TransAlpha: Lightweight Design Empowers Stock Return Forecasting

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Abstract

In intraday stock return forecasting, existing Transformer methods face high computational complexity and do not explicitly handle noisy predictors. We propose TransAlpha, a light-weight Transformer variant tailored for cross section data to advance end-to-end forecasting methods with three novel components (Cross-Sectional Denoising for signal purification, Temporal Attention Gating for trend weighting, and Smart Pooling to avoid information loss) along with a multi-component hybrid loss function. We validate on full A-share market stock data and four key segments (CSI 300/500/1000/2000) with 400 proprietary alpha factors of 15-minute frequencies. TransAlpha outperforms state-of-the-art baselines in predictive power and portfolio profitability, indicating tailored Transformer models have significant practical value in quantitative trade.

1 Introduction

Stock return forecasting has advanced with AI. A solid forecasting method and stable prediction results can impact portfolio optimization and trading strategies. Practical stock forecasting methods can be categorized into time series forecasting models that use temporal sequences of individual stocks and multi-factor models that learn universal factor-return relationships across stocks and time via cross-sectional data. In recent years, Transformer [Vaswani *et al.*, 2017] approaches rise as an alternative for time series forecasting. Despite their success in processing language tokens, Transformers fail to replicate breakthroughs in time series forecasting. Influential work such as DLinear [Zeng *et al.*, 2023] is skeptical about whether complex Transformer architectures can outperform linear models. In particular, stock forecasting fundamentally differs from other time series forecasting tasks in the following aspects of challenges: (1) *Weak signal-to-noise ratio*: predictive features (alpha) signals are subtle, prune to noise and overfitting [Fama, 1970]. Signals are diluted if model has multiple compositions and residual connection blocks, which can decrease predictive power; (2) *High dimensionality of cross-sectional data*: quantitative trading strategies contain hundreds of alpha factors, introducing inter-dependencies [Li *et al.*, 2024]; (3) *Non-stationarity and volatility*: market micro-structures shift rapidly; trained models cannot generalize across time. As a result, leading quantitative companies still rely on more robust and interpretable linear models to combine with existing trading strategies for stable profit, but invest heavily in Transformer and Large Language Model (LLM) research to explore possibilities improving model's predictive power.

Our work comes from a realistic production environment of a quantitative company: we demonstrate Transformer model theories can be transferred to a profitable pipeline using proprietary alpha factors in A-Share market. We propose **TransAlpha**, a lightweight transformer-based architecture for stock return forecasting. Our main contributions are three-fold:

- A systematic investigation that incorporates state-of-the-art time series model architectures into multi-factor framework to examine their effectiveness for stock return forecasting.
- A domain-tailored Transformer architecture with three novel components: *cross-sectional denoising*, *temporal attention gating*, and *smart pooling*, all validated by real trading data.
- An industry-aligned pipeline that enables for training and back-testing custom models under a realistic setup with custom strategies.

These components address universal challenges such as noise in high-dimensional data, inefficient attention, and information loss when pooling. We balance academic reproducibility and proprietary privacy by providing the processed data files with anonymous alpha factors.

The remainder of this paper is organized as follows: Section 2 reviews related work in time series forecasting methods and past stock forecasting attempts. Section 3 presents the TransAlpha architecture. Section 4 presents research questions and experimental results. Section 5 concludes.

2 Related Work

2.1 Times Series Forecasting

Traditional time series methods are maximum likelihood-based statistical models, such as ARIMA, and GARCH [Bollerslev, 1986]. Both methods and their variants assume

stationarity, which are usually unrealistic, especially in intraday price movements. Later, a shift to machine learning introduced tree-based models such as XGBoost [Chen and Guestrin, 2016], LightGBM [Ke *et al.*, 2017]. They can capture non-linearity without distribution or stationarity assumptions. Further, LSTMs [Hochreiter and Schmidhuber, 1997] addressed the vanishing gradient problem, and DeepAR [Salinas *et al.*, 2020] pioneered in probabilistic forecasting. In addition, Convolutional Neural Network (CNN) models such as TCN [Bai *et al.*, 2018] and TimesNet [Wu *et al.*, 2022] use convolutional layers to capture local temporal patterns. Modern TCN [donghao and wang xue, 2024] refines TCN with much larger effective receptive fields. Later, Transformer [Vaswani *et al.*, 2017] replaced LSTM's recurrent layers with self-attention, enabling long-range dependency modeling. Transformer adaptations for time series faced high computational complexity up to $\mathcal{O}(L^2)$, where L is sequence length. Many variants are introduced to tackle this issue and attempt novel structures to solve long-sequence forecasting problem. Informer [Zhou *et al.*, 2021] proposes probability sparse attention to approximate the full attention matrix. Autoformer [Wu *et al.*, 2021] decomposes series to trend and seasonal components. PatchTST [Nie *et al.*, 2023] frames time series as tokens. Pyraformer [Liu *et al.*, 2022] proposes pyramidal attention to hierarchically compress temporal information. Crossformer [Zhang and Yan, 2023] establishes a Hierarchical Encoder-Decoder (HED) to use the information at different scales; iTransformer [Liu *et al.*, 2024] simply applies the attention and feed-forward network on the inverted dimensions. New direction involves adapting LLM techniques [Zhang *et al.*, 2024]. Time-MoE [Shi *et al.*, 2025] used a sparse Mixture-of-Experts (MoE) design based on scaling laws [Kaplan *et al.*, 2020] with 2.4 billion parameters but only activate a subset of experts.

2.2 Stock Return Prediction

The fluctuation of stock prices is influenced by a complex array of factors. Therefore, there is a need to utilize machine learning techniques [Zou *et al.*, 2023]. Models must balance between predictive power and noise robustness. Successful adaptations can date back to support vector machines (SVMs) methods [Cao and Tay, 2003]. LSTMs and GRUs [Zhu *et al.*, 2024] were also adapted. Graph WaveNet, [Park *et al.*, 2025]) incorporates Graph Neural Networks (GNNs) and hypergraphs to capture higher-order stock relationships. Mamba [Gu and Dao, 2024] integrates selective State-Space models (SSMs) into a simplified end-to-end neural network architecture. MASTER [Li *et al.*, 2024] introduced market-guided attention to prioritize macroeconomic signals over price fluctuations; MIGA [Yu *et al.*, 2024] employed a MoE framework to partition experts by temporal frequency. Despite these advances, several gaps remain in the literature: (1) few works validate their models on high-dimensional alpha data from real production environment; (2) there are limited studies systematically studying performance of Transformer models in stock forecasting. (3) successful methods and insights are typically non-disclosed for proprietary concerns.

3 Methodology

3.1 Problem Formulation

We formalize stock return forecasting as a supervised learning task. Let $S = \{s_1, s_2, \ldots, s_N\}$ denote the A-share stock universe, where N represents the total number of stocks. Let T denote the set of 15-minute cross sections within the observation period. For each cross section $t \in T$, the alpha factor matrix at time t is denoted as $\mathbf{X_t} \in \mathbb{R}^{N\times D}$, where $D = 400$ is the dimension of alpha factors, and each row $x_{t,s} \in \mathbb{R}^D$ corresponds to the factor value vector of stock s at time t. The true return vector at time t is $\mathbf{Y_t} \in \mathbb{R}^N$, where each element $y_{t,s}$ represents the 15-minute forward raw return of stock s at time t.

We use a look-back window of fixed length $L = 16$, corresponding to 16 consecutive 15-minute cross sections. Then, we construct a sequence of factor matrices $\{\mathbf{X}_{t-L+1}, \mathbf{X}_{t-L+2}, \ldots, \mathbf{X}_t\}$, where each matrix inside describes the cross-sectional distribution of factor values across all stocks at a t. The forecasting model maps this temporal sequence of cross-sectional factor data to a predicted return vector $\hat{\mathbf{Y}}_{t+1} \in \mathbb{R}^N$ for the next 15-minute cross section:

$$\hat{\mathbf{Y}}_{t+1} = f(\mathbf{X}_{t-L+1}, \mathbf{X}_{t-L+2}, \ldots, \mathbf{X}_t; \Theta)$$

where f denotes the model, and Θ is the set of trainable parameters. The observation period T is partitioned into non-overlapping subsets of train, validation, and test segments.

3.2 Model

We propose **TransAlpha** for intraday cross-sectional stock return forecasting in the A-share market. The model addresses three challenges: (1) idiosyncratic noise in alpha factor signals, (2) time-step relevance heterogeneity in intraday trends, and (3) signal dilution induced by over-engineering. We formalize the model following section 3.1.

Let $\mathbf{X} = \{\mathbf{X}_{t-L+1}, \mathbf{X}_{t-L+2}, \ldots, \mathbf{X}_t\}$ denote the input to TransAlpha. $\mathbf{X}$ is a temporal sequence of cross-sectional alpha factor matrices, where $\mathbf{X} \in \mathbb{R}^{N\times D}$. The output is a predicted 15-minute forward return vector $\hat{\mathbf{Y}}_{t+1} \in \mathbb{R}^N$. To present the three core modules of the model, we define the intermediate variables first. Let $\mathbf{X}_{\text{denoise}} \in \mathbb{R}^{N\times L\times D}$ be the denoised factor, $\mathbf{Z} \in \mathbb{R}^{N\times L\times d}$ be the projected feature, and $\mathbf{Z}_{\text{gated}} \in \mathbb{R}^{N\times L\times d}$ be the time-weighted feature, where d is the model's hidden dimension. We use $d = 64$ for all baseline models. Let $\mathbf{Z}_{\text{pool}} \in \mathbb{R}^{N\times 2d}$ denote the aggregated features, and we define an output head that maps the aggregated features to predicted returns. The end-to-end workflow is demonstrated in Figure 1

Cross-Sectional Denoising The Cross-Section Denoising (CSD) module separates stock-specific alpha signals from market-wide systematic beta signals, with adaptive scaling to suppress noise while preserving predictive components. For an input $\mathbf{X} \in \mathbb{R}^{N\times L\times D}$, let β be the market-wide signal, and α be the stock-specific residual. They are defined and obtained by

$$\beta = \frac{1}{N}\sum_{i=1}^{N} \mathbf{X}_i, \;\; \alpha = \mathbf{X} - \beta,$$

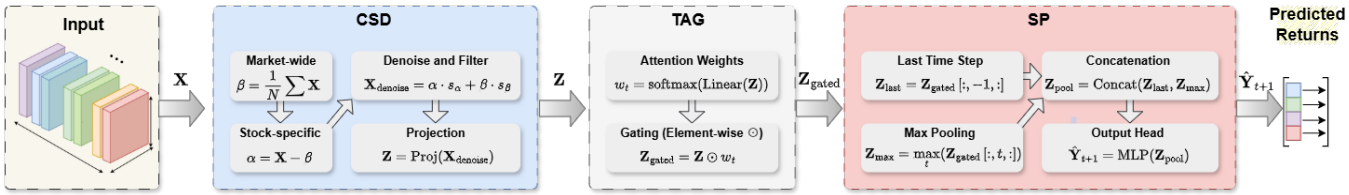


Figure 1: Overall model workflow for intraday cross-sectional return forecasting.

where $\beta \in \mathbb{R}^{1\times L\times D}$ and $\alpha \in \mathbb{R}^{N\times L\times D}$. We introduce a fixed scalar hyperparameter $\tau = 10^{-3}$ to partition the stock-specific alpha signal into noisy alphas ($|\alpha| \le \tau$) and non-noisy, predictive alphas ($|\alpha| > \tau$). Further, let $s_\alpha, s_\beta \in \mathbb{R}^{1\times 1\times D}$ be factor-wise trainable scaling tensors. s_α is applied exclusively to the non-noisy components α. During training, s_α is optimized to amplify factors with high predictive power and dampen factors with weak signals, without affecting noisy components. Similarly, s_β is applied uniformly to the market-wide systematic signal β. Training optimizes s_β to down-weight overly dominant systematic trends and up-weight stable, predictive market signals, ensuring a balanced combination of idiosyncratic and systematic components for return forecasting. We then combine both components and obtain the denoised input:

$$\mathbf{X}_{\text{denoise}} = \alpha\left(s_\alpha \odot \mathbf{1}(|\alpha| > \tau) + \mathbf{1}(|\alpha| \le \tau)\right) + \beta \odot s_\beta$$

where $\mathbf{1}(\cdot)$ is the indicator function and $\odot$ denotes element-wise multiplication.

Temporal Attention Gating The Temporal Attention Gating (TAG) module uses relevance to return predictions to weight time steps so that model can capture intraday trend with minimal complexity. The denoised sequence $\mathbf{X}_{\text{denoise}}$ is projected to model dimension d to yield $\mathbf{Z}$ via a feed-forward block.

$$\mathbf{Z} = \text{Dropout}(\text{ReLU}(\text{LayerNorm}(\text{Linear}(\mathbf{X}_{\text{denoise}})))),$$

where $\text{Linear}(\mathbf{X}) = \mathbf{W}\mathbf{X} + \mathbf{b}$ is a linear layer with trainable parameters $\mathbf{W}, \mathbf{b}$. We then transformed $\mathbf{Z}$ to $\mathbf{Z}_{\text{gated}} = \mathbf{Z} \odot \mathbf{w}_t$. The attention time-step weights $\mathbf{w}_t$ are computed as

$$\mathbf{w}_t = \text{Softmax}(\text{Linear}(\mathbf{Z})), \quad \mathbf{w}_t \in \mathbb{R}^{N\times L\times 1},$$

where $\mathbf{w}_t$ sums to 1 to ensure signal weights are normalized. TAG performs element-wise multiplication of attention weights with the entire temporal sequence to generate $\mathbf{Z}_{\text{gated}}$, while traditional approaches only applies gating to the final hidden state. Meanwhile, TAG replaces the complex multi-head attention with a single-head scalar-scoring attention layer and removes positional encoding for further simplification.

Smart Pooling and Output Head The Smart Pooling (SP) component aggregates time-weighted features into fixed-dimensional vectors by combining the most recent time step and max pooled peak signals with extreme volatility. Let $\mathbf{Z}_{\text{gated}} \in \mathbb{R}^{N\times L\times d}$ be output from TAG module, we define $\mathbf{Z}_{\text{last}}$ as the most recent time step, $\mathbf{Z}_{\text{max}}$ as the max-pooled feature, and $\mathbf{Z}_{\text{pool}}$ as the concatenated features, and denote $\hat{\mathbf{Y}}_{t+1}$ as the predicted returns. We present $\mathbf{Z}_{\text{last}}$ and $\mathbf{Z}_{\text{max}}$ using standard tensor indexing, where the first dimension is individual stocks, second dimension is intraday time steps and third dimension is model's hidden feature.

$$\mathbf{Z}_{\text{last}} = \mathbf{Z}_{\text{gated}}[:, -1, :], \quad \mathbf{Z}_{\text{max}} = \max_{t=1}^{L} \mathbf{Z}_{\text{gated}}[:, t, :],$$

$$\mathbf{Z}_{\text{pool}} = \text{Concat}(\mathbf{Z}_{\text{last}}, \mathbf{Z}_{\text{max}}), \quad \hat{\mathbf{Y}}_{t+1} = \text{MLP}(\mathbf{Z}_{\text{pool}}).$$

where MLP denotes a two-layer perceptron, and $\text{Concat}[\cdot, \cdot]$ denotes feature concatenation along the last dimension. The pooling used direct concatenation instead of average or sum in traditional pooling methods that lead to information loss.

3.3 Training

We design a multi-component loss function specifically adapted to intraday cross-sectional stock return forecasting. The loss is designed to balance regression performance, linear correlations between predicted and actual returns, relative rank accuracy, and regularization to penalize parameter size.

$$\mathcal{L} = \lambda_1\mathcal{L}_{\text{rank}} + \lambda_2\mathcal{L}_{\text{huber}} + \lambda_3\mathcal{L}_{\text{corr}} + \lambda_4\mathcal{L}_{\text{prod}} + \lambda_5\mathcal{L}_{\text{reg}},$$

where $\lambda_1, \ldots, \lambda_5$ are non-negative weighting coefficients. Let $\hat{\mathbf{Y}}_{t+1} = \{\hat{y}_{t+1,s}\}_{s\in S}$ and $\mathbf{Y}_{t+1} = \{y_{t+1,s}\}_{s\in S}$ be the vectors of predicted and true forward returns for time $t+1$, respectively, and $\bar{\hat{y}}_{t+1}, \bar{y}_{t+1}$ be their cross-sectional means. We elaborate on each loss component as follows. First, the quantile ranking loss $\mathcal{L}_{\text{rank}}$ penalizes misalignment between predicted and true rankings of top and bottom stocks by enforcing a minimum predicted return gap between the top 20% and bottom 20% of stocks, sorted by true returns, with a margin $m = 0.1$, formulated as:

$$\mathcal{L}_{\text{rank}} = \mathbb{E}\left[\max\left(0, m - (\hat{y}^{\text{top}}_{t+1,s} - \hat{y}^{\text{bottom}}_{t+1,s})\right)\right],$$

where $\hat{y}^{\text{top}}_{t+1,s}$ and $\hat{y}^{\text{bottom}}_{t+1,s}$ are predicted returns for top/bottom quantile stocks, and $\mathbb{E}[\cdot]$ denotes the expectation over training samples. Next, the Huber loss $\mathcal{L}_{\text{huber}}$ robustifies training against extreme returns by balancing mean squared error (MSE) for small prediction errors and mean absolute error (MAE) for outliers. Let $\epsilon_{t+1,s} = \hat{y}_{t+1,s} - y_{t+1,s}$ denote the prediction error for stock s, the loss with threshold $\delta = 1.0$ is:

$$\mathcal{L}_{\text{huber}} = \mathbb{E}\left[\begin{cases} 0.5\epsilon^2_{t+1,s}, & |\epsilon_{t+1,s}| \le \delta \\ \delta(|\epsilon_{t+1,s}| - 0.5\delta), & \text{otherwise} \end{cases}\right].$$

The correlation loss term $\mathcal{L}_{\text{corr}}$ minimizes $1 - \rho_{\text{pearson}}$, where $\rho_{pearson}$ is the pearson correlation coefficient. We denote

auxiliary terms for cross-covariance and the product of standard deviations:

$$\mathcal{C}_{\text{cov}} = \sum_{s\in S}(\hat{y}_{t+1,s} - \bar{\hat{y}}_{t+1})(y_{t+1,s} - \bar{y}_{t+1}),$$

$$\mathcal{C}_{\text{std}} = \sqrt{\sum_{s\in S}(\hat{y}_{t+1,s} - \bar{\hat{y}}_{t+1})^2}\sqrt{\sum_{s\in S}(y_{t+1,s} - \bar{y}_{t+1})^2},$$

such that $\mathcal{L}_{\text{corr}} = 1 - \mathcal{C}_{\text{cov}}/\mathcal{C}_{\text{std}}$. The product correlation loss $\mathcal{L}_{\text{prod}}$ jointly maximize both correlations. Given a cross-sectional vector of values $\mathbf{V} = \{v_s\}_{s\in S}$, the rank operator maps $\mathbf{V}$ to a rank vector by $\text{rank}(\mathbf{V}) = \{r_s\}_{s\in S}$, where r_s is the ordinal rank of v_s in $\mathbf{V}$ (1 smallest, N largest). The operator converts continuous return values into ordinal ranks. Consequently, $\rho_{\text{pearson}} = \mathcal{C}_{\text{cov}}/\mathcal{C}_{\text{std}}$ and

$$\rho_{\text{spearman}} = \rho\left(\text{rank}(\hat{\mathbf{Y}}_{t+1}), \text{rank}(\mathbf{Y}_{t+1})\right)$$

Then, the product loss is $\mathcal{L}_{\text{prod}} = 1 - \rho_{\text{pearson}} \cdot \rho_{\text{spearman}}$.

Finally, the regularization loss $\mathcal{L}_{\text{reg}} = \lambda_{\text{reg}}\|\theta\|_2^2$ (with $\lambda_{\text{reg}} = 10^{-5}$) prevents overfitting to training data noise, where $\|\cdot\|_2$ denotes the ℓ_2 norm. The weighting coefficients for the total loss function are chosen to prioritize ranking and correlation objectives. We set small weights for huber and regularization components. The final utilized weights are determined empirically: $\lambda_1 = 0.4$, $\lambda_2 = 0.05$, $\lambda_3 = 0.4$, $\lambda_4 = 0.1$, $\lambda_5 = 0.05$.

3.4 Inference

After obtaining the trained model, we map the test file's cross-sectional sequence, with input batch size B, to return predictions in the next time period. For each cross section t, we maintain a sliding look-back window of length L and apply two preliminary filters before feeding the batch.

Look-back Completeness Filter The completeness filter discards sequences which do not contain enough valid time steps ($< L$) in a look-back window. Formally, the filter retains only sequences satisfying:

$$\sum_{\tau=t-L+1}^{t} \mathbf{1}(X_\tau \neq \emptyset) = L,$$

where $\emptyset$ represent an empty factor matrix without valid stocks at time τ.

NaN Elimination Filter For each time step τ in a complete look-back window, the NaN elimination filter removes rows with missing or non-finite factor values, typically caused by trading halts or data feed errors. Let $\mathbf{X}_\tau(i,j)$ denote the j-th factor value of the i-th stock at time τ. The cleaned cross-sectional matrix $\tilde{\mathbf{X}}_\tau \in \mathbb{R}^{\tilde{N}_t\times D}$, where $\tilde{N}_t \leq N_t$ is the number of valid stocks at time τ) is defined as,

$$\tilde{\mathbf{X}}_\tau = \{\mathbf{X}_\tau(i,:) \mid \mathbf{X}_\tau(i,j) \in \mathbb{R}_{\text{fin}}\, \forall j \in \{1,\ldots,D\}\}.$$

where $\mathbf{X}_\tau(i,:)$ denotes the i-th row of $\mathbf{X}_\tau$, and $\mathbb{R}_{\text{fin}} = \mathbb{R} \setminus \{\text{NaN}, \pm\infty\}$ denotes the set of finite real numbers. The filter ensures all elements of $\tilde{\mathbf{X}}_\tau$ are valid real numbers, maintaining numerical stability of forward pass. The filtered sequence $\tilde{\mathbf{X}}_t = \{\tilde{\mathbf{X}}_{t-L+1}, \ldots, \tilde{\mathbf{X}}_t\}$ is then reshaped into a three-dimensional tensor $\mathbf{X}$ compatible with the TransAlpha model input size, which is then feeded into the forward pass workflow in Algorithm 1.

$$\mathbf{X} = \text{Reshape}(\tilde{\mathbf{X}_t}) \in \mathbb{R}^{\tilde{N}_t\times L\times D}.$$

Algorithm 1 TransAlpha Forward Pass

Input: $\mathbf{X} \in \mathbb{R}^{B\times L\times D}$, d_{model}, τ, $\{\mathbf{s}_\alpha, \mathbf{s}_\beta, \mathbf{W}, \mathbf{b}\}$ **Output**: $\hat{\mathbf{Y}} \in \mathbb{R}^{B\times 1}$

Step 1: Cross-Sectional Denoising
$\beta = \frac{1}{B}\sum_{i=1}^{B}\mathbf{X}_i \in \mathbb{R}^{1\times L\times D}$
$\alpha = \mathbf{X} - \beta \in \mathbb{R}^{B\times L\times D}$
$\alpha_{\text{scaled}} = \alpha\,(\mathbf{s}_\alpha \odot \mathbf{1}(|\alpha| > \tau) + \mathbf{1}(|\alpha| \leq \tau))$
$\beta_{\text{scaled}} = \beta \odot \mathbf{s}_\beta$
$\mathbf{X}_{\text{denoise}} = \alpha_{\text{scaled}} + \beta_{\text{scaled}} \in \mathbb{R}^{B\times L\times D}$
Step 2: Input Projection to Model Dimension
$\mathbf{Z}_1 = \text{Linear}(\mathbf{X}_{\text{denoise}}) \in \mathbb{R}^{B\times L\times d_{\text{model}}}$
$\mathbf{Z}_2 = \text{LayerNorm}(\mathbf{Z}_1) \in \mathbb{R}^{B\times L\times d_{\text{model}}}$
$\mathbf{Z}_3 = \text{ReLU}(\mathbf{Z}_2) \in \mathbb{R}^{B\times L\times d_{\text{model}}}$
Step 3: Temporal Attention Gating
$\mathbf{w}_t = \text{Softmax}(\text{Linear}(\mathbf{Z}_3)) \in \mathbb{R}^{B\times L\times 1}$
$\mathbf{Z}_{\text{gated}} = \mathbf{Z}_3 \odot \mathbf{w}_t \in \mathbb{R}^{B\times L\times d_{\text{model}}}$
Step 4: Smart Temporal Pooling
$\mathbf{Z}_{\text{last}} = \mathbf{Z}_{\text{gated}}[:,-1,:] \in \mathbb{R}^{B\times d_{\text{model}}}$
$\mathbf{Z}_{\text{max}} = \max_{t=1}^{L}\mathbf{Z}_{\text{gated}}[:,t,:] \in \mathbb{R}^{B\times d_{\text{model}}}$
$\mathbf{Z}_{\text{pool}} = \text{Concat}(\mathbf{Z}_{\text{last}}, \mathbf{Z}_{\text{max}}) \in \mathbb{R}^{B\times 2d_{\text{model}}}$
Step 5: Output Head
$\hat{\mathbf{Y}} = \text{MLP}(\mathbf{Z}_{\text{pool}}) \in \mathbb{R}^{B\times 1}$
Return: $\hat{\mathbf{Y}}$

3.5 Convergence Analysis

For simplicity, we sketch TransAlpha's convergence to the true return $\mathbf{Y}_{t+1}$ under three mild assumptions. (1) Multi-component loss $\mathcal{L}$ is Lipschitz continuous. (2) Model parameters (s_α, s_β, $\mathbf{W}$) are bounded via $\mathcal{L}_{reg}$ in a compact parameter space Θ. (3) Training uses mini-batch Adam with decreasing learning rate $\eta_k \propto 1/\sqrt{k}$. The expected loss satisfies

$$\mathbb{E}[\mathcal{L}(\Theta_k)] - \mathcal{L}(\Theta^*) \leq \frac{C}{\sqrt{k}},$$

where $C > 0$ is a constant, Θ^* is optimal parameter. As epochs $k \to \infty$, $\|\hat{\mathbf{Y}}_{t+1}(\Theta_k) - \mathbf{Y}_{t+1}\|_2 \to 0$.

3.6 Complexity Analysis

Let h be the number of attention heads in baseline models, K be TCN kernel size, G be crossformer's segment size. TransAlpha's time complexity is derived by calculating float-point operations. The input projection is the dominant term.

$$T_{\text{CSD}} = \mathcal{O}(NLD),\ \ T_{\text{Proj}} = \mathcal{O}(NLDd),$$
$$T_{\text{TAG}} = \mathcal{O}(NLd),\ \ T_{\text{MLP}} = \mathcal{O}(Nd^2),$$
$$T_{\text{Total}} = T_{\text{CSD}} + T_{\text{Proj}} + T_{\text{TAG}} + T_{\text{MLP}} = \mathcal{O}(NLDd).$$

where T_{CSD} is CSD's mean aggregation and element-wise operations on input tensors, T_{Proj} is input projection's linear mapping of D-dimensional alpha factors to d-dimensional

Model	Time Complexity	Space Complexity
TransAlpha	$\mathcal{O}(NLDd)$	$\mathcal{O}(NLDd)$
DLinear	$\mathcal{O}(NLDd)$	$\mathcal{O}(NLDd)$
TCN	$\mathcal{O}(NLdK)$	$\mathcal{O}(NLDd)$
Informer	$\mathcal{O}(NLd \log L)$	$\mathcal{O}(NLDd)$
Autoformer	$\mathcal{O}(NLd)$	$\mathcal{O}(NLDd)$
Pyraformer	$\mathcal{O}(NLd \log L)$	$\mathcal{O}(NLDd)$
Crossformer	$\mathcal{O}(NLdL/G)$	$\mathcal{O}(NLDd)$
iTransformer	$\mathcal{O}(NL^2d/h)$	$\mathcal{O}(NLDd)$

Table 1: Time and Space Complexity Summary

model features. T_{TAG} is TAG's linear layer and element-wise gating on $N \times L \times d$ features, and T_{MLP} is the output MLP's time complexity which contains two linear layers operated on $2d$-dimensional pooled features. Table 1 summaries the time complexity of TransAlpha and baseline models.

TransAlpha's space complexity is dominated by intermediate activation tensors ($N \times L \times d$), resulting in an asymptotic complexity of $\mathcal{O}(NLd)$, identical to all baseline models. Trainable parameters $\mathcal{O}(Dd + d^2)$ are negligible in comparison to activation memory usage. In terms of time efficiency, TransAlpha ranks the best, highlighting its lightweight characteristic. Autoformer has the same nominal $\mathcal{O}(NLd)$ time complexity, but its practical efficiency is lower due to Fast Fourier Transform (FFT) during decomposition. Crossformer introduces an extra L/G overhead factor. Informer and Pyraformer add a $\log L$ factor. iTransformer introduces an L^2/h factor, and TCN adds a kernel size factor K.

4 Experiments

We formulate three core research questions (RQs).

- **RQ1**: Are Transformer models effective in general? How is TransAlpha's predictive power across different market segments?
- **RQ2**: Can the models transfer their predictive power into profit in back-test?
- **RQ3**: Are the proposed architectures effective?
- **RQ4**: Do TransAlpha's prediction patterns exhibit distinct characteristics?

4.1 Experimental Set up

Data Set Details We evaluate on an intraday dataset directly coming from production environment, covering the entire A-share market (Shanghai and Shenzhen Stock Exchanges), with four key market segments (CSI 300, CSI 500, CSI 1000, and CSI 2000) for subset modeling to assess generalization ability across market capitalization. The dataset contains 400 proprietary alpha factors in 15-minute frequency cross-sectionals stored in HDF5 format and are normalized without extreme values. The observation period is non-overlapping, consisted of training (2021-01-04 to 2023-09-28), validation (2023-10-09 to 2023-12-29), and testing (2024-01-02 to 2024-12-31) sets to avoid look-ahead bias and ensure out-of-sample evaluation. There are $N_d = 242$ trade days, each from 09:45 am to 15:00 pm daily ($N_t = 16$ cross sections per day, total of $T = N_d \times N_t = 3856$). Transaction costs are applied only on position liquidation at 0.1% per trade, inclusive of fees.

Baseline Models We compare TransAlpha against 3 categories of baselines. Linear models include DLinear [Zeng *et al.*, 2023], RLinear [Li *et al.*, 2023], and TiDE [Das *et al.*, 2023]. Non-Transformer DL models include GRU [Chung *et al.*, 2014], DeepAR [Salinas *et al.*, 2020], and TCN [Bai *et al.*, 2018], TimesNet [Wu *et al.*, 2022], Modern TCN [donghao and wang xue, 2024]. Transformer models include Informer [Zhou *et al.*, 2021], Autoformer [Wu *et al.*, 2021], PatchTST [Nie *et al.*, 2023], Pyraformer [Liu *et al.*, 2022], Crossformer [Zhang and Yan, 2023], Fedformer [Zhou *et al.*, 2022] and iTransformer [Liu *et al.*, 2024].

Implementation Details Our model is implemented in PyTorch 2.7.0 with CUDA11.8. All experiments are conducted on a server equipped with an AMD EPYC 7T83 64-Core Processor (256 total CPUs across 2 NUMA nodes, 64 physical cores per socket, 128 siblings per node) and 1.5 TiB system memory. For training, we utilized a cluster of four NVIDIA GeForce RTX 4090 GPUs (24564 MiB VRAM per GPU). We use grid search to perform hyperparameter optimization and obtain optimal values based on validation set. We trained the model separately for all market subsets and adopted a naive long-short 50 strategy to back-test.

Evaluation Metrics Stock price forecasting's success is measured by trading profitability rather than point prediction accuracy. Traditional forecasting metrics such as MSE fail to capture the relative performance rankings that drive quant trading strategies. We use the Information Coefficient (IC), Rank IC, Information Coefficient Information Ratio (ICIR) and Rank ICIR to quantify predictive power. We evaluate a model's profitability power using the Annualized Return (AR), Information Ratio (IR), Sharp Ratio (SR), Maximum Drawdown (MDD) and Turn over Rate (TR).

4.2 RQ1 Model Predictive Power

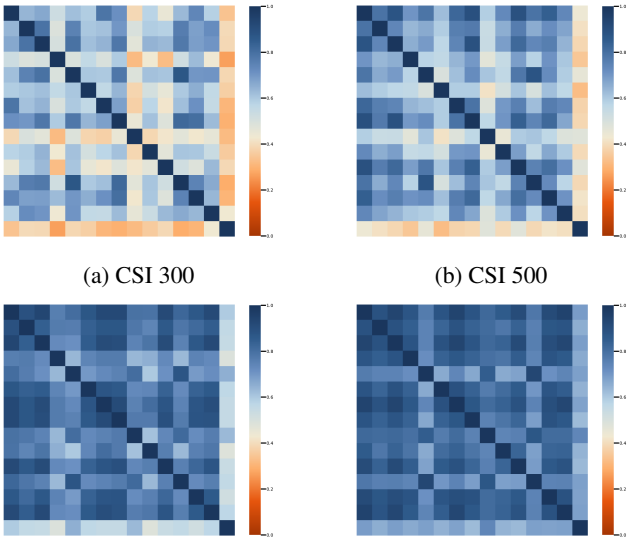
We experiment on both the full market data and all CSI indices subsets to evaluate TransAlpha's predictive power under different market segments, via these standard metrics. See Table 3's first four columns. Overall, TransAlpha's predictive power is consistent across all subsets and constantly among the top models. Notably, subsets with more stocks do not always mean performance increase.

4.3 RQ2 Backtest Result

Overall, TransAlpha offers strong AR, IR and SR, with notable lead in SR. Most importantly, strong predictive power does not necessarily transfer to profitability, a sign of overfitting, with iTransformer as a typical example. MDD < 0.05 suggests worst peak-to-trough loss is less than 5% at any point. TR < 0.20 suggests it only needs to rebalance the portfolio by less than 20% regularly, consuming low trading costs and minimal operational hassle. TransAlpha maintains all lower than the empirical thresholds, offering stable predictions.

Model	Subset	IC	Rank IC	ICIR	Rank ICIR	AR	IR	SR	MDD	TR
No CSD	CSI 300	0.0594 (0.1583) ↓	0.0726 (0.1673)	0.3755 (2.6629) ↓	0.4340 (2.3042) ↓	0.2761 (0.0997)	3.1715 (0.0879) ↓	2.8670 (0.0843) ↓	0.0550 ↓	0.2105 ↓
	CSI 500	0.0671 (0.1582) ↓	0.0704 (0.1569)	0.4240 (2.3583) ↓	0.4487 (2.2288) ↓	0.2785 (0.0953) ↓	3.0832 (0.0731) ↓	2.8317 (0.0730) ↓	0.0548 ↓	0.2090 ↓
	CSI 1000	0.0966 (0.1271)	0.0727 (0.1504) ↓	0.7598 (1.3161)	0.4835 (2.0682) ↓	0.2733 (0.1033) ↓	3.0285 (0.0885) ↓	2.7356 (0.0847) ↓	0.0594 ↓	0.2142 ↓
	CSI 2000	0.1412 (0.0958)	0.1029 (0.1130) ↓	1.4745 (0.6782)	0.9110 (1.0977)	0.4861 (0.0717) ↓	7.7130 (0.0879)	7.2162 (0.0857)	0.0202	0.2447 ↓
	Full Market	0.1430 (0.0825)	0.0972 (0.1251)	1.7331 (0.5770)	0.7769 (1.2872)	0.4333 (0.1095) ↓	4.1331 (0.0797)	3.9085 (0.0798)	0.0918 ↓	0.2557 ↓
No TAG	CSI 300	0.0604 (0.1619) ↓	0.0730 (0.1707)	0.3730 (2.6813) ↓	0.4275 (2.3390) ↓	0.2710 (0.0939) ↓	2.9056 (0.0653) ↓	2.6877 (0.0661) ↓	0.0623 ↓	0.1909
	CSI 500	0.0671 (0.1582) ↓	0.0704 (0.1567)	0.4246 (2.3552) ↓	0.4495 (2.2249) ↓	0.2795 (0.1001) ↓	3.1722 (0.0873) ↓	2.8746 (0.0834) ↓	0.0548 ↓	0.2093 ↓
	CSI 1000	0.0966 (0.1271)	0.0726 (0.1500) ↓	0.7597 (1.3163)	0.4842 (2.0654) ↓	0.2729 (0.0969) ↓	2.9461 (0.0716) ↓	2.7063 (0.0718) ↓	0.0594 ↓	0.2163 ↓
	CSI 2000	0.1407 (0.0962) ↓	0.1022 (0.1123) ↓	1.4625 (0.6838) ↓	0.9102 (1.0986)	0.4780 (0.0693) ↓	7.5524 (0.0804)	7.1118 (0.0798)	0.0202	0.2472 ↓
	Full Market	0.1406 (0.0834)	0.0941 (0.1210) ↓	1.6856 (0.5933)	0.7782 (1.2851)	0.3851 (0.1058) ↓	3.8507 (0.0796) ↓	3.6110 (0.0814) ↓	0.0877 ↓	0.2507 ↓

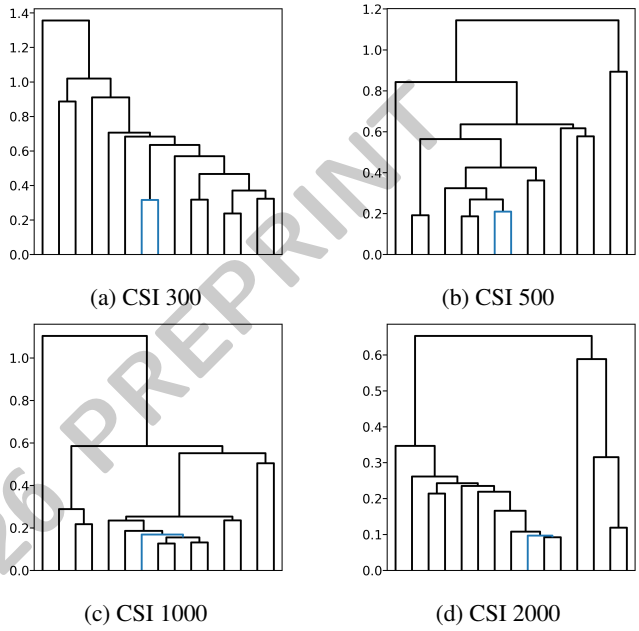
Table 2: Ablation results: ↓ on the right of a metric indicates worse performance compared to TransAlpha.



(a) CSI 300 (b) CSI 500

(c) CSI 1000 (d) CSI 2000

Figure 2: Pairwise correlation heatmaps of model predictions: first row and column are TransAlpha, with the rest models sorted in alphabetical order.



(a) CSI 300 (b) CSI 500

(c) CSI 1000 (d) CSI 2000

Figure 3: Hierarchical dendrograms obtained by hierarchical clustering with TransAlpha highlighted in blue.

4.4 RQ3 Ablation Study

We include an ablation study to test the effectiveness of core components in TransAlpha by removing CSD and TAG portion respectively. Table 2 shows an evident drop in backtest metrics especially IR and SR after removing either core components, which indicates the components are effective in boosting profitability. Specifically, CSD can reduce the over-fitting issue, which can be generalized to other high-dimensional forecasting tasks. TAG also verifies its efficiency gain over standard multi-head attention $\mathcal{O}(NLD)$ vs $\mathcal{O}(NL^2D)$.

4.5 RQ4 Pattern distinction

The model's generated predictions offer distinct patterns from heatmaps and dendrograms of hierarchical clustering. See Figure 2, 3. On large-cap subsets (CSI 300 and CSI 500), the correlations are much lower, indicating the model learned distinct pattern compared to other baselines.

5 Conclusions

This paper tackles challenges of forecasting noisy cross-section data in a real stock market context. We introduce TransAlpha, a lightweight Transformer variant. Extensive experiments suggest it outperforms on core trading metrics and its core components are effective to handle noise. Beyond finance, CSD has the potential to denoise sensor data in manufacturing; TAG can prioritize time steps in patient monitoring; Smart Pooling can aggregate sparse signals in traffic flow. The experiments are exclusively conducted on A-Share market, using proprietary alpha factors from a single quantitative firm. Also, TransAlpha relies on a fixed look-back window and static loss function weights. In future work, we will extend to American stock markets and include MoE components with tailored experts to scale up parameter size, incorporating methods to adapt dynamic market conditions. Finally, we will test the architecture in different forecasting tasks, such as the benchmark data sets in long-range time series forecasting.

Model	Subset	IC	Rank IC	ICIR	Rank ICIR	AR	IR	SR	MDD	TR
DLinear	CSI 300	0.0594 (0.1654)	0.0734 (0.1718)	0.3589 (2.7867)	0.4271 (2.3414)	0.2806 (0.0946)	3.4093 (0.0866)	3.0843 (0.0832)	0.0414	0.2144
	CSI 500	0.0553 (0.1623)	0.0639 (0.1659)	0.3408 (2.9347)	0.3851 (2.5966)	0.2505 (0.0904)	2.8461 (0.0686)	2.6050 (0.0689)	0.0396	0.2000
	CSI 1000	0.0709 (0.1581)	0.0749 (0.1828)	0.4483 (2.2306)	0.4099 (2.4399)	0.3191 (0.1253)	2.9161 (0.0906)	2.6640 (0.0862)	0.0677	0.1995
	CSI 2000	0.1090 (0.0996)	0.1021 (0.1080)	1.0942 (0.9139)	0.9459 (1.0572)	0.4938 (0.0650)	8.0408 (0.0761)	7.6304 (0.0756)	0.0222	0.2407
	Full Market	0.0968 (0.0890)	0.0909 (0.1079)	1.0879 (0.9192)	0.8419 (1.1878)	0.4883 (0.0731)	6.8408 (0.0694)	6.5296 (0.0697)	0.0286	0.2461
RLinear	CSI 300	0.0558 (0.1486)	0.0662 (0.1546)	0.3757 (2.6618)	0.4282 (2.3353)	0.2258 (0.0852)	2.9396 (0.0804)	2.6264 (0.0784)	0.0454	0.2174
	CSI 500	0.0561 (0.1467)	0.0628 (0.1409)	0.3825 (2.6141)	0.4453 (2.2455)	0.2343 (0.0821)	3.2582 (0.0862)	2.9063 (0.0823)	0.0326	0.2510
	CSI 1000	0.0713 (0.1245)	0.0633 (0.1279)	0.5724 (1.7471)	0.4948 (2.0209)	0.2297 (0.0801)	3.1378 (0.0794)	2.8153 (0.0795)	0.0374	0.2364
	CSI 2000	0.1084 (0.1141)	0.1031 (0.1326)	0.9496 (1.0531)	0.7777 (1.2859)	0.4856 (0.0903)	5.7123 (0.0761)	5.4123 (0.0760)	0.0562	0.1986
	Full Market	0.1000 (0.0890)	0.0880 (0.1066)	1.1238 (0.8899)	0.8257 (1.2110)	0.4254 (0.0751)	5.9529 (0.0748)	5.6182 (0.0766)	0.0363	0.2472
TiDE	CSI 300	0.0524 (0.1696)	0.0679 (0.1699)	0.3090 (3.2360)	0.3997 (2.5018)	0.2506 (0.0994)	2.8438 (0.0843)	2.5575 (0.0808)	0.0625	0.1958
	CSI 500	0.0558 (0.1339)	0.0548 (0.1196)	0.4170 (2.3981)	0.4579 (2.1840)	0.2133 (0.0694)	3.2947 (0.0761)	2.9460 (0.0749)	0.0333	0.2326
	CSI 1000	0.0953 (0.1203)	0.0686 (0.1367)	0.7923 (1.2622)	0.5017 (1.9932)	0.2403 (0.0816)	2.9880 (0.0675)	2.7312 (0.0679)	0.0507	0.2395
	CSI 2000	0.1352 (0.0972)	0.1029 (0.1148)	1.3904 (0.7192)	0.8964 (1.1155)	0.4766 (0.0659)	7.3414 (0.0699)	7.0129 (0.0708)	0.0261	0.2438
	Full Market	0.1334 (0.0896)	0.0945 (0.1206)	1.4891 (0.6715)	0.7835 (1.2764)	0.3956 (0.0862)	4.8776 (0.0779)	4.5766 (0.0779)	0.0515	0.2650
GRU	CSI 300	0.0509 (0.1472)	0.0579 (0.1460)	0.3460 (2.8900)	0.3963 (2.5231)	0.1624 (0.0731)	2.3928 (0.0762)	2.0680 (0.0742)	0.0494	0.2124
	CSI 500	0.0467 (0.1130)	0.0437 (0.0889)	0.4134 (2.4188)	0.4916 (2.0342)	0.0990 (0.0468)	2.3152 (0.0785)	1.8153 (0.0782)	0.0184	0.2215
	CSI 1000	0.0945 (0.1197)	0.0681 (0.1312)	0.7897 (1.2663)	0.5188 (1.9274)	0.2413 (0.0890)	2.9601 (0.0793)	2.6689 (0.0780)	0.0535	0.2186
	CSI 2000	0.1324 (0.1032)	0.1043 (0.1158)	1.2834 (0.7792)	0.9006 (1.1104)	0.4941 (0.0742)	7.0501 (0.0753)	6.6904 (0.0740)	0.0270	0.2375
	Full Market	0.1366 (0.0832)	0.0895 (0.1227)	1.6417 (0.6091)	0.7296 (1.3707)	0.3727 (0.1075)	3.6468 (0.0781)	3.4171 (0.0798)	0.0773	0.2423
DeepAR	CSI 300	0.0447 (0.1243)	0.0474 (0.1170)	0.3594 (2.7825)	0.4050 (2.4693)	0.0850 (0.0502)	1.7528 (0.0694)	1.3313 (0.0692)	0.0420	0.2853
	CSI 500	0.0548 (0.1202)	0.0476 (0.0998)	0.4559 (2.1937)	0.4768 (2.0971)	0.1175 (0.0486)	2.4233 (0.0667)	2.0100 (0.0689)	0.0210	0.2926
	CSI 1000	0.0826 (0.1225)	0.0666 (0.1268)	0.6737 (1.4844)	0.5255 (1.9028)	0.2138 (0.0862)	2.5651 (0.0705)	2.3101 (0.0700)	0.0617	0.2744
	CSI 2000	0.1298 (0.1002)	0.0967 (0.1152)	1.2951 (0.7721)	0.8389 (1.1921)	0.4295 (0.0790)	5.6911 (0.0722)	5.3778 (0.0722)	0.0457	0.2710
	Full Market	0.1325 (0.0911)	0.0960 (0.1260)	1.4535 (0.6880)	0.7622 (1.3120)	0.4133 (0.1115)	4.0005 (0.0815)	3.7507 (0.0838)	0.0806	0.2558
TCN	CSI 300	0.0647 (0.1673)	0.0704 (0.1619)	0.3867 (2.5858)	0.4349 (2.2994)	0.2515 (0.0883)	3.2175 (0.0839)	2.8933 (0.0810)	0.0459	0.2177
	CSI 500	0.0658 (0.1536)	0.0668 (0.1372)	0.4285 (2.3335)	0.4867 (2.0547)	0.2454 (0.0830)	3.2390 (0.0811)	2.9230 (0.0790)	0.0478	0.2415
	CSI 1000	0.0992 (0.1152)	0.0638 (0.1143)	0.8615 (1.1608)	0.5584 (1.7910)	0.1798 (0.0759)	2.4904 (0.0721)	2.1921 (0.0727)	0.0503	0.2642
	CSI 2000	0.1400 (0.1049)	0.1015 (0.1175)	1.3348 (0.7492)	0.8636 (1.1580)	0.4320 (0.0803)	5.6475 (0.0730)	5.3355 (0.0731)	0.0488	0.2650
	Full Market	0.1423 (0.0925)	0.0941 (0.1290)	1.5386 (0.6499)	0.7294 (1.3709)	0.3599 (0.1219)	3.1836 (0.0822)	2.9632 (0.0861)	0.1035	0.2616
TimesNet	CSI 300	0.0386 (0.1216)	0.0454 (0.1247)	0.3173 (3.1516)	0.3641 (2.7466)	0.1112 (0.0588)	2.0070 (0.0735)	1.6271 (0.0719)	0.0250	0.2382
	CSI 500	0.0462 (0.1436)	0.0543 (0.1480)	0.3219 (3.1063)	0.3666 (2.7275)	0.1530 (0.0900)	1.8597 (0.0791)	1.5890 (0.0773)	0.0578	0.2083
	CSI 1000	0.0580 (0.1357)	0.0589 (0.1498)	0.4275 (2.3394)	0.3932 (2.5430)	0.2060 (0.1009)	2.1980 (0.0782)	1.9562 (0.0766)	0.0656	0.1816
	CSI 2000	0.0945 (0.1003)	0.0793 (0.1019)	0.9425 (1.0610)	0.7779 (1.2855)	0.3193 (0.0645)	5.0714 (0.0703)	4.7309 (0.0704)	0.0280	0.2150
	Full Market	0.1027 (0.0977)	0.0880 (0.1184)	1.0507 (0.9517)	0.7436 (1.3448)	0.4672 (0.0860)	5.9321 (0.0802)	5.5830 (0.0804)	0.0382	0.2234
Modern TCN	CSI 300	0.0370 (0.1197)	0.0452 (0.1186)	0.3086 (3.2403)	0.3808 (2.6263)	0.0765 (0.0538)	1.5312 (0.0770)	1.1146 (0.0750)	0.0387	0.2491
	CSI 500	0.0481 (0.1175)	0.0498 (0.1112)	0.4089 (2.4454)	0.4477 (2.2339)	0.1174 (0.0604)	2.2258 (0.0875)	1.7955 (0.0858)	0.0308	0.2389
	CSI 1000	0.0749 (0.1237)	0.0646 (0.1307)	0.6052 (1.6522)	0.4940 (2.0243)	0.2157 (0.0888)	2.7566 (0.0870)	2.4416 (0.0836)	0.0604	0.2424
	CSI 2000	0.1210 (0.1032)	0.1044 (0.1104)	1.1724 (0.8530)	0.9454 (1.0578)	0.5300 (0.0673)	8.6434 (0.0811)	8.1692 (0.0796)	0.0193	0.2427
	Full Market	0.1169 (0.0943)	0.0982 (0.1148)	1.2401 (0.8064)	0.8557 (1.1687)	0.5048 (0.0923)	5.9864 (0.0800)	5.6504 (0.0815)	0.0497	0.2395
Informer	CSI 300	0.0609 (0.1540)	0.0651 (0.1500)	0.3955 (2.5284)	0.4341 (2.3034)	0.2375 (0.0798)	3.3658 (0.0823)	3.0108 (0.0802)	0.0337	0.2160
	CSI 500	0.0677 (0.1465)	0.0686 (0.1473)	0.4621 (2.1638)	0.4655 (2.1484)	0.2623 (0.0888)	3.1701 (0.0747)	2.8887 (0.0747)	0.0490	0.2198
	CSI 1000	0.0990 (0.1302)	0.0723 (0.1455)	0.7602 (1.3154)	0.4969 (2.0124)	0.2724 (0.0969)	3.2091 (0.0879)	2.8998 (0.0843)	0.0542	0.2347
	CSI 2000	0.1389 (0.0983)	0.0984 (0.1081)	1.4125 (0.7079)	0.9106 (1.0982)	0.4248 (0.0667)	6.9632 (0.0813)	6.5212 (0.0827)	0.0268	0.2600
	Full Market	0.1379 (0.0895)	0.1002 (0.1263)	1.5421 (0.6485)	0.7936 (1.2600)	0.4715 (0.0965)	5.4929 (0.0842)	5.1440 (0.0848)	0.0611	0.2369
Autoformer	CSI 300	0.0533 (0.1527)	0.0635 (0.1541)	0.3487 (2.8678)	0.4119 (2.4276)	0.2075 (0.0836)	2.6930 (0.0769)	2.3952 (0.0750)	0.0374	0.1932
	CSI 500	0.0626 (0.1346)	0.0605 (0.1307)	0.4652 (2.1496)	0.4625 (2.1621)	0.2330 (0.0750)	3.4679 (0.0816)	3.1039 (0.0800)	0.0254	0.2119
	CSI 1000	0.0868 (0.1278)	0.0714 (0.1385)	0.6790 (1.4727)	0.5154 (1.9401)	0.2758 (0.0915)	3.3197 (0.0808)	3.0226 (0.0796)	0.0534	0.2298
	CSI 2000	0.1368 (0.0935)	0.0979 (0.1057)	1.4633 (0.6834)	0.9262 (1.0796)	0.4351 (0.0625)	7.0588 (0.0700)	6.7164 (0.0715)	0.0204	0.2479
	Full Market	0.1340 (0.0909)	0.0948 (0.1136)	1.4735 (0.6787)	0.8346 (1.1981)	0.4091 (0.0900)	4.8444 (0.0784)	4.5505 (0.0802)	0.0634	0.2513
PatchTST	CSI 300	0.0548 (0.1398)	0.0621 (0.1463)	0.3922 (2.5495)	0.4246 (2.3553)	0.2148 (0.0795)	2.8648 (0.0741)	2.5684 (0.0720)	0.0423	0.2067
	CSI 500	0.0593 (0.1484)	0.0625 (0.1537)	0.3999 (2.5004)	0.4066 (2.4594)	0.2362 (0.0931)	2.8923 (0.0879)	2.5823 (0.0842)	0.0544	0.2083
	CSI 1000	0.0860 (0.1211)	0.0669 (0.1435)	0.7101 (1.4082)	0.4659 (2.1462)	0.2323 (0.0910)	2.6472 (0.0714)	2.4019 (0.0708)	0.0553	0.2165
	CSI 2000	0.1255 (0.0966)	0.0919 (0.1000)	1.3000 (0.7692)	0.9183 (1.0890)	0.4287 (0.0644)	7.2279 (0.0787)	6.7812 (0.0792)	0.0195	0.2411
	Full Market	0.1283 (0.0783)	0.0936 (0.1182)	1.6394 (0.6100)	0.7919 (1.2629)	0.4163 (0.0834)	5.2717 (0.0761)	4.9650 (0.0769)	0.0461	0.2437
Pyraformer	CSI 300	0.0451 (0.1598)	0.0609 (0.1637)	0.2819 (3.5479)	0.3719 (2.6888)	0.2033 (0.0911)	2.4738 (0.0820)	2.1867 (0.0789)	0.0488	0.1660
	CSI 500	0.0642 (0.1608)	0.0689 (0.1605)	0.3993 (2.5047)	0.4296 (2.3277)	0.3017 (0.0896)	3.4552 (0.0687)	3.2095 (0.0693)	0.0341	0.1911
	CSI 1000	0.0897 (0.1237)	0.0673 (0.1280)	0.7254 (1.3786)	0.5256 (1.9027)	0.2502 (0.0752)	3.3878 (0.0685)	3.1060 (0.0682)	0.0359	0.2286
	CSI 2000	0.1370 (0.0904)	0.0979 (0.1094)	1.5159 (0.6597)	0.8954 (1.1168)	0.4818 (0.0795)	6.6934 (0.0815)	6.2949 (0.0815)	0.0208	0.2171
	Full Market	0.1387 (0.0928)	0.1030 (0.1329)	1.4950 (0.6689)	0.7751 (1.2902)	0.4962 (0.1057)	5.3727 (0.0875)	5.0262 (0.0878)	0.0552	0.2177
Crossformer	CSI 300	0.0618 (0.1790)	0.0773 (0.1892)	0.3452 (2.8968)	0.4088 (2.4462)	0.3078 (0.1104)	2.9571 (0.0739)	2.7336 (0.0724)	0.0667	0.1581
	CSI 500	0.0674 (0.1446)	0.0627 (0.1361)	0.4660 (2.1458)	0.4604 (2.1722)	0.2495 (0.0800)	3.2096 (0.0700)	2.9358 (0.0702)	0.0408	0.2141
	CSI 1000	0.0992 (0.1244)	0.0734 (0.1461)	0.7977 (1.2536)	0.5024 (1.9906)	0.2860 (0.0979)	3.0840 (0.0730)	2.8380 (0.0729)	0.0613	0.2078
	CSI 2000	0.1387 (0.0969)	0.1031 (0.1161)	1.4303 (0.6992)	0.8882 (1.1259)	0.4806 (0.0722)	7.1629 (0.0785)	6.7686 (0.0783)	0.0253	0.2407
	Full Market	0.1406 (0.0870)	0.0997 (0.1300)	1.6151 (0.6191)	0.7669 (1.3039)	0.4568 (0.0985)	4.9025 (0.0777)	4.6373 (0.0794)	0.0623	0.2400
iTransformer	CSI 300	0.0670 (0.1676)	0.0756 (0.1787)	0.3999 (2.5008)	0.4229 (2.3646)	0.2809 (0.1063)	2.9206 (0.0807)	2.6607 (0.0789)	0.0796	0.1896
	CSI 500	0.0702 (0.1478)	0.0677 (0.1463)	0.4749 (2.1058)	0.4623 (2.1631)	0.2493 (0.0864)	2.9615 (0.0698)	2.7100 (0.0696)	0.0547	0.2199
	CSI 1000	0.0958 (0.1291)	0.0694 (0.1380)	0.7419 (1.3479)	0.5026 (1.9896)	0.2280 (0.0918)	2.5196 (0.0690)	2.2919 (0.0685)	0.0707	0.2452
	CSI 2000	0.1390 (0.1000)	0.1035 (0.1140)	1.3899 (0.7195)	0.9076 (1.1018)	0.4678 (0.0746)	6.3857 (0.0694)	6.0901 (0.0707)	0.0349	0.2322
	Full Market	0.1424 (0.0904)	0.1011 (0.1329)	1.5742 (0.6352)	0.7613 (1.3136)	0.4427 (0.1154)	4.0472 (0.0794)	3.8241 (0.0806)	0.0988	0.2368
Fedformer	CSI 300	0.0357 (0.1555)	0.0499 (0.1601)	0.2297 (4.3544)	0.3116 (3.2092)	0.1404 (0.0874)	1.8281 (0.0856)	1.5294 (0.0819)	0.0474	0.1646
	CSI 500	0.0363 (0.1378)	0.0442 (0.1450)	0.2632 (3.7992)	0.3046 (3.2828)	0.0737 (0.0847)	0.9381 (0.0779)	0.6734 (0.0772)	0.0724	0.2055
	CSI 1000	0.0218 (0.1234)	0.0374 (0.1415)	0.1766 (5.6634)	0.2646 (3.7792)	0.0576 (0.0987)	0.6054 (0.0722)	0.3922 (0.0721)	0.0898	0.1565
	CSI 2000	0.0303 (0.0624)	0.0297 (0.0790)	0.4849 (2.0623)	0.3755 (2.6629)	0.0262 (0.0497)	0.5306 (0.0680)	0.1262 (0.0670)	0.0604	0.2049
	Full Market	0.0371 (0.0829)	0.0424 (0.1043)	0.4472 (2.2360)	0.4060 (2.4629)	0.1522 (0.0753)	2.2543 (0.0831)	1.9175 (0.0845)	0.0310	0.1763
TransAlpha	CSI 300	0.0664* (0.1597)	0.0713‡ (0.1620)	**0.4159** (2.4046)	**0.4401** (2.2722)	0.2730† (0.0878)	**3.5075** (0.0840)	**3.1769** (0.0805)	0.0392	0.1931
	CSI 500	0.0697* (0.1605)	**0.0696** (0.1524)	0.4345 (2.3013)	0.4568 (2.1889)	0.2840* (0.0859)	**3.3877** (0.0686)	**3.1336** (0.0692)	0.0383	0.2160
	CSI 1000	0.0966† (0.1316)	0.0732* (0.1490)	0.7346 (1.3614)	0.4910 (2.0366)	0.2823† (0.1016)	3.1184 (0.0845)	**2.8341** (0.0811)	0.0569	0.2161
	CSI 2000	**0.1406** (0.1021)	**0.1056** (0.1188)	1.3771 (0.7262)	0.8887 (1.1252)	0.4940† (0.0707)	7.0237 (0.0684)	6.7332 (0.0695)	0.0318	0.2324
	Full Market	0.1376‡ (0.0846)	0.0944 (0.1257)	1.6269* (0.6147)	0.7509 (1.3318)	0.3866 (0.1065)	3.7897 (0.0789)	3.5636 (0.0793)	0.0868	0.2398

Table 3: Metrics across CSI subsets in (mean (std)) format; 1st: bold, 2nd: *, 3rd: †, 4th: ‡

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