{\pm.001}$
	PatchTST	$0.366_{\pm.000}$	$0.379_{\pm.001}$	$0.356_{\pm.001}$	$0.379_{\pm.001}$	$0.363_{\pm.000}$	$\mathbf{0.378}_{\pm.001}$	$\mathbf{0.354}_{\pm.000}$	$0.378_{\pm.001}$
	TimeMixer	$0.356_{\pm.001}$	$0.381_{\pm.001}$	$0.357_{\pm.000}$	$0.383_{\pm.002}$	$\mathbf{0.352}_{\pm.001}$	$\mathbf{0.378}_{\pm.001}$	$0.353_{\pm.001}$	$0.379_{\pm.002}$
	TimeBridge	$0.359_{\pm.002}$	$0.379_{\pm.001}$	$0.358_{\pm.001}$	$0.380_{\pm.001}$	$0.355_{\pm.002}$	$\mathbf{0.377}_{\pm.001}$	$\mathbf{0.354}_{\pm.001}$	$0.378_{\pm.001}$
ETTm2	DLinear	$0.289_{\pm.007}$	$0.344_{\pm.006}$	$0.286_{\pm.008}$	$0.342_{\pm.007}$	$0.280_{\pm.005}$	$0.338_{\pm.006}$	$\mathbf{0.278}_{\pm.007}$	$\mathbf{0.337}_{\pm.006}$
	MixLinear	$0.279_{\pm.000}$	$0.327_{\pm.000}$	$0.268_{\pm.001}$	$0.320_{\pm.001}$	$0.272_{\pm.000}$	$0.321_{\pm.000}$	$\mathbf{0.265}_{\pm.001}$	$\mathbf{0.317}_{\pm.001}$
	PatchTST	$0.264_{\pm.001}$	$0.314_{\pm.000}$	$0.262_{\pm.001}$	$0.314_{\pm.000}$	$0.264_{\pm.001}$	$0.314_{\pm.000}$	$\mathbf{0.261}_{\pm.001}$	$\mathbf{0.314}_{\pm.000}$
	TimeMixer	$0.265_{\pm.003}$	$0.316_{\pm.001}$	$0.262_{\pm.001}$	$0.314_{\pm.001}$	$0.263_{\pm.003}$	$0.315_{\pm.001}$	$\mathbf{0.260}_{\pm.001}$	$\mathbf{0.313}_{\pm.000}$
	TimeBridge	$0.269_{\pm.003}$	$0.319_{\pm.002}$	$0.268_{\pm.001}$	$0.318_{\pm.000}$	$0.267_{\pm.003}$	$0.317_{\pm.002}$	$\mathbf{0.267}_{\pm.001}$	$\mathbf{0.317}_{\pm.000}$
Solar	DLinear	$0.274_{\pm.000}$	$0.270_{\pm.001}$	$0.212_{\pm.001}$	$0.243_{\pm.002}$	$0.273_{\pm.000}$	$0.271_{\pm.001}$	$\mathbf{0.212}_{\pm.001}$	$\mathbf{0.242}_{\pm.001}$
	MixLinear	$0.332_{\pm.001}$	$0.336_{\pm.000}$	$0.246_{\pm.002}$	$0.290_{\pm.002}$	$0.307_{\pm.000}$	$0.306_{\pm.000}$	$\mathbf{0.242}_{\pm.002}$	$\mathbf{0.283}_{\pm.002}$
	PatchTST	$0.257_{\pm.005}$	$0.288_{\pm.002}$	$0.226_{\pm.004}$	$0.267_{\pm.004}$	$0.251_{\pm.005}$	$0.284_{\pm.007}$	$\mathbf{0.225}_{\pm.004}$	$\mathbf{0.265}_{\pm.003}$
	TimeMixer	$0.205_{\pm.003}$	$0.243_{\pm.003}$	$0.200_{\pm.001}$	$0.237_{\pm.002}$	$0.204_{\pm.002}$	$0.243_{\pm.004}$	$\mathbf{0.200}_{\pm.001}$	$\mathbf{0.237}_{\pm.002}$
	TimeBridge	$0.201_{\pm.001}$	$0.236_{\pm.002}$	$0.199_{\pm.001}$	$0.234_{\pm.002}$	$0.201_{\pm.001}$	$0.235_{\pm.002}$	$\mathbf{0.199}_{\pm.001}$	$\mathbf{0.234}_{\pm.002}$
Weather	DLinear	$0.252_{\pm.001}$	$0.298_{\pm.002}$	$0.236_{\pm.000}$	$\mathbf{0.281}_{\pm.000}$	$0.250_{\pm.001}$	$0.297_{\pm.002}$	$\mathbf{0.236}_{\pm.000}$	$0.281_{\pm.000}$
	MixLinear	$0.268_{\pm.001}$	$0.293_{\pm.001}$	$0.246_{\pm.001}$	$0.273_{\pm.000}$	$0.265_{\pm.000}$	$0.291_{\pm.001}$	$\mathbf{0.245}_{\pm.001}$	$\mathbf{0.272}_{\pm.001}$
	PatchTST	$0.254_{\pm.001}$	$0.278_{\pm.001}$	$0.248_{\pm.001}$	$0.273_{\pm.000}$	$0.253_{\pm.001}$	$0.277_{\pm.001}$	$\mathbf{0.247}_{\pm.001}$	$\mathbf{0.273}_{\pm.000}$
	TimeMixer	$0.231_{\pm.001}$	$0.260_{\pm.001}$	$0.230_{\pm.001}$	$0.259_{\pm.001}$	$0.230_{\pm.001}$	$0.259_{\pm.001}$	$\mathbf{0.229}_{\pm.001}$	$\mathbf{0.258}_{\pm.001}$
	TimeBridge	$0.237_{\pm.001}$	$0.262_{\pm.000}$	$0.237_{\pm.001}$	$0.262_{\pm.001}$	$0.237_{\pm.001}$	$\mathbf{0.262}_{\pm.000}$	$\mathbf{0.236}_{\pm.001}$	$0.262_{\pm.001}$
Electricity	DLinear	$0.178_{\pm.000}$	$0.271_{\pm.000}$	$0.170_{\pm.000}$	$0.264_{\pm.000}$	$0.177_{\pm.000}$	$0.271_{\pm.000}$	$\mathbf{0.170}_{\pm.000}$	$\mathbf{0.264}_{\pm.000}$
	MixLinear	$0.191_{\pm.004}$	$0.279_{\pm.004}$	$0.176_{\pm.001}$	$0.265_{\pm.001}$	$0.188_{\pm.003}$	$0.277_{\pm.003}$	$\mathbf{0.175}_{\pm.000}$	$\mathbf{0.265}_{\pm.001}$
	PatchTST	$0.205_{\pm.002}$	$0.303_{\pm.003}$	$0.198_{\pm.002}$	$0.295_{\pm.003}$	$0.200_{\pm.002}$	$0.298_{\pm.002}$	$\mathbf{0.195}_{\pm.002}$	$\mathbf{0.293}_{\pm.003}$
	TimeMixer	$0.170_{\pm.000}$	$0.260_{\pm.001}$	$0.168_{\pm.000}$	$0.258_{\pm.000}$	$0.169_{\pm.000}$	$0.259_{\pm.001}$	$\mathbf{0.168}_{\pm.000}$	$\mathbf{0.258}_{\pm.000}$
	TimeBridge	$0.171_{\pm.001}$	$0.259_{\pm.001}$	$0.169_{\pm.000}$	$0.258_{\pm.000}$	$0.170_{\pm.001}$	$0.258_{\pm.001}$	$\mathbf{0.169}_{\pm.000}$	$\mathbf{0.257}_{\pm.000}$

Table 4: Complementarity with CCM, averaged over four horizons (three seeds); SDs: Appendix G.

Backbone	DLinear								PatchTST							
Model	CCM		+TSA		+LPC		+TASCT		CCM		+TSA		+LPC		+TASCT	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	0.437	0.439	0.436	**0.439**	0.435	0.439	**0.434**	0.439	0.438	0.437	0.438	0.434	0.434	0.435	**0.432**	**0.432**
ETTh2	0.434	0.440	0.430	0.439	0.425	0.435	**0.422**	**0.434**	0.364	0.396	0.362	0.395	0.361	0.394	**0.359**	**0.393**
ETTm1	0.366	0.381	0.360	**0.376**	0.362	0.379	**0.357**	0.376	0.365	0.380	0.361	0.378	0.362	0.378	**0.356**	**0.375**
ETTm2	0.277	0.332	0.277	0.332	0.273	0.330	**0.273**	**0.330**	0.263	0.314	0.261	0.314	0.263	0.313	**0.260**	**0.313**
Solar	0.273	0.297	0.236	0.276	0.271	0.290	**0.233**	**0.272**	0.249	0.283	0.228	0.265	0.241	0.281	**0.227**	**0.262**
Weather	0.259	0.303	0.247	0.292	0.256	0.301	**0.245**	**0.291**	0.253	0.277	0.248	0.272	0.251	0.276	**0.246**	**0.271**
Electricity	0.202	0.296	0.194	0.286	0.187	0.282	**0.180**	**0.275**	0.199	0.294	0.186	0.280	0.194	0.288	**0.184**	**0.277**

Table 5: LIFT complementarity (four horizons, three seeds); details: Appendices G and I.

Backbone	DLinear								PatchTST							
Model	LIFT		+TSA		+LPC		+TASCT		LIFT		+TSA		+LPC		+TASCT	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	0.437	0.436	0.437	**0.435**	0.435	0.437	**0.435**	0.436	0.4562	0.441	0.462	0.444	**0.451**	**0.441**	0.4561	0.443
ETTh2	0.430	0.440	0.429	0.439	0.425	0.437	**0.424**	**0.437**	0.358	0.392	0.358	0.391	0.357	0.390	**0.356**	**0.390**
ETTm1	0.363	0.377	0.359	**0.375**	0.360	0.378	**0.356**	0.376	0.364	0.382	0.366	0.382	**0.362**	**0.380**	0.362	0.381
ETTm2	0.355	0.353	0.341	0.352	0.311	0.348	**0.306**	**0.347**	0.2671	0.316	0.271	0.319	**0.264**	**0.315**	0.2668	0.316
Solar	0.208	0.244	0.205	0.245	0.208	**0.244**	**0.205**	0.245	0.207	0.240	0.203	0.241	0.207	**0.240**	**0.203**	0.241
Weather	0.229	0.266	0.227	**0.264**	0.228	0.266	**0.226**	0.264	0.232	0.264	0.230	**0.262**	0.231	0.263	**0.229**	0.262
Electricity	0.167	0.258	0.165	**0.257**	0.167	0.258	**0.165**	0.257	0.171	0.263	0.169	0.261	0.170	0.262	**0.168**	**0.261**

5.4 Complementarity with Existing Forecasting Plugins

Tables 4 and 5 evaluate TSA, LPC, and their combination on frozen CCM and LIFT forecasters. All entries average three seeds (2027, 2026, 2025) and four horizons; Appendix B details the composition training and selection protocols. The full combination reduces dataset-averaged MSE on all seven datasets for both backbones with CCM and LIFT. These results support additional temporal correction as a complementary enhancement to the existing plugins. Appendix G also compares standalone enhancements. In the supplementary δ-Adapter comparison (Table 12), TASCT has lower MSE in 10 of 14 backbone–dataset averages and lower MAE in 13, averaging four horizons and three seeds.

5.5 Computational Cost

We measure inference cost on an RTX 5090 in FP32 across DLinear and PatchTST, seven datasets, and four horizons ($L = 192$). Batch sizes follow the backbone recipes: 8 or 32 for DLinear on ETT, and 128 otherwise. All timings use CUDA Graph replay with device-resident inputs and cached previous-origin forecasts. TSA adds approximately 3.5–4.1K learned parameters, including gate coefficients; mean batch latency is 2.86 ms for Native and 3.73 ms with TSA (+0.87 ms). LPC uses approximately 3.2–25.0K fitted deployment coefficients and takes 0.38 ms per batch on average. Both timing averages weight the 56 settings equally and use the optimized inference implementation.

6 Conclusion

We presented TASCT, a modular framework combining temporal–spectral input adaptation with level-preserving forecast calibration. TSA preserves the historical mean while adapting temporal–spectral patterns; LPC preserves the pre-calibration forecast mean while correcting its trajectory. Weather–MixLinear diagnostics provide observational motivation through a variability–error association and probe-correctable residual information. Experiments across five backbones and seven datasets show broad accuracy gains, with particularly strong improvements for linear forecasters. The individual and combined gains support input adaptation and output calibration as complementary tools for improving time-series forecasting.

AI USE STATEMENT

In this work, we did not use generative AI tools for any tasks designated as requiring disclosure. We used generative AI tools for brainstorming, sourcing and searching for information, and editing the manuscript to improve readability. The authors reviewed all AI-assisted suggestions, checked information and references against their original sources before use, and verified that language edits preserved the intended meaning. We take responsibility for the final content of this work, including any text, claims, or artifacts produced with the aid of generative AI.

REPRODUCIBILITY STATEMENT

Section 4 describes the proposed method and training procedure, and Section 5.1 specifies the experimental setup. Appendices A and B provide implementation details and training configurations. Appendices C–G document diagnostic protocols, ablations, and additional comparisons, while Appendix H reports per-seed forecasting results. We will publicly release the code upon acceptance.

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A TSA AND LPC IMPLEMENTATION DETAILS

For $L = 192$, multi-scale temporal correction uses pooling factors $\mathcal{S} = \{1, 4, 16\}$, patch length 8, stride 4, and separate $8 \to 32 \to 8$ MLPs with GELU activations. Frequency-grouped correction uses three groups and separate $16 \to 16 \to 16$ GELU MLPs, with patch length 16 and stride 8. For the 97 real-FFT bins, the first group contains DC and the four highest-energy eligible bins; the second contains the next 20 highest-energy bins; the remaining bins, including Nyquist, form the third group. The masks are fixed from training data and may contain non-contiguous frequencies. Both branches replicate-pad the right boundary before patch extraction, normalize overlap sums by coverage counts, and crop reconstructions to the required length. The final linear layers are initialized to zero, so the initial adapted input equals the original history. TSA learning rates are on the order of 10^{-5}–10^{-3}.

The gate pools each of the history, local correction, and frequency correction to eight values per channel, yielding 24 features. Its shared $24 \to 8 \to 2$ network uses GELU followed by a scaled tanh, with $\rho = 0.15$; each final branch weight is independently clipped to $[\ell, u] = [0.25, 0.75]$ after adding its static anchor and dynamic offset. Weights are constant across time within a window and channel and need not sum to one. After joint branch–backbone training with weights $(0.5, 0.5)$, the static anchors and dynamic gate are trained sequentially, with the branches and backbone frozen. The gate's final layer is zero-initialized so dynamic training starts at the static anchor.

Backbone normalization. All variants share channel-wise standardization using training-set statistics. Within each backbone, DLinear applies no per-window normalization; MixLinear subtracts and restores the window mean without dividing by its standard deviation. PatchTST uses RevIN with normalization enabled and learned affine parameters disabled; TimeMixer enables its internal normalization with learned affine parameters; TimeBridge normalizes by the window mean and standard deviation and restores the output scale. These settings are identical for Native and TSA-augmented models. TSA's internal branch standardization neither replaces nor disables them.

Gate fitting. The gate penalty is $0.01 \ \mathrm{mean}_{i,c,b}[E_{i,c,b}(g_{i,c,b} - a_{c,b})^2]$, where $E_{i,c,b}$ is the temporal mean square of the frozen, normalized branch correction ($b \in \{\mathrm{loc}, \mathrm{freq}\}$). Static fitting uses anchor $a_{c,b} = 0.5$; dynamic fitting uses the fitted static weights. Each stage runs for eight epochs on at most 4,096 evenly spaced training origins, with batch size 64 and validation checkpoint selection; backbone and branch parameters remain frozen.

Contextual coefficient shrinkage. Let W be the pooled ridge map, W_k the four block-specific maps, and G the regularized feature Gram matrix. A centered orthonormal temporal basis Q is obtained from the SVD of the whitened feature–residual cross-moment, followed by QR orthogonalization. For direction q_j, define $s_j = (Wq_j)^\top G(Wq_j)$ and $d_j = \frac{1}{4}\sum_{k=1}^{4}((W_k - W)q_j)^\top G((W_k - W)q_j)$. The shrinkage is $r_j = s_j/(s_j + d_j/3)$; the first three directions are protected with $r_j = 1$, and numerically zero denominators also use $r_j = 1$. The deployed map is $\frac{1}{2}WQ\,\mathrm{diag}(r)Q^\top$, before channel-wise fusion. Fitting this map requires five ridge solves and one basis SVD, without backbone updates; these offline operations are excluded from inference timings.

B COMPARISON METHODS AND TRAINING CONFIGURATIONS

All comparisons use the same dataset splits, channel order, training-set standardization, lookback length $L = 192$, and horizons $H \in \{96, 192, 336, 720\}$ as the main experiments. The predictive objective is $0.5\,\mathrm{MSE} + 0.5\,\mathrm{MAE}$. CCM uses seeds 2027, 2026, and 2025. Results below report the evaluated local integrations of the released mechanisms into our backbone implementations.

xCPD code availability. As of September 24, 2026, the official repository[1] did not provide the xCPD (Li et al., 2026) implementation. We therefore omit xCPD from the experimental comparison.

CCM integration. We use the released CCM cluster assigner and attention implementation. DLinear retains its decomposition kernel of length 25 and replaces the seasonal and trend projec-

[1] https://github.com/Clearloveyuan/xCPD

tions with cluster-wise linear mappings. PatchTST retains its temporal encoder and uses cluster-wise mappings in the flattened prediction head. The number of clusters is $\lceil 0.3C \rceil$, and the similarity-loss coefficient is 0.3. Cluster embeddings have dimensions 64 for DLinear and 16 for PatchTST.

The integration averages newly produced prototypes over the training batch, detaches them, and stores them in a checkpointed buffer for subsequent batches. Channel-pair distances are averaged over the batch for the similarity objective. Cluster weights are mixed before the output projection, an algebraically equivalent implementation of mixing expert outputs. These adaptations make prototype state and multivariate batches compatible with the shared pipeline.

DLinear training. On ETT, the maximum budget is ten epochs, with patience three and checkpoint selection by validation mixed loss after every epoch. Batch size is eight for ETTm1 and 32 for the other ETT datasets. Initial learning rates are 0.005 for ETTh1, 0.05 for ETTh2, 0.0001 for ETTm1, and 0.001/0.001/0.01/0.01 for ETTm2 at the four horizons. The type1 schedule retains the initial rate for epochs one and two, then halves it each epoch. Solar, Weather, and Electricity use 16 epochs, batch size 128, and constant learning rate 0.001; checkpoints are selected by validation MSE every two epochs.

PatchTST training. The backbone uses three layers, four attention heads, model dimension 16, feed-forward dimension 128, patch length 16, stride eight, and RevIN with affine parameters disabled. Training uses batch size 128 and 16 epochs. OneCycle scheduling uses a warm-up fraction of 0.3 and a peak rate of 0.0001, increased to 0.0003 on Solar. Validation MSE is evaluated every two epochs for checkpoint selection.

LIFT integration and training. We initialize the released LIFT wrapper around each selected Native checkpoint and freeze the Native parameters. LIFT alone is fitted on Train using Adam, batch size 128, a constant learning rate of 0.001, and 16 epochs of the mixed predictive objective. The checkpoint with the lowest full-validation MSE, evaluated every two epochs, is retained. This stage reuses Native forecasts and history-derived leader identities, shifts, and correlations. The selected LIFT checkpoint, including its frozen Native backbone, forms the starting forecaster for the composition experiments.

TSA execution protocol for CCM and LIFT. For Tables 4–5, we load the selected CCM or LIFT forecaster, keep all its parameters frozen in evaluation mode, and train the newly inserted TSA through that forecaster. The initial TSA stage uses equal branch weights, the mixed predictive objective, and the TSA energy penalty with coefficient 0.001. DLinear on ETT uses up to ten epochs, patience three, and validation mixed-loss selection each epoch; the other DLinear settings and PatchTST use 16 epochs and validation-MSE selection every two epochs. Batch sizes follow their backbone recipes above. DLinear uses a constant TSA rate (the corresponding selected TSA rate on ETT and 0.001 elsewhere); PatchTST uses OneCycle with warm-up fraction 0.3 and peak TSA rate 0.001, or 0.0003 on Solar. For LIFT, the original history-derived leader metadata remains fixed, while the backbone forward pass is recomputed on the TSA-adapted input.

After selecting and freezing the TSA branches, we fit the static and then dynamic gates for eight epochs each using Adam with learning rate 0.01, batch size 64, gradient clipping at 1, and at most 4,096 evenly spaced Train origins. Each stage retains its lowest validation-MSE checkpoint, including the initial gate as a candidate and evaluating every two epochs. LPC is subsequently fitted with the calibration procedure in Sections 4.4 and 5.1; the +LPC and +TSA+LPC arms use the selected original and TSA-enhanced forecasters, respectively. Thus, the composition experiments train the added input adapter on an already fitted forecaster, whereas the main TSA experiments jointly train TSA and the backbone.

MixLinear training. The main-table backbone uses Adam for 16 epochs with constant learning rate and validation-MSE selection every two epochs. The tuples (period length, retained low-frequency bins, temporal mixing weight, learning rate, batch size) are (24, 1, 0.95, 0.03, 256) for ETTh1; (24, 8, 0.5, 0.02, 256) for ETTh2; (2, 96, 0.99, 0.005, 64) for ETTm1; (4, 1, 0.99, 0.02, 64) for ETTm2; (4, 1, 0.5, 0.02, 64) for Weather and Solar; and (24, 8, 0.01, 0.03, 64) for Electricity. These backbone settings are shared across the four horizons and three seeds.

TimeMixer training. We use three encoder layers, model dimension 16, feed-forward dimension 32, dropout 0.1, channel-independent processing, normalization, and moving-average decomposition with kernel size 25. Three average-pooling downsampling layers use a factor of two. Training uses Adam for 16 epochs, effective batch size 128, gradient clipping at 1, and OneCycle scheduling with peak learning rate 0.001 and warm-up fraction 0.2. Checkpoints are selected by validation MSE every two epochs. Solar and Electricity GPU runs accumulate microbatches of 16 to the effective batch size.

TimeBridge training. For ETTh1, ETTh2, Weather, Solar, and Electricity, the recipe uses RevIN, period length 24, model/feed-forward dimensions 128/128, eight heads, three integrated-attention layers, one patch-downsampling layer, zero channel-attention layers, stable length six, GELU, dropout zero, and attention dropout 0.15. Adam uses batch size 64, 16 epochs, constant learning rate 0.0002, gradient clipping at 1, and validation-MSE selection every two epochs. ETTm1 and ETTm2 use the corresponding released per-horizon recipe for all three seeds (2027, 2026, and 2025): period length 48, model dimension 64, four heads, up to 100 epochs, and early-stopping patience 15 for ETTm1 or ten for ETTm2. These runs use OneCycle scheduling with peak backbone rate 0.0002 and warm-up fraction 0.2; the TSA peak rate is 0.001. Within each dataset–horizon setting, the backbone recipe is fixed across seeds and matched between Native and TSA-enhanced runs, which share the mixed predictive objective.

C Residual Probe Protocol and Temporal Breakdown

We reuse frozen native MixLinear forecasts on Weather with $L = 192$, $H = 96$, and seeds 2027, 2026, and 2025. Observations are standardized channel-wise using training-set statistics. The backbone checkpoints were selected using validation data; no backbone is retrained for this diagnostic. All comparisons use the same cached windows, excluding the first origin of each split to match the original diagnostic that also considered preceding forecasts.

For each window and channel, the probe target is the residual $Y - \widehat{Y}$ after subtracting its temporal mean. We average the 96-step forecast over 16 consecutive, non-overlapping six-step segments. These features are standardized using statistics from the probe's fitting subset. A ridge mapping with an unpenalized intercept maps the resulting 16 features to a 96-step correction, with parameters shared across all channels. The correction is constrained to have zero temporal mean, preserving the original predicted level.

We place a chronological cut at 60% of the validation target interval. Fitting windows end before the cut, and selection windows begin at or after it, so their target intervals do not overlap. This gives 3,066 fitting and 2,013 selection windows. We select the ridge penalty from $\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 10\}$ by selection-set shape MSE; all three seeds select 10^{-4}. We then refit the mapping and feature standardization on the full validation set. The intercept-only control is the mean centered validation residual at each forecast lead, averaged across windows and channels, and is likewise fitted on the full validation set. It supplies the same correction curve to every window and channel. Test observations are used only for evaluation.

The full test evaluation contains 10,443 windows per seed. Table 6 reports shape-error reductions on its chronological halves (5,221 and 5,222 windows). The probe's gains are concentrated in the first half, while the intercept-only correction is effectively neutral in both halves. The full-test result therefore establishes correctable residual structure in this setting, with its magnitude varying over time. Reported mean percentage reductions are arithmetic means of the per-seed reductions.

Table 6: Shape-error reduction (%) relative to Native across chronological test halves.

	Intercept only		Linear probe	
Seed	First half	Second half	First half	Second half
2027	-0.017	-0.004	4.753	0.827
2026	-0.017	-0.004	4.720	0.461
2025	-0.017	-0.004	4.642	-0.187
Mean	-0.017	-0.004	4.705	0.367

D Input Variability Diagnostics

Figures 3 and 4 extend Figure 1 to all 21 channels, using MixLinear with $L = 192$, $H = 96$, and seed 2027. Within each channel, all test windows are grouped by local-variability quintile using the same definition as Section 4.1.1; both models use identical groups. Boxes show the interquartile range and median, with whiskers extending to observations within 1.5 interquartile ranges. Outlier markers are hidden, but no observations are excluded from the statistics. Vertical scales vary across channels. For the main-text scatter plot, points are displayed at stride 24 and the moving mean uses all windows within ± 7.5 percentile points.

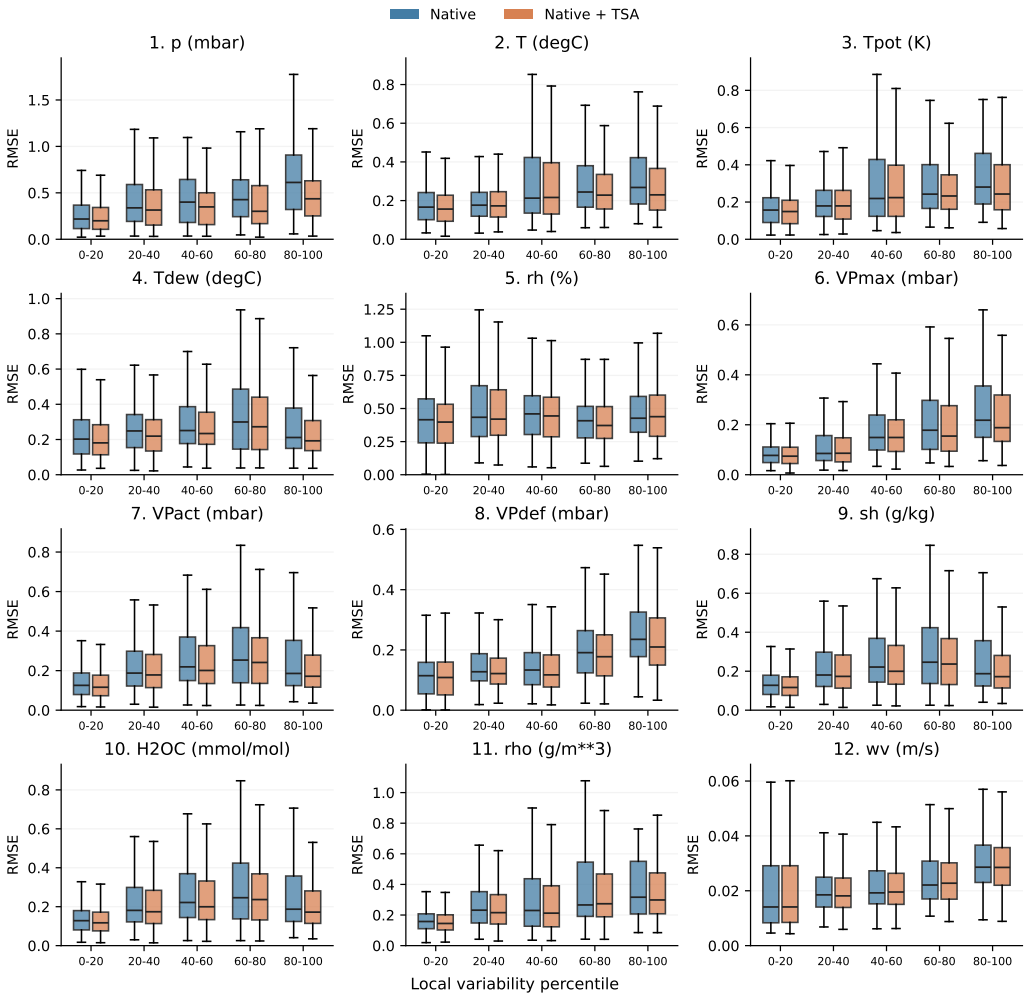

Figure 3: Window RMSE by local-variability quintile for Weather channels 1–12.

Appendix D: All-channel diagnostics (continued).

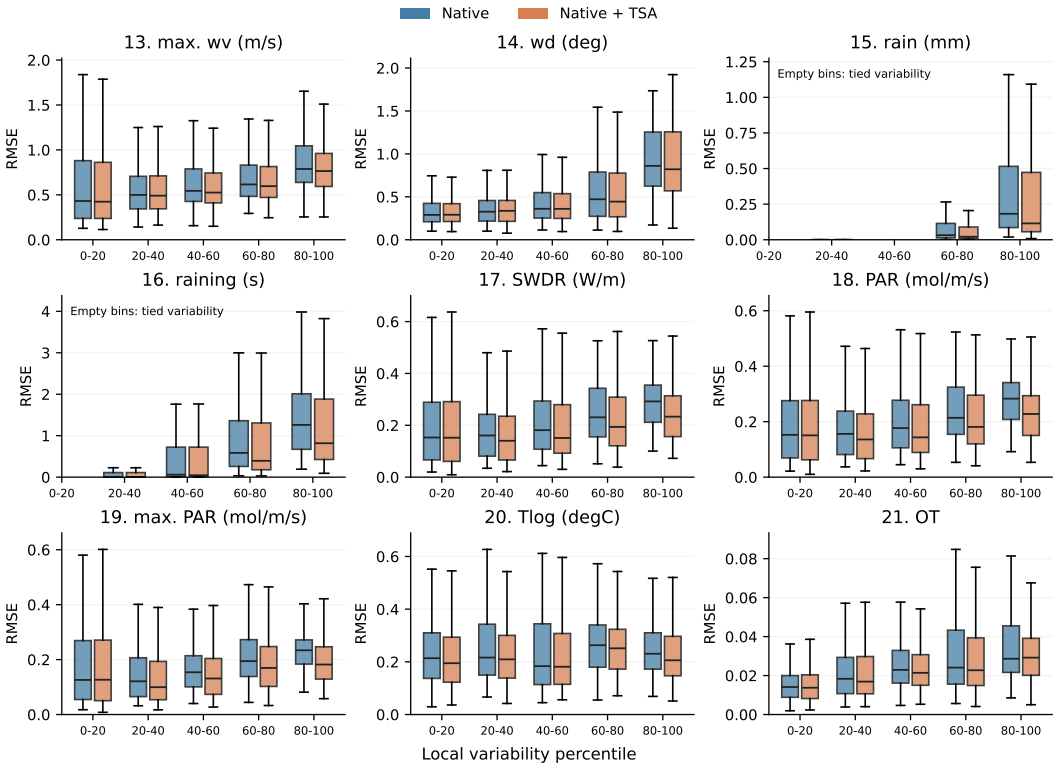

Figure 4: Window RMSE by local-variability quintile for Weather channels 13–21. Empty groups caused by tied variability values are marked.

E TSA Branch Ablations and Input Controls

We compare TSA with input-side controls and its component variants. *Temporal only* retains the multi-scale temporal correction, whereas *Spectral only* retains the frequency-grouped correction. *Residual MLP* is an approximately parameter-matched input adapter, and *Native + RevIN* serves as a normalization control. *TSA before gate fitting* includes both correction branches before gate fitting; *Full TSA* includes the fitted gates, and *Full TSA + LPC* additionally applies output calibration.

Figure 5 summarizes relative MSE reductions computed from four-horizon, three-seed mean MSE against each corresponding Native baseline. Higher is better; Solar uses a different vertical scale. Connected points compare alternative ablation configurations rather than sequential training stages. The following tables provide the per-horizon results.

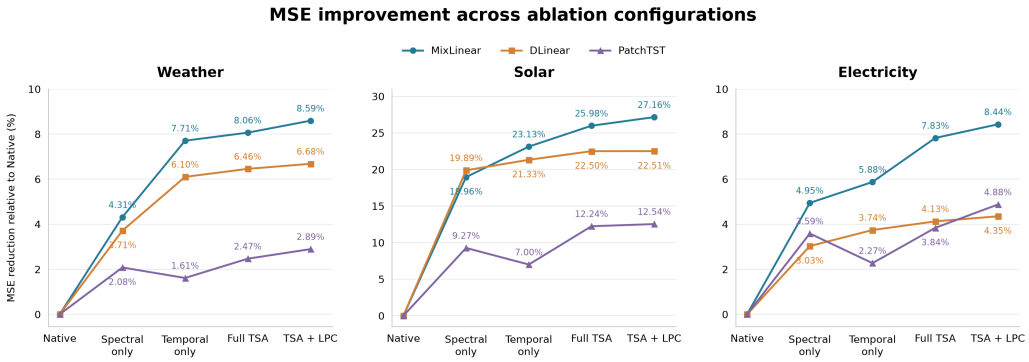

Figure 5: Input ablation gains on Weather, Solar, and Electricity. Full TSA improves on both single branches in all nine backbone–dataset groups, with further gains from LPC.

Residual MLP architecture and parameter matching. The residual MLP uses two fully connected layers with biases and a GELU activation between them, mapping $192 \to d \to 192$ along the temporal dimension with weights shared across channels. The hidden width is $d = 9$ for Weather and Solar and $d = 10$ for Electricity. Its output projection is initialized to zero, so the input correction starts at zero. The MLP contains $192d + d + 192d + 192 = 385d + 192$ learned parameters: 3,657 for Weather and Solar and 4,042 for Electricity. Table 7 compares these counts with full TSA, including its gate parameters. Counts refer to the input-side modules and exclude the forecasting backbone and LPC; the absolute relative difference is below 3.3% for all three datasets.

Table 7: Input-adapter parameter counts for the residual MLP and full TSA. Relative difference is $(N_{\mathrm{MLP}}/N_{\mathrm{TSA}} - 1) \times 100\%$.

Dataset	Residual MLP	Full TSA (with gates)	Relative difference
Weather	3,657	3,548	$+3.07\%$
Solar	3,657	3,780	-3.25%
Electricity	4,042	4,148	-2.56%

Table 8: Per-horizon input ablations and residual control: MixLinear on Weather, Solar, and Electricity. Entries average seeds 2027, 2026, and 2025. LPC is applied only in the final row of each horizon group; bold denotes the lowest displayed mean within each group and metric column, including ties.

		MixLinear					
		Weather		Solar		Electricity	
H	Variant	MSE	MAE	MSE	MAE	MSE	MAE
96	Native	0.192264	0.235225	0.273568	0.315631	0.160694	0.251205
	Native + RevIN	0.192264	0.235225	0.273568	0.315631	0.160695	0.251206
	Residual MLP	0.177085	0.219864	0.225050	0.249801	0.150569	0.242784
	Temporal only	0.168029	0.210587	0.201795	0.255957	0.150492	0.241509
	Spectral only	0.178125	0.219834	0.214634	0.280394	0.152940	0.243915
	TSA before gate fitting	0.169734	0.211937	0.197725	0.252905	0.149504	0.240171
	Full TSA	0.167756	0.210344	0.195130	0.249539	0.146238	0.238248
	Full TSA + LPC	**0.166634**	**0.209832**	**0.192803**	**0.245418**	**0.145493**	**0.237888**
192	Native	0.235982	0.272487	0.305628	0.292221	0.180035	0.269106
	Native + RevIN	0.235982	0.272487	0.305628	0.292221	0.180035	0.269106
	Residual MLP	0.223601	0.259689	0.261755	0.264012	0.168953	0.259537
	Temporal only	0.212751	0.250525	0.242538	0.269376	0.166251	0.256227
	Spectral only	0.223967	0.259907	0.248909	0.271561	0.168020	0.258318
	TSA before gate fitting	0.214113	0.251398	0.235769	0.266893	0.163593	0.253369
	Full TSA	0.211608	0.249739	0.233528	0.265320	0.161576	0.252002
	Full TSA + LPC	**0.210255**	**0.249026**	**0.231663**	**0.262131**	**0.160525**	**0.251251**
336	Native	0.286119	0.308029	0.366309	0.360118	0.196870	0.285511
	Native + RevIN	0.286119	0.308029	0.366309	0.360118	0.196870	0.285511
	Residual MLP	0.273023	0.296975	0.312756	0.311286	0.187193	0.278167
	Temporal only	0.266082	0.290977	0.287206	0.321980	0.183777	0.273334
	Spectral only	0.275515	0.299114	0.297751	0.333624	0.184646	0.274881
	TSA before gate fitting	0.267144	0.292070	0.271275	0.315057	0.181929	0.271722
	Full TSA	0.264457	0.290012	0.268781	0.314149	0.180037	0.270391
	Full TSA + LPC	**0.263182**	**0.288738**	**0.261669**	**0.301347**	**0.178445**	**0.269139**
720	Native	0.356861	0.355200	0.382257	0.376421	0.227801	0.310948
	Native + RevIN	0.356861	0.355200	0.382257	0.376421	0.227801	0.310948
	Residual MLP	0.345850	0.344996	0.316856	**0.321268**	0.223524	0.306275
	Temporal only	0.341801	0.343052	0.289082	0.331929	0.219904	0.302534
	Spectral only	0.347416	0.348311	0.314660	0.338521	0.221938	0.304627
	TSA before gate fitting	0.342245	0.343685	0.286515	0.329466	0.220189	0.302538
	Full TSA	0.341013	0.342801	0.285331	0.329217	0.217635	0.300804
	Full TSA + LPC	**0.339089**	**0.340680**	**0.281007**	0.322573	**0.216376**	**0.300035**

Table 8: Per-horizon input ablations and residual control (continued): DLinear on Weather, Solar, and Electricity. Entries average seeds 2027, 2026, and 2025. LPC is applied only in the final row of each horizon group; bold denotes the lowest displayed mean within each group and metric column, including ties.

		DLinear					
		Weather		Solar		Electricity	
H	Variant	MSE	MAE	MSE	MAE	MSE	MAE
96	Native	0.182014	0.232357	0.222755	0.239786	0.152450	0.245838
	Native + RevIN	0.182905	0.222366	0.230495	0.222128	0.153484	0.244550
	Residual MLP	0.173187	0.224244	0.203995	0.233660	0.147448	0.240350
	Temporal only	0.164630	0.217172	0.180549	0.223697	0.144003	0.237404
	Spectral only	0.172892	0.226769	0.185283	0.227407	0.144577	0.238515
	TSA before gate fitting	0.166223	0.216393	0.179445	0.222429	0.146241	0.238760
	Full TSA	0.163857	**0.215371**	0.179129	0.222008	0.142800	0.236658
	Full TSA + LPC	**0.163129**	0.215434	**0.179044**	**0.221482**	**0.142372**	**0.236406**
192	Native	0.223126	0.274128	0.262847	0.260473	0.164155	0.256494
	Native + RevIN	0.226795	0.259838	0.272419	0.245550	0.165675	0.255386
	Residual MLP	0.216589	0.266610	0.243999	0.253338	0.161338	0.253576
	Temporal only	0.206791	0.259235	0.211941	0.239171	0.157999	0.250487
	Spectral only	0.211509	0.263795	0.214028	0.243371	0.159229	0.252273
	TSA before gate fitting	0.208812	0.259930	0.210447	**0.238226**	0.159870	0.251959
	Full TSA	0.205750	**0.258110**	0.208221	0.238421	0.157354	0.250463
	Full TSA + LPC	**0.205420**	0.258264	**0.208213**	0.238369	**0.156859**	**0.250103**
336	Native	0.270470	0.316539	0.303295	0.287074	0.180001	0.275185
	Native + RevIN	0.275663	**0.295070**	0.316351	0.269876	0.182926	0.272534
	Residual MLP	0.265435	0.311436	0.276637	0.279990	0.178140	0.273306
	Temporal only	0.252676	0.296045	0.231459	0.256409	0.174010	0.269238
	Spectral only	0.260153	0.305374	0.235783	0.259418	0.175208	0.270352
	TSA before gate fitting	0.253799	0.296376	0.229516	**0.253212**	0.175699	0.269959
	Full TSA	0.252236	0.295912	0.227540	0.253544	0.173302	0.268454
	Full TSA + LPC	**0.251818**	0.296044	**0.227521**	0.253457	**0.172923**	**0.268235**
720	Native	0.333962	0.368592	0.305425	0.291425	0.213893	0.305456
	Native + RevIN	0.345722	**0.342028**	0.318640	0.272484	0.222067	0.304197
	Residual MLP	0.332638	0.366805	0.280273	0.285168	0.213165	0.304533
	Temporal only	0.323878	0.357666	0.237002	0.259133	0.207904	**0.300145**
	Spectral only	0.327524	0.360608	0.241573	0.262873	0.209958	0.302367
	TSA before gate fitting	0.324613	0.356464	0.234873	0.257231	0.210164	0.301899
	Full TSA	0.322539	0.355453	0.233186	0.256439	0.207727	0.300411
	Full TSA + LPC	**0.321748**	0.355445	**0.233177**	**0.256421**	**0.207427**	0.300300

Table 8: Per-horizon input ablations and residual control (continued): PatchTST on Weather, Solar, and Electricity. Entries average seeds 2027, 2026, and 2025. LPC is applied only in the final row of each horizon group; bold denotes the lowest displayed mean within each group and metric column, including ties.

		PatchTST					
		Weather		Solar		Electricity	
H	Variant	MSE	MAE	MSE	MAE	MSE	MAE
96	Native	0.178166	0.219098	0.221266	0.263339	0.178466	0.280541
	Native + RevIN	0.178166	0.219098	0.221266	0.263339	0.178466	0.280541
	Residual MLP	0.176447	0.218018	0.207891	0.251722	0.174205	0.275947
	Temporal only	0.173445	0.213565	0.195620	0.241392	0.172131	0.275378
	Spectral only	0.171904	0.214351	0.198097	0.250809	0.169420	0.272054
	TSA before gate fitting	0.173395	0.214352	0.195365	0.251835	0.170600	0.272844
	Full TSA	0.170554	**0.211864**	0.188806	0.243518	0.168109	0.270448
	Full TSA + LPC	**0.169621**	0.212042	**0.187467**	**0.240612**	**0.165917**	**0.267812**
192	Native	0.221683	0.256045	0.252803	0.284013	0.190008	0.290116
	Native + RevIN	0.221683	0.256045	0.252803	0.284013	0.190008	0.290116
	Residual MLP	0.218144	0.253091	0.244678	0.281303	0.188275	0.288029
	Temporal only	0.217232	0.252282	0.230898	0.270922	0.185802	0.286966
	Spectral only	0.215615	0.252138	0.228759	0.273022	0.182251	0.282434
	TSA before gate fitting	0.217384	0.252227	0.230415	0.284820	0.184434	0.284684
	Full TSA	0.214990	0.251019	0.222361	0.267158	0.182514	0.282583
	Full TSA + LPC	**0.213986**	**0.250796**	**0.221236**	**0.264705**	**0.180228**	**0.279954**
336	Native	0.272759	0.293338	0.280256	0.305621	0.207056	0.305427
	Native + RevIN	0.272759	0.293338	0.280256	0.305621	0.207056	0.305427
	Residual MLP	0.267860	0.290122	0.278253	0.303937	0.207134	0.305231
	Temporal only	0.268551	0.290522	0.271316	0.298425	0.203192	0.302699
	Spectral only	0.267601	0.290618	0.255481	0.283494	0.200178	0.298876
	TSA before gate fitting	0.268473	0.289994	0.253344	0.283280	0.201511	0.300098
	Full TSA	0.266562	0.289419	0.243830	0.276978	0.199696	0.298249
	Full TSA + LPC	**0.265685**	**0.289373**	**0.243364**	**0.276081**	**0.197399**	**0.295645**
720	Native	0.345179	0.342352	0.275584	0.298084	0.246162	0.334877
	Native + RevIN	0.345179	0.342352	0.275584	0.298084	0.246162	0.334877
	Residual MLP	0.342564	0.341069	0.271765	0.301257	0.245518	0.334169
	Temporal only	0.342130	0.340874	0.259954	0.289157	0.241896	0.332084
	Spectral only	0.341506	0.340753	0.252097	0.280301	0.240379	0.329904
	TSA before gate fitting	0.342048	0.340421	0.255542	0.289060	0.242018	0.331490
	Full TSA	0.340549	0.340123	0.248815	0.279392	0.239832	0.329455
	Full TSA + LPC	**0.339038**	**0.339359**	**0.248733**	**0.279194**	**0.238086**	**0.327679**

F LPC Component Ablations

F.1 Component and Centering Ablations

We evaluate five backbones on seven datasets, four horizons, and seeds 2027, 2026, and 2025 (420 runs). Each variant uses the same frozen Native backbone predictions. We compare contextual correction alone, consistency correction alone, full LPC, and LPC with temporal centering removed from both fitting and application. History normalization remains unchanged. Each variant follows the original calibration interval, chronological folds, ridge regularization, shrinkage, and coefficient bounds; fusion weights are refitted for the retained components.

Across 140 backbone–dataset–horizon settings averaged over three seeds, full LPC improves MSE in 139 settings and MAE in 124; the uncentered variant improves them in 119 and 102 settings. Mean relative reductions are 1.146%/0.734% for full LPC and 1.053%/0.486% for the uncentered variant (MSE/MAE), weighting settings equally. Centered LPC achieves lower MSE in 63 of the 140 direct comparisons and lower MAE in 72. Thus, allowing level changes benefits some settings, while centering yields fewer degradations relative to Native and slightly larger average gains. Mean absolute forecast-level shifts are approximately 2.0×10^{-9} and 0.0249, respectively, on the standardized scale, averaging runs equally.

Table 9: LPC component errors (MSE/MAE), averaged over four horizons and three seeds.

Backbone	Dataset	Native	Contextual	Consistency	Full LPC	Uncentered
DLinear	ETTh1	0.4533/0.4535	0.4485/0.4513	0.4515/0.4534	0.4475/0.4516	0.4600/0.4662
DLinear	ETTh2	0.4312/0.4417	0.4248/0.4376	0.4284/0.4398	0.4236/0.4368	0.4171/0.4361
DLinear	ETTm1	0.3645/0.3800	0.3627/0.3805	0.3636/0.3792	0.3618/0.3798	0.3660/0.3868
DLinear	ETTm2	0.2887/0.3435	0.2805/0.3387	0.2873/0.3425	0.2800/0.3382	0.2714/0.3308
DLinear	Solar	0.2736/0.2697	0.2734/0.2708	0.2734/0.2698	0.2732/0.2709	0.2697/0.2807
DLinear	Weather	0.2524/0.2979	0.2504/0.2976	0.2523/0.2978	0.2503/0.2975	0.2484/0.2970
DLinear	Electricity	0.1776/0.2707	0.1775/0.2706	0.1773/0.2708	0.1771/0.2706	0.1774/0.2709
MixLinear	ETTh1	0.4223/0.4211	0.4210/0.4206	0.4219/0.4223	0.4208/0.4217	0.4241/0.4229
MixLinear	ETTh2	0.3686/0.3952	0.3671/0.3945	0.3676/0.3945	0.3663/0.3939	0.3741/0.4032
MixLinear	ETTm1	0.3776/0.3870	0.3714/0.3834	0.3766/0.3863	0.3709/0.3830	0.3755/0.3855
MixLinear	ETTm2	0.2788/0.3272	0.2730/0.3214	0.2776/0.3262	0.2725/0.3210	0.2731/0.3214
MixLinear	Solar	0.3319/0.3361	0.3085/0.3075	0.3288/0.3334	0.3070/0.3060	0.3035/0.3025
MixLinear	Weather	0.2678/0.2927	0.2651/0.2908	0.2672/0.2923	0.2648/0.2906	0.2607/0.2865
MixLinear	Electricity	0.1914/0.2792	0.1881/0.2766	0.1908/0.2791	0.1875/0.2766	0.1869/0.2760
PatchTST	ETTh1	0.4358/0.4362	0.4355/0.4360	0.4333/0.4350	0.4331/0.4348	0.4355/0.4358
PatchTST	ETTh2	0.3606/0.3937	0.3605/0.3936	0.3594/0.3926	0.3593/0.3925	0.3725/0.4036
PatchTST	ETTm1	0.3659/0.3794	0.3632/0.3778	0.3657/0.3793	0.3630/0.3777	0.3662/0.3795
PatchTST	ETTm2	0.2639/0.3139	0.2638/0.3139	0.2636/0.3135	0.2635/0.3136	0.2650/0.3143
PatchTST	Solar	0.2575/0.2878	0.2513/0.2841	0.2573/0.2875	0.2511/0.2839	0.2479/0.2793
PatchTST	Weather	0.2544/0.2777	0.2531/0.2774	0.2543/0.2776	0.2530/0.2774	0.2499/0.2747
PatchTST	Electricity	0.2054/0.3027	0.2026/0.3003	0.2031/0.2997	0.2005/0.2975	0.2003/0.2975
TimeMixer	ETTh1	0.4441/0.4401	0.4418/0.4391	0.4390/0.4378	0.4376/0.4372	0.4396/0.4379
TimeMixer	ETTh2	0.3681/0.3997	0.3681/0.3995	0.3662/0.3980	0.3663/0.3980	0.3752/0.4041
TimeMixer	ETTm1	0.3561/0.3814	0.3533/0.3793	0.3546/0.3802	0.3520/0.3782	0.3509/0.3774
TimeMixer	ETTm2	0.2647/0.3164	0.2642/0.3160	0.2635/0.3152	0.2632/0.3150	0.2629/0.3145
TimeMixer	Solar	0.2046/0.2433	0.2039/0.2431	0.2045/0.2432	0.2038/0.2431	0.2036/0.2417
TimeMixer	Weather	0.2307/0.2599	0.2302/0.2598	0.2304/0.2595	0.2300/0.2594	0.2291/0.2592
TimeMixer	Electricity	0.1696/0.2596	0.1696/0.2596	0.1692/0.2592	0.1692/0.2592	0.1690/0.2592
TimeBridge	ETTh1	0.4770/0.4587	0.4754/0.4580	0.4740/0.4596	0.4728/0.4590	0.4736/0.4587
TimeBridge	ETTh2	0.3669/0.4000	0.3667/0.3998	0.3647/0.3984	0.3645/0.3982	0.3721/0.4042
TimeBridge	ETTm1	0.3586/0.3792	0.3558/0.3775	0.3577/0.3785	0.3549/0.3769	0.3562/0.3777
TimeBridge	ETTm2	0.2686/0.3187	0.2680/0.3182	0.2677/0.3178	0.2671/0.3175	0.2656/0.3158
TimeBridge	Solar	0.2010/0.2355	0.2009/0.2354	0.2009/0.2355	0.2008/0.2354	0.2008/0.2353
TimeBridge	Weather	0.2373/0.2620	0.2368/0.2618	0.2370/0.2617	0.2366/0.2616	0.2355/0.2614
TimeBridge	Electricity	0.1706/0.2586	0.1703/0.2582	0.1703/0.2584	0.1700/0.2580	0.1696/0.2578

F.2 TEMPORAL-ENSEMBLE CONTROLS

Table 10 uses frozen MixLinear+TSA ($L = 192$, $H = 96$, stride one). Same-target averaging uses weight 0.5 or a channel-wise weight in $[0, 1]$ fitted by MSE on LPC's chronological held-out calibration blocks. The hybrid replaces consistency with the uncentered same-target difference and refits the original box-ridge fusion. All arms share test windows; averaging leaves the first origin and non-overlapping final lead unchanged. No backbone retraining or test fitting is performed.

Table 10: Output calibration: means over seeds 2027, 2026, and 2025; bold: lowest per column.

	Weather		Electricity	
Output treatment	MSE	MAE	MSE	MAE
None (TSA)	0.167756	0.210344	0.146238	0.238248
Fixed temporal average	0.167985	0.210824	0.146328	0.238162
Fitted temporal average	0.167490	0.210154	0.146205	0.238108
Full LPC	**0.166634**	**0.209832**	**0.145492**	0.237888
Contextual + temporal average	0.166654	0.209838	0.145901	**0.237814**

G ADDITIONAL COMPARISONS WITH FORECASTING PLUGINS

Table 11 compares Native, CCM, LIFT, and TASCT, with errors averaged over seeds 2027, 2026, and 2025 and four horizons. TASCT achieves the lowest MSE on 2 of seven datasets with DLinear and 3 with PatchTST. It improves on CCM in MSE on five datasets with DLinear and all seven with PatchTST. LIFT achieves the lowest MSE on Solar, Weather, and Electricity for both backbones, highlighting dataset-dependent strengths among the methods. The comparison uses matched backbone implementations and data settings, while retaining each method's recorded training recipe.

Table 11: Comparison with forecasting enhancement methods.

Backbone	DLinear								PatchTST							
Model	Native		+CCM		+LIFT		+TASCT		Native		+CCM		+LIFT		+TASCT	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	0.453	0.454	0.437	0.439	**0.437**	**0.436**	0.444	0.450	0.436	0.436	0.438	0.437	0.456	0.441	**0.431**	**0.435**
ETTh2	0.431	0.442	0.434	0.440	0.430	0.440	**0.420**	**0.435**	0.361	0.394	0.364	0.396	**0.358**	**0.392**	0.359	0.393
ETTm1	0.365	0.380	0.366	0.381	0.363	**0.377**	**0.363**	0.382	0.366	0.379	0.365	0.380	0.364	0.382	**0.354**	**0.378**
ETTm2	0.289	0.344	**0.277**	**0.332**	0.355	0.353	0.278	0.337	0.264	0.314	0.263	0.314	0.267	0.316	**0.261**	**0.314**
Solar	0.274	0.270	0.273	0.297	**0.208**	0.244	0.212	**0.242**	0.257	0.288	0.249	0.283	**0.207**	**0.240**	0.225	0.265
Weather	0.252	0.298	0.259	0.303	**0.229**	**0.266**	0.236	0.281	0.254	0.278	0.253	0.277	**0.232**	**0.264**	0.247	0.273
Electricity	0.178	0.271	0.202	0.296	**0.167**	**0.258**	0.170	0.264	0.205	0.303	0.199	0.294	**0.171**	**0.263**	0.195	0.293

Means over four horizons and seeds 2027, 2026, 2025. Bold: best per backbone at source precision.

Table 12: Comparison with δ-Adapter.

Dataset	Native		+δ-Adapter		+TASCT	
	MSE	MAE	MSE	MAE	MSE	MAE
DLinear						
ETTh1	$0.453_{\pm.013}$	$0.454_{\pm.010}$	$0.491_{\pm.012}$	$0.485_{\pm.008}$	$\mathbf{0.444}_{\pm.013}$	$\mathbf{0.450}_{\pm.010}$
ETTh2	$0.431_{\pm.011}$	$0.442_{\pm.007}$	$0.524_{\pm.030}$	$0.518_{\pm.018}$	$\mathbf{0.420}_{\pm.009}$	$\mathbf{0.435}_{\pm.003}$
ETTm1	$0.365_{\pm.000}$	$\mathbf{0.380}_{\pm.001}$	$0.387_{\pm.001}$	$0.411_{\pm.001}$	$\mathbf{0.363}_{\pm.001}$	$0.382_{\pm.001}$
ETTm2	$0.289_{\pm.007}$	$0.344_{\pm.006}$	$0.348_{\pm.019}$	$0.410_{\pm.013}$	$\mathbf{0.278}_{\pm.007}$	$\mathbf{0.337}_{\pm.006}$
Solar	$0.274_{\pm.000}$	$0.270_{\pm.001}$	$0.229_{\pm.000}$	$0.249_{\pm.000}$	$\mathbf{0.212}_{\pm.001}$	$\mathbf{0.242}_{\pm.001}$
Weather	$0.252_{\pm.001}$	$0.298_{\pm.002}$	$0.237_{\pm.002}$	$0.289_{\pm.002}$	$\mathbf{0.236}_{\pm.000}$	$\mathbf{0.281}_{\pm.000}$
Electricity	$0.178_{\pm.000}$	$0.271_{\pm.000}$	$\mathbf{0.168}_{\pm.001}$	$0.266_{\pm.001}$	$0.170_{\pm.000}$	$\mathbf{0.264}_{\pm.000}$
PatchTST						
ETTh1	$0.436_{\pm.003}$	$0.436_{\pm.002}$	$0.447_{\pm.003}$	$0.447_{\pm.002}$	$\mathbf{0.431}_{\pm.003}$	$\mathbf{0.435}_{\pm.002}$
ETTh2	$0.361_{\pm.001}$	$0.394_{\pm.001}$	$0.381_{\pm.005}$	$0.420_{\pm.005}$	$\mathbf{0.359}_{\pm.001}$	$\mathbf{0.393}_{\pm.001}$
ETTm1	$0.366_{\pm.000}$	$0.379_{\pm.001}$	$0.368_{\pm.002}$	$0.388_{\pm.002}$	$\mathbf{0.354}_{\pm.000}$	$\mathbf{0.378}_{\pm.001}$
ETTm2	$0.264_{\pm.001}$	$0.314_{\pm.000}$	$0.269_{\pm.001}$	$0.334_{\pm.002}$	$\mathbf{0.261}_{\pm.001}$	$\mathbf{0.314}_{\pm.000}$
Solar	$0.257_{\pm.005}$	$0.288_{\pm.002}$	$\mathbf{0.222}_{\pm.002}$	$0.266_{\pm.000}$	$0.225_{\pm.004}$	$\mathbf{0.265}_{\pm.003}$
Weather	$0.254_{\pm.001}$	$0.278_{\pm.001}$	$\mathbf{0.238}_{\pm.001}$	$0.283_{\pm.000}$	$0.247_{\pm.001}$	$\mathbf{0.273}_{\pm.000}$
Electricity	$0.205_{\pm.002}$	$0.303_{\pm.003}$	$\mathbf{0.186}_{\pm.001}$	$\mathbf{0.287}_{\pm.001}$	$0.195_{\pm.002}$	$0.293_{\pm.003}$

Mean$_{\pm\mathrm{SD}}$ over seeds 2027, 2026, 2025, after averaging four horizons within each seed. SD is the sample standard deviation. Bold: best mean per backbone at source precision.

G.1 Seed Variability of Plugin Complementarity

Tables 13 and 14 give sample standard deviations corresponding to Tables 4 and 5. For each seed, we first average the four horizons, then compute the sample SD across seeds 2027, 2026, and 2025 ($n = 3$, denominator $n - 1$).

Table 13: Seed standard deviations for CCM complementarity (MSE/MAE); means are in Table 4.

Backbone	DLinear								PatchTST							
Model	CCM		+TSA		+LPC		+TASCT		CCM		+TSA		+LPC		+TASCT	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	.0025	.0029	.0030	.0032	.0032	.0033	.0036	.0035	.0005	.0010	.0008	.0011	.0009	.0011	.0009	.0009
ETTh2	.0281	.0149	.0259	.0138	.0240	.0128	.0228	.0121	.0014	.0009	.0024	.0014	.0008	.0005	.0015	.0006
ETTm1	.0005	.0004	.0010	.0006	.0004	.0003	.0008	.0004	.0009	.0007	.0009	.0003	.0010	.0007	.0012	.0006
ETTm2	.0042	.0049	.0044	.0049	.0034	.0046	.0036	.0046	.0009	.0004	.0008	.0003	.0008	.0003	.0009	.0004
Solar	.0005	.0004	.0007	.0019	.0005	.0009	.0002	.0010	.0017	.0052	.0014	.0032	.0018	.0041	.0010	.0023
Weather	.0050	.0061	.0037	.0054	.0046	.0058	.0030	.0048	.0002	.0005	.0003	.0004	.0002	.0006	.0004	.0006
Electricity	.0062	.0042	.0068	.0046	.0016	.0016	.0020	.0021	.0013	.0017	.0013	.0019	.0013	.0020	.0012	.0018

Table 14: Seed standard deviations for LIFT complementarity (MSE/MAE); means are in Table 5.

Backbone	DLinear								PatchTST							
Model	LIFT		+TSA		+LPC		+TASCT		LIFT		+TSA		+LPC		+TASCT	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	.0026	.0003	.0023	.0004	.0017	.0002	.0016	.0001	.0038	.0019	.0010	.0016	.0028	.0017	.0004	.0014
ETTh2	.0153	.0079	.0150	.0077	.0143	.0073	.0141	.0071	.0012	.0012	.0013	.0013	.0012	.0013	.0015	.0015
ETTm1	.0002	.0004	.0006	.0004	.0000	.0004	.0005	.0005	.0013	.0008	.0007	.0005	.0011	.0007	.0006	.0003
ETTm2	.0289	.0019	.0170	.0009	.0126	.0016	.0080	.0008	.0031	.0015	.0027	.0012	.0026	.0014	.0023	.0012
Solar	.0009	.0015	.0009	.0014	.0009	.0014	.0009	.0014	.0001	.0012	.0008	.0007	.0001	.0011	.0008	.0007
Weather	.0010	.0008	.0009	.0009	.0011	.0007	.0010	.0007	.0010	.0004	.0011	.0002	.0010	.0003	.0010	.0002
Electricity	.0000	.0001	.0000	.0001	.0000	.0001	.0000	.0001	.0003	.0006	.0002	.0004	.0002	.0004	.0002	.0003

H PER-SEED FORECASTING RESULTS

The first five tables report all 420 backbone–dataset–horizon–seed combinations underlying the main experiments, with $L = 192$ and seeds 2027, 2026, and 2025. Each row gives MSE and MAE for Native, Native + TSA, Native + LPC, and TSA + LPC. Values are shown to six decimal places. Tables 2 and 3 summarize these paired variants across seeds and horizons.

Seed variability. For each of the 140 settings in Table 2, we compute the sample SD of the three seed-specific errors ($n = 3$, denominator $n-1$). Native has median per-setting SDs of 0.0016/0.0016 for MSE/MAE, with ranges 0.0000–0.0535 and 0.0002–0.0352, respectively. TASCT has median per-setting SDs of 0.0016/0.0014 for MSE/MAE, with ranges 0.0001–0.0711 and 0.0000–0.0295, respectively. These statistics describe seed-to-seed variability, not confidence intervals. Table 3 instead reports SDs of per-seed four-horizon averages. Displayed zero SDs may reflect rounding.

H.1 DLINEAR

Table 15: DLinear: per-seed MSE and MAE for all four variants.

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	2027	0.374237	0.390412	0.371122	0.390537	0.372978	0.390335	0.369681	0.390652
ETTh1	96	2026	0.409751	0.425598	0.396307	0.417660	0.394781	0.415757	0.385309	0.409892
ETTh1	96	2025	0.374827	0.390500	0.370106	0.391037	0.373467	0.390406	0.369431	0.391163
ETTh1	192	2027	0.436464	0.434463	0.425223	0.429412	0.428882	0.431315	0.423124	0.429721
ETTh1	192	2026	0.433965	0.431605	0.424750	0.426983	0.426933	0.428820	0.421900	0.427037
ETTh1	192	2025	0.454140	0.456332	0.446793	0.453153	0.447205	0.453359	0.443656	0.453117
ETTh1	336	2027	0.478854	0.465133	0.469602	0.460330	0.471617	0.463574	0.466912	0.460388
ETTh1	336	2026	0.456103	0.442176	0.453413	0.441317	0.454265	0.443652	0.453340	0.443424
ETTh1	336	2025	0.474669	0.462381	0.470377	0.458738	0.468246	0.460596	0.466757	0.458723
ETTh1	720	2027	0.498783	0.504138	0.498531	0.503860	0.495105	0.504346	0.495065	0.504246
ETTh1	720	2026	0.479345	0.488992	0.480744	0.489791	0.479673	0.491400	0.481096	0.492315
ETTh1	720	2025	0.568497	0.550638	0.567166	0.549897	0.556252	0.545180	0.555513	0.544693
ETTh2	96	2027	0.291609	0.345928	0.290424	0.345306	0.288398	0.342937	0.287842	0.342846
ETTh2	96	2026	0.359258	0.405325	0.335519	0.386391	0.319554	0.375610	0.303267	0.359452
ETTh2	96	2025	0.285533	0.342799	0.301938	0.358551	0.284558	0.342254	0.286651	0.343756
ETTh2	192	2027	0.361043	0.392555	0.357674	0.390423	0.359790	0.391742	0.355320	0.388822
ETTh2	192	2026	0.386069	0.412425	0.376338	0.403848	0.383202	0.411303	0.373081	0.402449
ETTh2	192	2025	0.388021	0.413869	0.371288	0.400912	0.385002	0.412632	0.368034	0.399434
ETTh2	336	2027	0.457312	0.461975	0.459606	0.467859	0.455030	0.461057	0.456238	0.466359
ETTh2	336	2026	0.422674	0.442297	0.432089	0.451439	0.420474	0.441051	0.429277	0.449818
ETTh2	336	2025	0.456298	0.461830	0.449923	0.458347	0.431836	0.447193	0.427131	0.444427
ETTh2	720	2027	0.574968	0.532533	0.574258	0.532361	0.570521	0.530191	0.569831	0.530028
ETTh2	720	2026	0.550811	0.525269	0.549901	0.525526	0.547473	0.523409	0.546608	0.523678
ETTh2	720	2025	0.640478	0.563611	0.645456	0.566902	0.637136	0.561856	0.642004	0.565116
ETTm1	96	2027	0.303442	0.340450	0.301893	0.342910	0.298945	0.338646	0.298718	0.340241
ETTm1	96	2026	0.304361	0.343220	0.305007	0.347503	0.299606	0.340984	0.301440	0.344310
ETTm1	96	2025	0.303973	0.342495	0.301789	0.342476	0.299292	0.340193	0.298779	0.339929
ETTm1	192	2027	0.342529	0.367475	0.342255	0.368953	0.338986	0.366380	0.339352	0.367926
ETTm1	192	2026	0.340097	0.362662	0.337876	0.363512	0.337213	0.362462	0.335209	0.362742
ETTm1	192	2025	0.341198	0.365600	0.343301	0.369720	0.338016	0.365155	0.340544	0.368668
ETTm1	336	2027	0.375501	0.385011	0.374405	0.386379	0.373833	0.385492	0.371696	0.386469
ETTm1	336	2026	0.376044	0.386439	0.376147	0.387823	0.374153	0.386559	0.373681	0.388237
ETTm1	336	2025	0.376471	0.386131	0.376452	0.388049	0.374378	0.386342	0.373450	0.387968
ETTm1	720	2027	0.436241	0.425021	0.440937	0.427524	0.434805	0.426530	0.439212	0.430308
ETTm1	720	2026	0.439759	0.432068	0.444564	0.435200	0.438347	0.433111	0.443382	0.437706
ETTm1	720	2025	0.434907	0.423838	0.438236	0.425987	0.434109	0.425690	0.436985	0.428995
ETTm2	96	2027	0.171964	0.260891	0.170142	0.257489	0.170816	0.260023	0.168987	0.256727
ETTm2	96	2026	0.173401	0.261435	0.172104	0.259461	0.171279	0.259538	0.170145	0.257648
ETTm2	96	2025	0.171745	0.260072	0.170092	0.258293	0.170504	0.259060	0.168829	0.257240
ETTm2	192	2027	0.233516	0.302812	0.232516	0.303449	0.229989	0.298989	0.227989	0.299944

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Table 15 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTm2	192	2026	0.235756	0.307300	0.229767	0.300878	0.233377	0.305778	0.227490	0.299309
ETTm2	192	2025	0.235602	0.304726	0.235419	0.304658	0.231639	0.300943	0.231341	0.300587
ETTm2	336	2027	0.302255	0.353111	0.290169	0.347390	0.291766	0.345613	0.286496	0.345358
ETTm2	336	2026	0.304143	0.360944	0.298314	0.357962	0.300266	0.358862	0.293480	0.355058
ETTm2	336	2025	0.346980	0.395247	0.335549	0.386825	0.327628	0.385381	0.318755	0.378444
ETTm2	720	2027	0.439075	0.442060	0.438285	0.442028	0.408912	0.423797	0.407800	0.423522
ETTm2	720	2026	0.419315	0.433027	0.421888	0.434515	0.409190	0.428318	0.410650	0.429075
ETTm2	720	2025	0.430185	0.440757	0.441211	0.449205	0.414292	0.432404	0.422384	0.439086
Solar	96	2027	0.223691	0.237409	0.179563	0.220761	0.222730	0.241273	0.179524	0.220479
Solar	96	2026	0.221854	0.240945	0.178242	0.222973	0.221048	0.244033	0.178136	0.222173
Solar	96	2025	0.222721	0.241004	0.179582	0.222291	0.222105	0.243228	0.179474	0.221792
Solar	192	2027	0.262676	0.260382	0.209381	0.238402	0.262449	0.261541	0.209376	0.238377
Solar	192	2026	0.263341	0.258127	0.207721	0.241071	0.263140	0.259542	0.207712	0.241001
Solar	192	2025	0.262523	0.262911	0.207561	0.235789	0.262345	0.264043	0.207551	0.235730
Solar	336	2027	0.303560	0.284476	0.228970	0.254296	0.303330	0.285284	0.228941	0.254196
Solar	336	2026	0.302510	0.288434	0.227539	0.256464	0.302347	0.288734	0.227522	0.256359
Solar	336	2025	0.303815	0.288314	0.226111	0.249872	0.303545	0.288948	0.226099	0.249815
Solar	720	2027	0.304778	0.292757	0.234018	0.255780	0.304660	0.292929	0.234010	0.255759
Solar	720	2026	0.305779	0.291342	0.232917	0.256598	0.305645	0.291512	0.232909	0.256584
Solar	720	2025	0.305717	0.290177	0.232623	0.256940	0.305573	0.290307	0.232613	0.256918
Weather	96	2027	0.182831	0.235029	0.163365	0.213981	0.181018	0.235603	0.162558	0.213911
Weather	96	2026	0.181513	0.229789	0.164981	0.217242	0.179759	0.230435	0.164273	0.217430
Weather	96	2025	0.181697	0.232252	0.163225	0.214890	0.180064	0.232963	0.162556	0.214962
Weather	192	2027	0.221817	0.271638	0.202851	0.252313	0.219729	0.271054	0.202247	0.252262
Weather	192	2026	0.223701	0.274873	0.207379	0.262270	0.221757	0.274362	0.207185	0.262304
Weather	192	2025	0.223858	0.275871	0.207022	0.259748	0.221823	0.275415	0.206828	0.260226
Weather	336	2027	0.271031	0.317886	0.250929	0.296487	0.269375	0.317326	0.250556	0.296471
Weather	336	2026	0.265762	0.307846	0.249435	0.287395	0.264207	0.307441	0.249131	0.287646
Weather	336	2025	0.274615	0.323884	0.256344	0.303854	0.272807	0.323435	0.255767	0.304014
Weather	720	2027	0.336595	0.372994	0.327970	0.363628	0.334132	0.371924	0.327272	0.363781
Weather	720	2026	0.333553	0.368409	0.321042	0.355937	0.330856	0.367384	0.320143	0.355533
Weather	720	2025	0.331737	0.364371	0.318606	0.346794	0.328304	0.362654	0.317829	0.347021
Electricity	96	2027	0.152561	0.245272	0.142920	0.236794	0.152132	0.245101	0.142462	0.236474
Electricity	96	2026	0.152463	0.246265	0.142554	0.236278	0.152081	0.246211	0.142122	0.236050
Electricity	96	2025	0.152327	0.245978	0.142925	0.236903	0.151962	0.245934	0.142532	0.236695
Electricity	192	2027	0.164192	0.256423	0.157289	0.249710	0.163674	0.256165	0.156780	0.249353
Electricity	192	2026	0.164129	0.256730	0.157424	0.250571	0.163548	0.256455	0.156940	0.250226
Electricity	192	2025	0.164144	0.256330	0.157348	0.251107	0.163613	0.256074	0.156856	0.250731
Electricity	336	2027	0.179789	0.274662	0.173089	0.268507	0.179251	0.274434	0.172717	0.268278
Electricity	336	2026	0.180398	0.276246	0.173742	0.269772	0.179754	0.275844	0.173363	0.269577
Electricity	336	2025	0.179816	0.274648	0.173074	0.267083	0.179328	0.274432	0.172690	0.266851
Electricity	720	2027	0.213521	0.304718	0.207502	0.299554	0.213200	0.304739	0.207266	0.299475
Electricity	720	2026	0.213921	0.305230	0.207397	0.299962	0.213441	0.305174	0.207109	0.299882
Electricity	720	2025	0.214237	0.306419	0.208283	0.301717	0.213793	0.306368	0.207907	0.301544

H.2 MIXLINEAR

Table 16: MixLinear: per-seed MSE and MAE for all four variants.

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	2027	0.375557	0.388338	0.370130	0.390432	0.373668	0.387739	0.366948	0.390013
ETTh1	96	2026	0.376445	0.387743	0.371265	0.390138	0.374172	0.387438	0.369042	0.390229
ETTh1	96	2025	0.374592	0.387767	0.374208	0.390924	0.373322	0.387480	0.370056	0.390318
ETTh1	192	2027	0.438357	0.427793	0.426537	0.419117	0.434056	0.426087	0.422415	0.420591
ETTh1	192	2026	0.417808	0.411903	0.422387	0.416087	0.416739	0.412675	0.419391	0.417136
ETTh1	192	2025	0.415356	0.412371	0.420825	0.414719	0.414861	0.412790	0.417788	0.416047
ETTh1	336	2027	0.458909	0.435805	0.452891	0.433397	0.455746	0.436530	0.451974	0.436188

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Table 16 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	336	2026	0.459874	0.436792	0.452470	0.431767	0.457334	0.437786	0.451276	0.434873
ETTh1	336	2025	0.454528	0.435736	0.451042	0.432234	0.453460	0.436322	0.450369	0.434791
ETTh1	720	2027	0.430395	0.446491	0.434163	0.443130	0.430792	0.448026	0.433907	0.446435
ETTh1	720	2026	0.431213	0.441854	0.444041	0.443474	0.431454	0.444024	0.443105	0.448110
ETTh1	720	2025	0.434509	0.441161	0.447174	0.444109	0.434058	0.444009	0.445518	0.449240
ETTh2	96	2027	0.301219	0.345883	0.285305	0.338104	0.295847	0.342820	0.283911	0.336908
ETTh2	96	2026	0.300063	0.344201	0.284998	0.338172	0.295709	0.341596	0.283609	0.336963
ETTh2	96	2025	0.301905	0.346370	0.284710	0.338455	0.296442	0.343086	0.283712	0.337588
ETTh2	192	2027	0.370711	0.389340	0.357232	0.382161	0.368115	0.387935	0.356498	0.381728
ETTh2	192	2026	0.368884	0.389625	0.354749	0.383169	0.366880	0.388501	0.354179	0.382664
ETTh2	192	2025	0.369744	0.390096	0.360045	0.384073	0.367542	0.388834	0.358999	0.383316
ETTh2	336	2027	0.396744	0.414768	0.388644	0.411512	0.395594	0.414377	0.389048	0.411769
ETTh2	336	2026	0.400317	0.416702	0.391444	0.414603	0.398302	0.415758	0.391277	0.414286
ETTh2	336	2025	0.391617	0.413575	0.391727	0.414905	0.390524	0.413072	0.391787	0.414694
ETTh2	720	2027	0.406083	0.430256	0.404809	0.432709	0.405653	0.429820	0.404497	0.431886
ETTh2	720	2026	0.407007	0.430501	0.404845	0.432873	0.406593	0.430114	0.404717	0.432304
ETTh2	720	2025	0.408780	0.430811	0.407097	0.433470	0.408164	0.430321	0.406846	0.432983
ETTm1	96	2027	0.314123	0.349157	0.304465	0.346216	0.307213	0.344551	0.299045	0.342232
ETTm1	96	2026	0.314269	0.350059	0.307885	0.350211	0.307234	0.344907	0.301636	0.345334
ETTm1	96	2025	0.315066	0.350359	0.302324	0.346733	0.307146	0.344794	0.297962	0.342980
ETTm1	192	2027	0.351423	0.369776	0.347678	0.374237	0.344926	0.366535	0.340030	0.369973
ETTm1	192	2026	0.350827	0.369071	0.343501	0.369779	0.344192	0.365835	0.337484	0.366407
ETTm1	192	2025	0.350804	0.369663	0.340208	0.368876	0.344408	0.366409	0.333274	0.365286
ETTm1	336	2027	0.391876	0.396944	0.372133	0.391138	0.384575	0.392130	0.366944	0.388411
ETTm1	336	2026	0.395589	0.398196	0.371593	0.390424	0.386614	0.393118	0.366877	0.388061
ETTm1	336	2025	0.391296	0.396906	0.373496	0.390252	0.384517	0.392260	0.368482	0.388069
ETTm1	720	2027	0.452724	0.430816	0.431100	0.428134	0.446676	0.428063	0.425095	0.425784
ETTm1	720	2026	0.453066	0.432277	0.431379	0.427035	0.447099	0.428988	0.426408	0.425371
ETTm1	720	2025	0.449947	0.430525	0.431814	0.427118	0.446511	0.428452	0.426442	0.424743
ETTm2	96	2027	0.181676	0.266502	0.171517	0.256183	0.175783	0.259845	0.169137	0.253204
ETTm2	96	2026	0.182388	0.266171	0.174042	0.257516	0.176756	0.259837	0.171471	0.254350
ETTm2	96	2025	0.180932	0.266611	0.173185	0.257296	0.175228	0.260093	0.170632	0.254204
ETTm2	192	2027	0.240819	0.303909	0.233265	0.298168	0.235006	0.297972	0.230222	0.294615
ETTm2	192	2026	0.241856	0.304233	0.234993	0.298980	0.236306	0.298374	0.231662	0.295235
ETTm2	192	2025	0.242071	0.305549	0.235051	0.299075	0.235712	0.298841	0.231786	0.295562
ETTm2	336	2027	0.298961	0.341519	0.286810	0.334231	0.291717	0.334874	0.283455	0.330734
ETTm2	336	2026	0.296817	0.341016	0.287183	0.336026	0.289973	0.334596	0.283942	0.332533
ETTm2	336	2025	0.295747	0.340807	0.285352	0.333712	0.288921	0.334409	0.282393	0.330503
ETTm2	720	2027	0.395137	0.396576	0.378114	0.389501	0.388535	0.390766	0.374448	0.385662
ETTm2	720	2026	0.394358	0.396607	0.378825	0.390224	0.387842	0.390831	0.374975	0.386413
ETTm2	720	2025	0.394718	0.396895	0.378095	0.391219	0.387919	0.390992	0.375748	0.388235
Solar	96	2027	0.274055	0.315822	0.192746	0.245094	0.253436	0.285739	0.191311	0.242058
Solar	96	2026	0.273960	0.315205	0.195029	0.252265	0.253298	0.285845	0.192196	0.247339
Solar	96	2025	0.272688	0.315866	0.197616	0.251258	0.252292	0.285779	0.194902	0.246856
Solar	192	2027	0.306692	0.290164	0.229700	0.260773	0.291238	0.276447	0.228192	0.257738
Solar	192	2026	0.306002	0.293186	0.236298	0.268157	0.291261	0.278568	0.234207	0.264905
Solar	192	2025	0.304189	0.293312	0.234586	0.267031	0.289568	0.278243	0.232590	0.263751
Solar	336	2027	0.366091	0.360283	0.271348	0.316183	0.340543	0.328201	0.263926	0.302841
Solar	336	2026	0.366679	0.360837	0.267646	0.314568	0.340636	0.327867	0.260812	0.301993
Solar	336	2025	0.366156	0.359234	0.267349	0.311696	0.340209	0.327057	0.260270	0.299207
Solar	720	2027	0.383238	0.376847	0.281127	0.326796	0.344440	0.332459	0.276932	0.320160
Solar	720	2026	0.381408	0.376842	0.281724	0.327589	0.343282	0.332799	0.277728	0.321180
Solar	720	2025	0.382124	0.375574	0.293143	0.333265	0.343979	0.332549	0.288362	0.326380
Weather	96	2027	0.191784	0.234420	0.168017	0.210654	0.188963	0.232582	0.167036	0.210167
Weather	96	2026	0.194790	0.237380	0.167695	0.210334	0.192121	0.235643	0.166333	0.209746
Weather	96	2025	0.190216	0.233874	0.167557	0.210044	0.187751	0.232201	0.166534	0.209583
Weather	192	2027	0.236480	0.271768	0.211536	0.249800	0.233357	0.269825	0.210217	0.249077
Weather	192	2026	0.236208	0.273178	0.211956	0.249775	0.233587	0.271214	0.210478	0.248979
Weather	192	2025	0.235257	0.272516	0.211332	0.249643	0.232893	0.270599	0.210070	0.249021
Weather	336	2027	0.286158	0.307599	0.263647	0.289478	0.282966	0.305540	0.262253	0.288053

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Table 16 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Weather	336	2026	0.285550	0.307824	0.263448	0.289355	0.282659	0.305842	0.262070	0.288027
Weather	336	2025	0.286649	0.308664	0.266276	0.291205	0.284002	0.306902	0.265222	0.290135
Weather	720	2027	0.356382	0.355341	0.339916	0.341739	0.352787	0.352615	0.338154	0.339764
Weather	720	2026	0.357299	0.354938	0.340709	0.342783	0.352918	0.351940	0.338527	0.340372
Weather	720	2025	0.356902	0.355321	0.342412	0.343880	0.353278	0.352756	0.340587	0.341905
Electricity	96	2027	0.160600	0.250612	0.146658	0.238451	0.158790	0.249857	0.145804	0.237993
Electricity	96	2026	0.161010	0.251885	0.145839	0.237896	0.159087	0.250576	0.145169	0.237671
Electricity	96	2025	0.160473	0.251119	0.146219	0.238398	0.158785	0.250238	0.145505	0.238001
Electricity	192	2027	0.170234	0.259266	0.159991	0.249870	0.168684	0.258605	0.159146	0.249474
Electricity	192	2026	0.199435	0.288545	0.164393	0.255631	0.186564	0.279660	0.163063	0.254301
Electricity	192	2025	0.170436	0.259506	0.160343	0.250504	0.168915	0.258879	0.159367	0.249979
Electricity	336	2027	0.187530	0.276421	0.178863	0.268992	0.185532	0.275398	0.177324	0.267902
Electricity	336	2026	0.187342	0.276436	0.178863	0.268816	0.185321	0.275316	0.177442	0.267858
Electricity	336	2025	0.215738	0.303674	0.182385	0.273366	0.202758	0.294753	0.180568	0.271657
Electricity	720	2027	0.227412	0.310631	0.217676	0.300604	0.224955	0.308769	0.216422	0.299921
Electricity	720	2026	0.227992	0.312557	0.217931	0.301079	0.225307	0.309362	0.216566	0.300148
Electricity	720	2025	0.228000	0.309655	0.217298	0.300728	0.225553	0.308251	0.216140	0.300035

H.3 PATCHTST

Table 17: PatchTST: per-seed MSE and MAE for all four variants.

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	2027	0.390168	0.407013	0.390529	0.409335	0.386757	0.404493	0.386180	0.407012
ETTh1	96	2026	0.386857	0.403754	0.383151	0.403367	0.383921	0.401607	0.378909	0.401226
ETTh1	96	2025	0.388296	0.404526	0.384417	0.402676	0.385308	0.402282	0.380641	0.401051
ETTh1	192	2027	0.434650	0.431000	0.433592	0.430110	0.431596	0.429167	0.430552	0.429196
ETTh1	192	2026	0.431386	0.427601	0.428965	0.427303	0.429142	0.426680	0.426888	0.426880
ETTh1	192	2025	0.433314	0.429525	0.430654	0.428459	0.430470	0.427910	0.428616	0.427940
ETTh1	336	2027	0.463424	0.445856	0.458998	0.442904	0.460836	0.444747	0.457658	0.443833
ETTh1	336	2026	0.459780	0.442463	0.452822	0.440294	0.457686	0.441955	0.451944	0.441180
ETTh1	336	2025	0.461593	0.444181	0.454094	0.441000	0.459031	0.443152	0.452802	0.441763
ETTh1	720	2027	0.467131	0.471157	0.465577	0.470724	0.464168	0.470208	0.462157	0.469535
ETTh1	720	2026	0.456389	0.462978	0.456267	0.462961	0.453854	0.462336	0.454497	0.462997
ETTh1	720	2025	0.456896	0.464485	0.457734	0.464284	0.454101	0.463511	0.455534	0.464110
ETTh2	96	2027	0.286185	0.340003	0.285204	0.339085	0.284600	0.338580	0.283992	0.337829
ETTh2	96	2026	0.285970	0.340373	0.286415	0.340289	0.284461	0.338995	0.285499	0.339295
ETTh2	96	2025	0.285455	0.339446	0.285342	0.339012	0.283889	0.337947	0.284053	0.337655
ETTh2	192	2027	0.360035	0.386946	0.358781	0.385166	0.358333	0.385618	0.357683	0.384293
ETTh2	192	2026	0.359924	0.387966	0.357436	0.385783	0.358787	0.387030	0.356712	0.385211
ETTh2	192	2025	0.358772	0.386681	0.357204	0.385739	0.357408	0.385472	0.356367	0.385024
ETTh2	336	2027	0.390393	0.412089	0.389349	0.413400	0.389065	0.410917	0.389090	0.413201
ETTh2	336	2026	0.390813	0.415499	0.392363	0.416275	0.389700	0.414456	0.391728	0.415712
ETTh2	336	2025	0.389442	0.413600	0.389444	0.414077	0.387880	0.412155	0.388720	0.413280
ETTh2	720	2027	0.406019	0.433424	0.405844	0.434048	0.404890	0.432188	0.405531	0.433464
ETTh2	720	2026	0.407832	0.434813	0.406584	0.434714	0.407172	0.433972	0.406546	0.434317
ETTh2	720	2025	0.406487	0.433818	0.406623	0.434399	0.405295	0.432580	0.406051	0.433646
ETTm1	96	2027	0.303276	0.343130	0.298214	0.343991	0.299875	0.339825	0.296485	0.342207
ETTm1	96	2026	0.305033	0.343090	0.294931	0.341638	0.300634	0.339617	0.293548	0.340066
ETTm1	96	2025	0.303902	0.342815	0.298884	0.345947	0.299562	0.339085	0.296456	0.343139
ETTm1	192	2027	0.342348	0.364640	0.336204	0.366176	0.339562	0.363036	0.334232	0.365160
ETTm1	192	2026	0.342941	0.366564	0.333616	0.364431	0.340211	0.364813	0.331572	0.363369
ETTm1	192	2025	0.343425	0.366108	0.334695	0.365247	0.340903	0.364484	0.333071	0.364163
ETTm1	336	2027	0.378644	0.386545	0.366056	0.387115	0.375345	0.385214	0.363482	0.386199
ETTm1	336	2026	0.377477	0.386700	0.367805	0.387032	0.374130	0.385229	0.365831	0.386275
ETTm1	336	2025	0.379884	0.387491	0.365695	0.387288	0.376944	0.386099	0.363111	0.386139
ETTm1	720	2027	0.437428	0.421181	0.426303	0.422506	0.435784	0.420855	0.423329	0.422122

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Table 17 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTm1	720	2026	0.439864	0.424193	0.425111	0.421078	0.438058	0.423997	0.424182	0.421307
ETTm1	720	2025	0.436447	0.420678	0.425388	0.420523	0.434767	0.420109	0.423881	0.420281
ETTm2	96	2027	0.167216	0.250877	0.166779	0.250953	0.166670	0.250267	0.166327	0.250355
ETTm2	96	2026	0.167691	0.251265	0.167975	0.251908	0.167193	0.250625	0.167456	0.251165
ETTm2	96	2025	0.167069	0.250925	0.167500	0.251455	0.166527	0.250297	0.166878	0.250593
ETTm2	192	2027	0.228354	0.291945	0.227067	0.292172	0.228026	0.291695	0.226577	0.291595
ETTm2	192	2026	0.227111	0.291167	0.229325	0.292331	0.226825	0.290993	0.228829	0.291848
ETTm2	192	2025	0.227506	0.291005	0.228046	0.291912	0.227138	0.290816	0.227584	0.291409
ETTm2	336	2027	0.283526	0.329116	0.280934	0.328394	0.283098	0.328991	0.280498	0.328054
ETTm2	336	2026	0.282510	0.328655	0.280841	0.328583	0.282063	0.328475	0.280355	0.328038
ETTm2	336	2025	0.283324	0.329166	0.279994	0.327828	0.282766	0.328875	0.280141	0.327835
ETTm2	720	2027	0.379436	0.384757	0.369844	0.383556	0.379231	0.384732	0.370237	0.383634
ETTm2	720	2026	0.377183	0.384062	0.370887	0.383913	0.376798	0.384097	0.371555	0.384068
ETTm2	720	2025	0.376213	0.383455	0.369977	0.383833	0.375737	0.383419	0.369831	0.383677
Solar	96	2027	0.220118	0.262579	0.196770	0.258602	0.213565	0.255601	0.193727	0.252149
Solar	96	2026	0.228684	0.260862	0.182724	0.233132	0.224619	0.256225	0.182564	0.232464
Solar	96	2025	0.214997	0.266578	0.186923	0.238819	0.206989	0.259040	0.186110	0.237223
Solar	192	2027	0.253595	0.285367	0.215487	0.261373	0.246125	0.274707	0.214689	0.259207
Solar	192	2026	0.255637	0.282822	0.225552	0.267708	0.247213	0.289408	0.223954	0.264827
Solar	192	2025	0.249179	0.283850	0.226045	0.272394	0.240777	0.274938	0.225066	0.270082
Solar	336	2027	0.283767	0.304058	0.246618	0.277242	0.276113	0.295617	0.246054	0.276425
Solar	336	2026	0.285057	0.310955	0.253582	0.287370	0.276298	0.316145	0.252984	0.285997
Solar	336	2025	0.271944	0.301851	0.231290	0.266323	0.265304	0.292179	0.231056	0.265820
Solar	720	2027	0.269273	0.289788	0.248190	0.276701	0.266371	0.290136	0.248154	0.276567
Solar	720	2026	0.283833	0.304760	0.255924	0.288724	0.279042	0.306560	0.255721	0.288292
Solar	720	2025	0.273645	0.299705	0.242332	0.272751	0.270958	0.296343	0.242322	0.272723
Weather	96	2027	0.178347	0.218722	0.171644	0.212390	0.177312	0.218987	0.170470	0.212615
Weather	96	2026	0.179066	0.219281	0.170536	0.211774	0.177643	0.219487	0.169717	0.211951
Weather	96	2025	0.177084	0.219290	0.169481	0.211427	0.176328	0.219596	0.168675	0.211559
Weather	192	2027	0.220933	0.254959	0.215421	0.250726	0.219563	0.254623	0.214369	0.250459
Weather	192	2026	0.222783	0.256528	0.214803	0.250988	0.221093	0.256076	0.214241	0.250766
Weather	192	2025	0.221334	0.256648	0.214747	0.251342	0.220168	0.256384	0.213349	0.251162
Weather	336	2027	0.272055	0.292452	0.267112	0.289490	0.270784	0.292153	0.266075	0.289507
Weather	336	2026	0.273730	0.293840	0.266500	0.289458	0.272090	0.293376	0.266066	0.289385
Weather	336	2025	0.272493	0.293721	0.266073	0.289309	0.271190	0.293441	0.264914	0.289227
Weather	720	2027	0.344872	0.341937	0.340987	0.339994	0.342927	0.341015	0.339190	0.339148
Weather	720	2026	0.345921	0.342591	0.340481	0.340168	0.343777	0.341624	0.339393	0.339488
Weather	720	2025	0.344745	0.342528	0.340177	0.340208	0.343035	0.341774	0.338532	0.339442
Electricity	96	2027	0.175479	0.277063	0.165972	0.267366	0.171214	0.272365	0.163991	0.264882
Electricity	96	2026	0.179597	0.282052	0.169261	0.272887	0.174133	0.275870	0.167296	0.270406
Electricity	96	2025	0.180322	0.282509	0.169093	0.271091	0.174699	0.276512	0.166465	0.268148
Electricity	192	2027	0.187200	0.286906	0.181068	0.280814	0.183110	0.282451	0.178963	0.278385
Electricity	192	2026	0.191374	0.291839	0.184261	0.285200	0.186088	0.286032	0.182087	0.282568
Electricity	192	2025	0.191449	0.291604	0.182213	0.281736	0.185810	0.285600	0.179634	0.278909
Electricity	336	2027	0.204272	0.302278	0.197790	0.295946	0.200322	0.298223	0.195665	0.293483
Electricity	336	2026	0.208681	0.307320	0.201390	0.300814	0.203260	0.301451	0.198982	0.297988
Electricity	336	2025	0.208215	0.306683	0.199909	0.297988	0.202863	0.301048	0.197550	0.295466
Electricity	720	2027	0.243715	0.332247	0.236689	0.325845	0.239471	0.328264	0.235128	0.324241
Electricity	720	2026	0.248103	0.336978	0.244003	0.334464	0.242641	0.331583	0.241991	0.332246
Electricity	720	2025	0.246669	0.335406	0.238803	0.328058	0.241813	0.330753	0.237139	0.326552

H.4 TIMEMIXER

Table 18: TimeMixer: per-seed MSE and MAE for all four variants.

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	2027	0.380250	0.397101	0.380330	0.395684	0.376363	0.394572	0.374649	0.392724
ETTh1	96	2026	0.378205	0.398961	0.378578	0.398530	0.374370	0.396419	0.374232	0.395938
ETTh1	96	2025	0.383009	0.397116	0.375895	0.394117	0.375518	0.393107	0.372493	0.391726
ETTh1	192	2027	0.441515	0.430934	0.431483	0.425061	0.435587	0.429330	0.427551	0.423963
ETTh1	192	2026	0.429735	0.424274	0.438439	0.427240	0.424984	0.422278	0.433172	0.426556
ETTh1	192	2025	0.420144	0.420222	0.422885	0.420698	0.416956	0.418583	0.418803	0.419558
ETTh1	336	2027	0.479245	0.457244	0.478957	0.457193	0.470345	0.452380	0.471025	0.452838
ETTh1	336	2026	0.475372	0.450683	0.474972	0.449069	0.471997	0.451127	0.471785	0.450040
ETTh1	336	2025	0.477073	0.456036	0.462701	0.441564	0.468710	0.451374	0.458502	0.441259
ETTh1	720	2027	0.483617	0.481223	0.483814	0.481341	0.473924	0.476333	0.474594	0.476743
ETTh1	720	2026	0.490996	0.483443	0.569399	0.526376	0.481872	0.480158	0.566484	0.526104
ETTh1	720	2025	0.490104	0.484462	0.488349	0.484084	0.480939	0.480263	0.480417	0.480244
ETTh2	96	2027	0.291094	0.345546	0.290600	0.344965	0.288532	0.342896	0.288063	0.342302
ETTh2	96	2026	0.292631	0.347263	0.288265	0.346160	0.291456	0.346105	0.287235	0.345110
ETTh2	96	2025	0.293852	0.346861	0.293121	0.345860	0.292081	0.345298	0.291461	0.344365
ETTh2	192	2027	0.361907	0.389070	0.362502	0.388939	0.360287	0.387637	0.360996	0.387603
ETTh2	192	2026	0.365867	0.392483	0.364889	0.391922	0.362991	0.390189	0.362234	0.389764
ETTh2	192	2025	0.366633	0.393751	0.365550	0.392642	0.364444	0.391932	0.363388	0.390829
ETTh2	336	2027	0.394274	0.417533	0.394733	0.417601	0.391862	0.415506	0.392470	0.415668
ETTh2	336	2026	0.390288	0.414920	0.392018	0.416680	0.388620	0.413326	0.390460	0.415177
ETTh2	336	2025	0.396158	0.419282	0.396040	0.419187	0.392780	0.416517	0.392786	0.416514
ETTh2	720	2027	0.427205	0.444469	0.414195	0.436073	0.426360	0.443404	0.414299	0.435626
ETTh2	720	2026	0.419639	0.444431	0.418614	0.443691	0.419787	0.444041	0.418837	0.443321
ETTh2	720	2025	0.417821	0.440241	0.417636	0.440347	0.416477	0.439008	0.416237	0.439071
ETTm1	96	2027	0.292789	0.340161	0.290507	0.339779	0.287941	0.336534	0.285598	0.335731
ETTm1	96	2026	0.289355	0.340665	0.291773	0.343449	0.284429	0.336952	0.285728	0.338980
ETTm1	96	2025	0.293610	0.341905	0.291521	0.338988	0.286889	0.335845	0.285891	0.334533
ETTm1	192	2027	0.344303	0.374267	0.340109	0.373216	0.335909	0.368659	0.331368	0.367216
ETTm1	192	2026	0.340498	0.371724	0.340885	0.370096	0.336211	0.367501	0.336491	0.366936
ETTm1	192	2025	0.336127	0.366255	0.337639	0.368172	0.331141	0.362229	0.331219	0.362931
ETTm1	336	2027	0.362553	0.386905	0.371671	0.393002	0.358938	0.384228	0.366838	0.389510
ETTm1	336	2026	0.364673	0.389472	0.368237	0.392122	0.362145	0.386838	0.364278	0.389216
ETTm1	336	2025	0.367919	0.388576	0.366839	0.388848	0.363266	0.385288	0.361790	0.385492
ETTm1	720	2027	0.429386	0.426140	0.427813	0.427226	0.427610	0.425082	0.425459	0.426110
ETTm1	720	2026	0.424305	0.425653	0.428295	0.429669	0.423364	0.425059	0.426766	0.428715
ETTm1	720	2025	0.427801	0.425658	0.432280	0.427444	0.425806	0.424295	0.429523	0.425831
ETTm2	96	2027	0.174563	0.253997	0.168432	0.252000	0.172740	0.252445	0.167111	0.250771
ETTm2	96	2026	0.171151	0.255289	0.171233	0.250600	0.169525	0.253120	0.169549	0.249240
ETTm2	96	2025	0.169634	0.254002	0.169680	0.253533	0.168183	0.252494	0.168255	0.251955
ETTm2	192	2027	0.231690	0.295200	0.228533	0.293055	0.229729	0.293183	0.226824	0.291167
ETTm2	192	2026	0.227637	0.293516	0.227962	0.293347	0.225576	0.291651	0.225804	0.291514
ETTm2	192	2025	0.235179	0.294448	0.228413	0.292183	0.233958	0.293396	0.227327	0.291084
ETTm2	336	2027	0.281950	0.328546	0.280696	0.328174	0.280623	0.327387	0.279255	0.326932
ETTm2	336	2026	0.277906	0.325906	0.277428	0.325543	0.276911	0.325147	0.276497	0.324900
ETTm2	336	2025	0.280071	0.329126	0.279180	0.328667	0.278301	0.327482	0.277440	0.327095
ETTm2	720	2027	0.375705	0.388315	0.371999	0.383630	0.373923	0.387420	0.370734	0.382603
ETTm2	720	2026	0.367758	0.384772	0.366403	0.384176	0.367304	0.384145	0.365906	0.383572
ETTm2	720	2025	0.383594	0.393808	0.370424	0.383207	0.381261	0.392383	0.368690	0.381917
Solar	96	2027	0.175198	0.219599	0.174977	0.216243	0.174736	0.218602	0.174811	0.216090
Solar	96	2026	0.174598	0.218442	0.173480	0.213082	0.174081	0.216940	0.173250	0.213094
Solar	96	2025	0.179062	0.227472	0.172884	0.212313	0.177389	0.227446	0.172399	0.212648
Solar	192	2027	0.202861	0.243309	0.196237	0.236238	0.202484	0.242621	0.196122	0.236252
Solar	192	2026	0.199022	0.237301	0.196064	0.232244	0.198420	0.236475	0.195875	0.232360
Solar	192	2025	0.199881	0.236600	0.198054	0.235515	0.198834	0.236501	0.197921	0.235530
Solar	336	2027	0.219497	0.254650	0.212048	0.250764	0.217095	0.255413	0.211768	0.250652
Solar	336	2026	0.212288	0.248825	0.207461	0.243751	0.212162	0.248616	0.207234	0.243835
Solar	336	2025	0.225943	0.262112	0.213623	0.248929	0.224464	0.263621	0.213496	0.248740

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Table 18 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Solar	720	2027	0.225081	0.260877	0.219825	0.256292	0.225029	0.260815	0.219781	0.256204
Solar	720	2026	0.219308	0.253817	0.217196	0.251856	0.219290	0.253798	0.217121	0.251833
Solar	720	2025	0.222034	0.256032	0.215151	0.251543	0.221992	0.255976	0.215087	0.251502
Weather	96	2027	0.153628	0.196490	0.151166	0.193430	0.152879	0.196055	0.150613	0.192987
Weather	96	2026	0.150792	0.193624	0.149861	0.191917	0.150541	0.193618	0.149390	0.191593
Weather	96	2025	0.152016	0.194848	0.150322	0.192330	0.151511	0.194502	0.149784	0.192008
Weather	192	2027	0.194218	0.234982	0.194417	0.233995	0.193878	0.234605	0.194090	0.233702
Weather	192	2026	0.193927	0.235271	0.192747	0.234829	0.192714	0.234331	0.192312	0.234442
Weather	192	2025	0.195035	0.238013	0.193133	0.235008	0.194772	0.238001	0.192793	0.234841
Weather	336	2027	0.250247	0.279560	0.249188	0.277571	0.249713	0.279046	0.248333	0.276985
Weather	336	2026	0.249557	0.277067	0.248549	0.276200	0.249183	0.276687	0.248263	0.275857
Weather	336	2025	0.248330	0.276545	0.245269	0.274830	0.247453	0.275900	0.244678	0.274167
Weather	720	2027	0.327169	0.331351	0.328602	0.332892	0.326432	0.330537	0.327861	0.332302
Weather	720	2026	0.325062	0.329508	0.325353	0.329760	0.323976	0.328845	0.324580	0.329269
Weather	720	2025	0.327832	0.331297	0.329625	0.332931	0.326413	0.330328	0.328158	0.331841
Electricity	96	2027	0.137429	0.229928	0.136594	0.229024	0.137113	0.229571	0.136181	0.228586
Electricity	96	2026	0.137648	0.230030	0.136546	0.229005	0.137329	0.229795	0.136171	0.228701
Electricity	96	2025	0.137117	0.229627	0.135949	0.228242	0.136793	0.229311	0.135582	0.227922
Electricity	192	2027	0.155488	0.246469	0.154622	0.245425	0.155099	0.246025	0.154123	0.244938
Electricity	192	2026	0.155243	0.245832	0.154354	0.245007	0.154822	0.245439	0.153887	0.244551
Electricity	192	2025	0.155459	0.246022	0.154735	0.245550	0.155031	0.245558	0.154234	0.245011
Electricity	336	2027	0.173716	0.265058	0.172823	0.263662	0.173288	0.264457	0.172392	0.263212
Electricity	336	2026	0.173057	0.263658	0.172585	0.263055	0.172734	0.263379	0.172201	0.262690
Electricity	336	2025	0.173724	0.264772	0.173023	0.264021	0.173338	0.264349	0.172593	0.263584
Electricity	720	2027	0.213395	0.299835	0.210834	0.296890	0.212779	0.298871	0.210562	0.296532
Electricity	720	2026	0.210778	0.295708	0.209849	0.295347	0.210668	0.295643	0.209679	0.295233
Electricity	720	2025	0.211976	0.298222	0.209884	0.295923	0.211795	0.298036	0.209558	0.295583

H.5 TIMEBRIDGE

Table 19: TimeBridge: per-seed MSE and MAE for all four variants.

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	2027	0.375413	0.398370	0.369683	0.393950	0.371702	0.397459	0.363437	0.391575
ETTh1	96	2026	0.371665	0.394701	0.370658	0.394528	0.365089	0.391746	0.364676	0.392226
ETTh1	96	2025	0.373865	0.397501	0.374925	0.395594	0.365910	0.394001	0.365694	0.392741
ETTh1	192	2027	0.461326	0.447961	0.432381	0.430770	0.457760	0.448483	0.426413	0.431158
ETTh1	192	2026	0.449857	0.444723	0.428928	0.428482	0.447005	0.445840	0.423277	0.428963
ETTh1	192	2025	0.441537	0.440575	0.438884	0.438612	0.437469	0.440912	0.434960	0.439173
ETTh1	336	2027	0.506500	0.474294	0.456696	0.440322	0.503431	0.475880	0.455192	0.441362
ETTh1	336	2026	0.474199	0.455225	0.474314	0.455179	0.471223	0.457523	0.471065	0.456796
ETTh1	336	2025	0.499089	0.470771	0.494409	0.466592	0.496221	0.471565	0.489955	0.469322
ETTh1	720	2027	0.606952	0.534561	0.615890	0.533004	0.602058	0.536836	0.611553	0.533969
ETTh1	720	2026	0.530199	0.502524	0.556943	0.511011	0.527145	0.503884	0.552907	0.512872
ETTh1	720	2025	0.633240	0.542928	0.475792	0.471626	0.628021	0.544197	0.470086	0.475680
ETTh2	96	2027	0.296717	0.348546	0.294200	0.346471	0.292785	0.345759	0.291328	0.344204
ETTh2	96	2026	0.305153	0.351948	0.308670	0.354063	0.303113	0.350251	0.306437	0.352349
ETTh2	96	2025	0.302782	0.352154	0.300381	0.349657	0.298851	0.349349	0.295247	0.345605
ETTh2	192	2027	0.360430	0.390942	0.360156	0.390414	0.357535	0.388755	0.357141	0.388241
ETTh2	192	2026	0.358309	0.391419	0.369136	0.395239	0.355865	0.389566	0.366537	0.393718
ETTh2	192	2025	0.367414	0.399266	0.364660	0.391929	0.364554	0.397462	0.361230	0.389459
ETTh2	336	2027	0.394458	0.419592	0.398984	0.419920	0.392014	0.417587	0.397038	0.418284
ETTh2	336	2026	0.389687	0.414666	0.390115	0.414906	0.387181	0.412623	0.387389	0.412854
ETTh2	336	2025	0.398810	0.422804	0.403220	0.421777	0.395901	0.420723	0.400643	0.420175
ETTh2	720	2027	0.407319	0.432104	0.407944	0.432458	0.406356	0.431330	0.406727	0.431582
ETTh2	720	2026	0.412720	0.439155	0.416815	0.442228	0.410811	0.437829	0.414869	0.440896
ETTh2	720	2025	0.409595	0.437840	0.408648	0.435129	0.408841	0.437077	0.408299	0.434594

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Table 19 (continued)

Data	H	Seed	Native		+TSA		+LPC		TSA+LPC	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTm1	96	2027	0.292112	0.335947	0.293112	0.337611	0.288366	0.332959	0.289700	0.334870
ETTm1	96	2026	0.290649	0.336706	0.297613	0.339025	0.287342	0.334214	0.293867	0.336202
ETTm1	96	2025	0.291127	0.336878	0.293169	0.336660	0.287408	0.334001	0.288805	0.333882
ETTm1	192	2027	0.337081	0.364462	0.340215	0.368889	0.332166	0.361270	0.335870	0.365901
ETTm1	192	2026	0.348022	0.370064	0.338036	0.365246	0.338636	0.364740	0.334747	0.363289
ETTm1	192	2025	0.331119	0.362381	0.332346	0.363156	0.327470	0.360108	0.329526	0.361545
ETTm1	336	2027	0.374422	0.389198	0.369973	0.391134	0.370940	0.387058	0.367775	0.389666
ETTm1	336	2026	0.369058	0.388011	0.366936	0.390374	0.365850	0.385920	0.363721	0.388288
ETTm1	336	2025	0.374879	0.391361	0.370382	0.393544	0.371789	0.389306	0.366998	0.391115
ETTm1	720	2027	0.435311	0.428367	0.431738	0.427546	0.432474	0.427139	0.428113	0.426120
ETTm1	720	2026	0.433758	0.424710	0.429716	0.424556	0.432360	0.424099	0.428145	0.424297
ETTm1	720	2025	0.426112	0.422695	0.427716	0.425424	0.424329	0.421797	0.425807	0.424725
ETTm2	96	2027	0.170204	0.251472	0.169771	0.251398	0.168959	0.250340	0.168320	0.249947
ETTm2	96	2026	0.169810	0.252698	0.169546	0.251974	0.168648	0.251405	0.168521	0.250945
ETTm2	96	2025	0.169635	0.252055	0.169184	0.251108	0.168408	0.250601	0.167826	0.249709
ETTm2	192	2027	0.235704	0.296284	0.238391	0.296838	0.234051	0.294923	0.235554	0.294994
ETTm2	192	2026	0.232115	0.294851	0.231741	0.293480	0.230387	0.293340	0.230167	0.292238
ETTm2	192	2025	0.235959	0.296966	0.231735	0.293066	0.234244	0.295496	0.230701	0.292097
ETTm2	336	2027	0.285799	0.332069	0.284666	0.331055	0.283728	0.330047	0.282844	0.329262
ETTm2	336	2026	0.282928	0.331698	0.286168	0.332138	0.281272	0.330692	0.284452	0.331244
ETTm2	336	2025	0.295074	0.338100	0.285747	0.331186	0.292661	0.336701	0.284282	0.329628
ETTm2	720	2027	0.378757	0.389948	0.383843	0.393072	0.378290	0.389324	0.383692	0.392829
ETTm2	720	2026	0.380105	0.392089	0.382282	0.394162	0.379188	0.391150	0.380389	0.393574
ETTm2	720	2025	0.387404	0.396567	0.383940	0.393492	0.385767	0.395654	0.383547	0.393457
Solar	96	2027	0.175226	0.213637	0.176820	0.216970	0.174904	0.213284	0.176276	0.216701
Solar	96	2026	0.175104	0.212591	0.174801	0.210524	0.174975	0.212459	0.174685	0.210238
Solar	96	2025	0.172165	0.211631	0.178104	0.215516	0.171954	0.211183	0.177542	0.215113
Solar	192	2027	0.201115	0.237591	0.199560	0.233575	0.200857	0.236977	0.199371	0.233505
Solar	192	2026	0.199954	0.235952	0.197379	0.232338	0.199858	0.235937	0.197322	0.232332
Solar	192	2025	0.198844	0.234975	0.196934	0.236613	0.198740	0.234884	0.196583	0.235620
Solar	336	2027	0.212898	0.247693	0.209147	0.244118	0.212788	0.247634	0.209037	0.244109
Solar	336	2026	0.212750	0.243533	0.208157	0.241776	0.212620	0.243499	0.208086	0.241765
Solar	336	2025	0.212062	0.243555	0.208509	0.243110	0.211931	0.243473	0.208349	0.242865
Solar	720	2027	0.218090	0.250964	0.213965	0.247180	0.218023	0.250963	0.213903	0.247192
Solar	720	2026	0.217144	0.246805	0.213220	0.245575	0.217049	0.246806	0.213169	0.245557
Solar	720	2025	0.216096	0.247225	0.211715	0.246573	0.216004	0.247235	0.211665	0.246567
Weather	96	2027	0.156157	0.197418	0.154490	0.195597	0.155584	0.197263	0.153855	0.195564
Weather	96	2026	0.156946	0.196904	0.157781	0.198587	0.156320	0.196899	0.157001	0.198151
Weather	96	2025	0.155613	0.196108	0.156166	0.197295	0.154875	0.196066	0.155714	0.197383
Weather	192	2027	0.200172	0.236037	0.198688	0.236207	0.199895	0.235925	0.198579	0.236294
Weather	192	2026	0.200963	0.238529	0.200381	0.239587	0.200545	0.238721	0.200015	0.239697
Weather	192	2025	0.201932	0.238651	0.202206	0.239744	0.201495	0.238810	0.201730	0.239572
Weather	336	2027	0.255024	0.279263	0.255548	0.279555	0.254650	0.278879	0.255171	0.279122
Weather	336	2026	0.255723	0.279589	0.253222	0.277844	0.255146	0.279159	0.252688	0.277514
Weather	336	2025	0.256343	0.278826	0.255085	0.278414	0.255789	0.278172	0.254727	0.277995
Weather	720	2027	0.334727	0.334179	0.339008	0.334921	0.333559	0.333383	0.337455	0.333776
Weather	720	2026	0.335814	0.334237	0.332688	0.334712	0.334430	0.332752	0.331605	0.334267
Weather	720	2025	0.337725	0.333721	0.334095	0.333746	0.336767	0.332740	0.333150	0.332792
Electricity	96	2027	0.139695	0.230181	0.138535	0.228839	0.139036	0.229233	0.137914	0.228093
Electricity	96	2026	0.139492	0.229728	0.138337	0.228889	0.138722	0.228809	0.137738	0.228245
Electricity	96	2025	0.139515	0.230740	0.138168	0.229546	0.138778	0.230019	0.137636	0.228900
Electricity	192	2027	0.155663	0.244790	0.154576	0.244188	0.155174	0.244308	0.154040	0.243698
Electricity	192	2026	0.155854	0.245006	0.154831	0.244278	0.155239	0.244364	0.154301	0.243746
Electricity	192	2025	0.156188	0.245491	0.154464	0.244033	0.155656	0.244866	0.153949	0.243549
Electricity	336	2027	0.174320	0.263306	0.171750	0.261583	0.173735	0.262667	0.171232	0.261040
Electricity	336	2026	0.172905	0.262596	0.172683	0.262321	0.172323	0.261949	0.172031	0.261613
Electricity	336	2025	0.175343	0.264537	0.172708	0.262211	0.174750	0.263930	0.172166	0.261657
Electricity	720	2027	0.213435	0.296089	0.211583	0.294830	0.213103	0.295864	0.211273	0.294635
Electricity	720	2026	0.211235	0.294764	0.209757	0.293869	0.210951	0.294582	0.209537	0.293714
Electricity	720	2025	0.213650	0.296510	0.212674	0.295819	0.212891	0.295716	0.212279	0.295518

H.6 CCM

Table 20 reports the corresponding per-seed CCM errors for DLinear and PatchTST.

Table 20: Per-seed forecasting errors for CCM. Error pairs are MSE / MAE.

Data	H	Seed 2027	Seed 2026	Seed 2025
(a) DLinear + CCM				
Data	H	Seed 2027	Seed 2026	Seed 2025
ETTh1	96	0.384460 / 0.401203	0.378709 / 0.393552	0.375731 / 0.392508
ETTh1	192	0.420739 / 0.418974	0.419917 / 0.417378	0.429234 / 0.427711
ETTh1	336	0.460699 / 0.445952	0.469442 / 0.451749	0.456714 / 0.445573
ETTh1	720	0.474675 / 0.485249	0.477664 / 0.488088	0.498105 / 0.505338
ETTh2	96	0.284188 / 0.339918	0.291408 / 0.347978	0.291619 / 0.348678
ETTh2	192	0.376833 / 0.405137	0.385376 / 0.411249	0.398876 / 0.421626
ETTh2	336	0.479807 / 0.472740	0.426446 / 0.440800	0.477776 / 0.472837
ETTh2	720	0.642866 / 0.563408	0.502926 / 0.493220	0.645809 / 0.563395
ETTm1	96	0.305378 / 0.342574	0.305478 / 0.342646	0.306730 / 0.344416
ETTm1	192	0.341762 / 0.364484	0.341782 / 0.364504	0.341936 / 0.364929
ETTm1	336	0.378790 / 0.388817	0.379587 / 0.388969	0.380585 / 0.390786
ETTm1	720	0.437773 / 0.425907	0.440408 / 0.428964	0.435400 / 0.423752
ETTm2	96	0.170833 / 0.259033	0.171604 / 0.256152	0.172836 / 0.260767
ETTm2	192	0.231902 / 0.299271	0.233993 / 0.305976	0.233419 / 0.302264
ETTm2	336	0.289094 / 0.341428	0.292018 / 0.346749	0.304459 / 0.356341
ETTm2	720	0.417143 / 0.431398	0.392048 / 0.400445	0.412174 / 0.428782
Solar	96	0.221097 / 0.258336	0.221724 / 0.251120	0.224102 / 0.268248
Solar	192	0.260571 / 0.289461	0.262410 / 0.308352	0.266368 / 0.278139
Solar	336	0.301444 / 0.316952	0.305405 / 0.313430	0.302336 / 0.320367
Solar	720	0.307757 / 0.323727	0.302961 / 0.313628	0.301926 / 0.318975
Weather	96	0.188108 / 0.241225	0.178848 / 0.223726	0.179080 / 0.228206
Weather	192	0.220748 / 0.268049	0.220574 / 0.267466	0.221556 / 0.266150
Weather	336	0.289039 / 0.330856	0.272685 / 0.311888	0.272284 / 0.315972
Weather	720	0.334869 / 0.369540	0.342866 / 0.383631	0.381816 / 0.425318
Electricity	96	0.177007 / 0.280784	0.176372 / 0.270147	0.193389 / 0.285088
Electricity	192	0.195504 / 0.284172	0.185040 / 0.284241	0.195345 / 0.283185
Electricity	336	0.199149 / 0.294769	0.196344 / 0.289449	0.208196 / 0.302820
Electricity	720	0.233677 / 0.328628	0.224531 / 0.319187	0.234883 / 0.324019
(b) PatchTST + CCM				
Data	H	Seed 2027	Seed 2026	Seed 2025
ETTh1	96	0.391189 / 0.407632	0.388097 / 0.404219	0.390305 / 0.405753
ETTh1	192	0.437629 / 0.432804	0.434795 / 0.430683	0.440128 / 0.433476
ETTh1	336	0.459246 / 0.441794	0.464976 / 0.445389	0.461125 / 0.442319
ETTh1	720	0.465223 / 0.470608	0.462181 / 0.468341	0.458233 / 0.463233
ETTh2	96	0.287365 / 0.341044	0.286601 / 0.340740	0.286783 / 0.340655
ETTh2	192	0.362355 / 0.389197	0.360493 / 0.387919	0.362524 / 0.389625
ETTh2	336	0.390796 / 0.414719	0.389777 / 0.414746	0.392796 / 0.416164
ETTh2	720	0.410469 / 0.436683	0.413532 / 0.439301	0.418619 / 0.442051
ETTm1	96	0.303427 / 0.343181	0.304671 / 0.343338	0.303417 / 0.342259
ETTm1	192	0.344138 / 0.366519	0.342862 / 0.366549	0.343991 / 0.366850
ETTm1	336	0.377119 / 0.385928	0.375898 / 0.386288	0.376972 / 0.386508
ETTm1	720	0.440893 / 0.425403	0.435869 / 0.420261	0.435793 / 0.420938
ETTm2	96	0.167980 / 0.251791	0.168037 / 0.251980	0.167163 / 0.251337
ETTm2	192	0.228109 / 0.292158	0.227654 / 0.291888	0.227176 / 0.291170
ETTm2	336	0.283481 / 0.328916	0.282076 / 0.327672	0.283101 / 0.329435
ETTm2	720	0.376443 / 0.383677	0.374534 / 0.383168	0.371490 / 0.381724
Solar	96	0.208072 / 0.260988	0.212044 / 0.252398	0.214348 / 0.257817
Solar	192	0.248037 / 0.285540	0.250708 / 0.292134	0.245930 / 0.279464
Solar	336	0.265408 / 0.289738	0.267873 / 0.287908	0.262928 / 0.291576
Solar	720	0.277244 / 0.320028	0.270006 / 0.296224	0.264614 / 0.287132
Weather	96	0.175798 / 0.216485	0.176371 / 0.217112	0.175015 / 0.217129
Weather	192	0.219339 / 0.253998	0.220843 / 0.255372	0.220592 / 0.256230

Continued on next page

Table 20 (continued)

Data	H	Seed 2027	Seed 2026	Seed 2025
Weather	336	0.271160 / 0.292204	0.270984 / 0.291344	0.271361 / 0.293064
Weather	720	0.344310 / 0.342025	0.344086 / 0.341048	0.343601 / 0.342037
Electricity	96	0.173732 / 0.273201	0.171678 / 0.270695	0.170108 / 0.268538
Electricity	192	0.184094 / 0.281878	0.184895 / 0.283502	0.183235 / 0.279712
Electricity	336	0.200511 / 0.296626	0.200678 / 0.296345	0.199130 / 0.294228
Electricity	720	0.241636 / 0.328386	0.238999 / 0.325959	0.237496 / 0.324243

I HIGHER-PRECISION LIFT COMPLEMENTARITY RESULTS

Table 21 expands Table 5 to six decimal places using the same recorded results: seeds 2027, 2026, and 2025 and horizons 96, 192, 336, and 720. Each entry averages the twelve underlying errors directly, before rounding. The execution protocol is described in Appendix B.

Table 21: Higher-precision results for Table 5. Each entry equally averages four horizons and three seeds. Bold denotes the lowest displayed mean within each backbone–dataset group and metric.

	LIFT		+TSA		+LPC		+TASCT	
Dataset	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
DLinear								
ETTh1	0.436717	0.435864	0.436723	**0.435476**	0.434865	0.436704	**0.434849**	0.436437
ETTh2	0.429769	0.439514	0.429234	0.439370	0.424574	0.436671	**0.424272**	**0.436633**
ETTm1	0.362762	0.377276	0.359158	**0.375479**	0.360167	0.377636	**0.356072**	0.375735
ETTm2	0.354754	0.352578	0.340615	0.351907	0.310847	0.347612	**0.305910**	**0.347316**
Weather	0.228833	0.265747	0.227250	**0.264349**	0.227925	0.265631	**0.226436**	0.264448
Solar	0.208267	0.244343	0.204665	0.245346	0.208207	**0.244218**	**0.204621**	0.245246
Electricity	0.166749	0.258129	0.165171	**0.256834**	0.166607	0.258423	**0.165081**	0.257090
PatchTST								
ETTh1	0.456167	0.441288	0.462428	0.443545	**0.451236**	**0.440673**	0.456073	0.442809
ETTh2	0.358054	0.391579	0.358094	0.391237	0.356504	0.390292	**0.356237**	**0.389779**
ETTm1	0.364402	0.381651	0.365647	0.382352	**0.361685**	**0.380209**	0.362381	0.380704
ETTm2	0.267073	0.316350	0.270681	0.318533	**0.264005**	**0.314602**	0.266828	0.316421
Weather	0.231695	0.263636	0.230067	**0.261855**	0.230743	0.263188	**0.229251**	0.261863
Solar	0.206924	0.240390	0.203465	0.241070	0.206719	**0.240205**	**0.203366**	0.240867
Electricity	0.170736	0.263354	0.168928	0.261270	0.169810	0.262284	**0.168322**	**0.260693**