Quantformer: from attention to profit with a quantitative transformer trading strategy

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Abstract

In traditional quantitative trading practice, navigating the complicated and dynamic financial market presents a persistent challenge. Fully capturing various market variables, including long-term information, as well as essential signals that may lead to profit remains a difficult task for learning algorithms. In order to tackle this challenge, this paper introduces quantformer, an enhanced neural network architecture based on transformers, to build investment factors. By transfer learning from sentiment analysis, quantformer not only exploits its original inherent advantages in capturing long-range dependencies and modeling complex data relationships, but is also able to solve tasks with numerical inputs and accurately forecast future returns over a given period. This work collects more than 5,000,000 rolling data of 4,601 stocks in the Chinese capital market from 2010 to 2019. The results of this study demonstrated the model's superior performance in predicting stock trends compared with other 100 factor-based quantitative strategies. Notably, the model's innovative use of transformer-liked model to establish factors, in conjunction with market sentiment information, has been shown to enhance the accuracy of trading signals significantly, thereby offering promising implications for the future of quantitative trading strategies. The implementation details and code is available on https://github.com/QuantFormer.

Keywords: quantformer, transformer, quantitative finance, stock selection, market sentiment.

1 Introduction

The goal of stock trading is to optimize the return on investment in the capital market according to the process of buying or selling one or more companies' shares. Traders obtain profit when a positive difference is generated by the fluctuation of stock price. However, stocks are influenced by a large number of factors, which constitute a complex system and make it difficult for people to make a profit. The assessment of a stock's evolving trend is inherently challenging due to the highly volatile and interconnected nature of the market, which sets it apart from typical time series modeling [1]. As a result, many strategies and tools have been built, in parallel with the development of capital markets, and quantitative strategies have been playing an important role among them.

Some traditional quantitative tools, such as the Markowitz portfolio theory [2] and the Capital Asset Pricing Model (CAPM) [3], focus mainly on static fundamental analysis. In other words, these strategies aim to make a profit by simple calculation and analysis. Since then, along with the development of computer science, more quantitative methods and tools have been introduced. Within these methods, factor-based strategies have attracted much attention. In 1993, [4] introduced their Fama-French Three Factor Model (FF3), which has become an influential model in quantitative trading. In 2015, Fama and French revised their model with a Five-Factor Asset Pricing Model (FF5) [5]. Besides this classical theory, numerous trading strategies have been published for decades. [6] built a optimal portfolio to catch future investment opportunities (FIO) by multi-factor models.

Quantitative trading with factors typically follows two primary approaches, which are shown in Figure 1. The first approach involves the computation of stock factor values. Based on these calculated values, stocks are ranked to establish a pool. Once this pool is established, assets are held for a predetermined period. Adjustments to the portfolio are then made at specific time intervals, ensuring alignment with evolving market conditions and factor readings. The second method employs a fixed pool of stocks, wherein factors guide the derivation of long/short signals. Traders can execute corresponding actions when they receive the signals from factors, allowing for a dynamic response to market fluctuations based on factor insights.

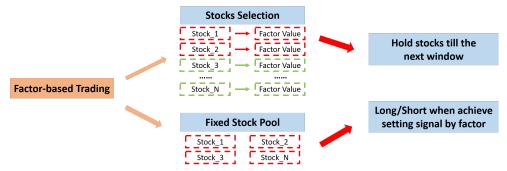


Fig. 1: Quantitative trading architecture with factors

In recent years, Machine Learning (ML) has become an instrumental tool for enhancing trading algorithms and decision-making processes. Its core principle, enabling systems to learn from and make decisions based on data, lends itself particularly well to the vast and dynamic landscapes of stock markets. [7] exploits machine learning algorithms based on manual indicators, but the underlying random walk hypothesis may hamper the task of understanding inherently non-stationary series. With the rise of different architectures, [8] finds some novel approaches to catch the sentiment of the market in trading data, which opened a new field in quantitative trading.

Although there exist several previous experiments with ML factors that attempted to fetch market sentiment in the quantitative finance field, this research still faces two difficulties. Firstly, in the field of sentiment analysis, which is a branch of Natural Language Processing (NLP, a field of computer science that aims to understand, interpret, and generate human language), models are used to convert words in text to word vectors through word embeddings to serve as inputs. However, financial datasets contain categorical data instead of words such as industry types, as well as quantitative data such as price fluctuation, turnover rate, and financial indicators. If the input comprises only categorical data, the time series can be treated as a sentence [9]. In most cases, the input will involve numerical data, which cannot be transformed via word embeddings.

Secondly, most NLP tasks can be transformed into sequence-to-sequence (seq2seq) problems, such as in machine translation, dialogue systems, and speech recognition. As an example, the transformer architecture is based on the seq2seq architecture [10]. To utilize existing outputs, decoders in transformer sequentially output samples and use masking operations to handle input sequences during training. However, in stock prediction, where the aim is often to accurately forecast future returns over a period, the transformer model is rarely used for such tasks.

To address these problems, we propose quantformer, which is a modified transformer architecture adapted to quantitative data, and used as an investment factor. Quantformer is able to input numerical data directly, which refers to a method similar to sentiment analysis. The paper is structured as follows. Section 2 discussed the previous quantitative financial works mainly based on machine learning. Sections 3 and 4 introduce quantformers. A factor based on quantformer will be trained and backtested. For the practical backtest, we collected data from more than 4,600 stocks in the past 14 years (from 2010 to 2023) from the data-collect platform. To comprehensively test the ability of the factor, we divided the data by different frequencies (Section 4.2) and trained under different training scales (Section 5.3). Finally, the result of the back-tests including the comparison between the quantformer-factor and other 100 factors as well as the insights gained from such comparative analysis will be discussed in Sections 4 and 5.

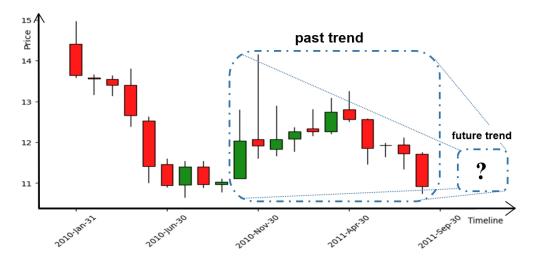


Figure 2: Example of stock prediction

2 Preliminaries

This section briefly introduces the related works about stock prediction with market sentiment and the development of quantitative financial trading methods, especially based on Machine Learning (ML) methods.

2.1 Stock data and market sentiment

It is known that, in some cases, stock data can be deemed to influence the future trend of a stock price [11]. [12, 13] have discussed the correlation between investor sentiment and stock market metrics such as turnover rate, indicating that investor feelings, both individual and institutional, significantly influence market behavior, affecting aspects such as volatility and returns. This relationship is not uniform but varies with changes in investor sentiment. It also highlights that investor psychology, especially during periods of high market stress can drastically impact market behavior and investor decisions. This link between sentiment and market performance is further affirmed by studies focusing on factors such as the turnover ratio, which are seen as reflective of market liquidity and investor behavior [14]. [15] built a new factor based on sentiment analysis with the average of trading signals from technical trading strategies to benchmark stocks of the S&P 500 index and DJIA. The sentiment factor shows correlation with stock returns. These findings underscore the mutual relationship between investor sentiment and market performance, demonstrating how psychological factors can drive market dynamics.

2.2 Applications of ML methods for trading

Machine learning exploits a range of algorithms and statistical techniques used for tasks such as regression, clustering, and classification. In past decades, there have been methods that have been increasingly applied to stock data due to their ability to process vast amounts of data and make predictions based on them, offering a potential advantage in the financial markets. At the same time, the finance sector, particularly quantitative trading, has started to be aware of the potential of deep learning models for predicting stock movements, portfolio optimization, and risks.

2.2.1 Support Vector Machines (SVM)

SVM has been used in quantitative trading, as it can manage high-dimensional spaces and intricacies found in datasets. [16] used SVMs to forecast financial time series in 2015, with a focus on the South Korean stock market, exhibiting the robustness of SVM against traditional statistical methods and some other computational techniques, setting a precedent for its adoption in financial forecasting. Similarly, [17] showcased SVMs' prowess in anticipating the movement direction of Japanese stock markets, especially when determining bullish or bearish market sentiments. [18] assessed SVMs' adaptability and precision in financial tasks such as portfolio and quantitative trading.

However, SVMs can also show some disadvantages in quantitative trading. In [19], SVM was underscored for the accuracy of overfitting. When applied to financial datasets, the model's propensity to fit too closely to the training data might lead to reduced generalization capabilities, making the strategy ineffective on unseen data. In high-frequency trading, though the model displayed competency in specific scenarios, researchers pinpointed potential limitations when grappling with certain volatile market dynamics, suggesting the need for adaptations [20].

2.2.2 Long Short-Term Memory (LSTM)

LSTM is a neural network architecture designed to capture long-term dependencies in sequential data [21]. LSTM neural networks can accentuate and effectively model volatile financial markets, showcasing significant improvements over traditional time series models. [22] combined LSTM with linear Kalman filter and set experiments on different volatility stocks to build strategies. [23] deployed LSTM with stacked autoencoders to forecast financial time series. [24] tested the efficacy of LSTM for price predictions they observed LSTMs' prowess in noisy data and their superiority in prediction accuracy over other conventional models. [25] combined LSTM with other architectures and found that these can enhance the feature extraction process, thereby improving prediction accuracy. For predicting stock prices, [26] harnessed the power of LSTM to unearth multi-frequency trading patterns. Their method underlined the adaptability of LSTMs in modeling complex situations inherent in stock prices.

2.2.3 Gated Recurrent Units (GRUs)

GRUs [27] are another neural network architecture which has emerged as a method in the quest for accurate financial forecasting. GRUs can capture long-term dependencies in time series data and have seen increasing popularity in the world of quantitative trading. [23] introduced a comprehensive deep-learning framework for financial time series, which incorporated GRUs alongside LSTM and stacked autoencoders. Their model, when applied to diverse datasets, performs better than traditional time series

models, accentuating the adaptability and robustness of GRUs. [28] centralized on LSTM networks, provided comparative insights into GRUs. However, in their analysis, LSTMs showed a slight edge in prediction accuracy, indicating that while GRUs are powerful, selecting between them and LSTMs may boil down to specific use cases and computational constraints. Beyond that, [29] presented a model fusing GRUs with Convolutional Neural Networks (CNN) [30]. The strategy to combine CNNs and GRUs also exhibits advantages for stock price prediction. [31] introduced the Attention-GRU model which combined attention and GRU to establish a new factor based on CVaR [32, 33] portfolio. The Attention-GRU model fitted market return, stocks return from 28 Dow Jones Industrial Average index (DJIA) stocks, which achieved better performance than other models in 8 metrics such as annual return, standard deviation and information ratio.

2.3 Transformer in quantitative trading

Transformer [10], which was introduced in 2017, has received considerable attention in the NLP field. According to its special encoder and decoder stacks with self-attention blocks, the transformer shows its advantage in stability, speed, and long-term memory compared with other traditional models. The transformer-based models such as GPT [34] and BERT [35] are the basis of the specific field of application. In the application field, transformer-based models such as ChatGPT [36], FinBERT [37, 38] and BloomberGPT [39] show advantages and ability in solving different types of problems in different fields. [40] utilized transformer to to predict the stock market index (including CSI 300, S&P 500, Hang Seng Index, and Nikkei 225) and concluded that the model could better catch the rules of stock market dynamics.

Similar to other neural sequence transduction models, transformer also has an encoder-decoder structure. The model takes as input a sequence of context which could be natural language sentences and generates output with texts depending on the input, similar to a translation according to the input or a predicted sentence. Transformer using stacks which are called self-attention and point-wise, which connect layers in the architecture for encoder and decoder. For these encoder and decoder layers, the self-attention method plays an important role in matrix calculation. The linear and softmax functions are used in the dot-product attention module. In the vanilla transformer model, multi-head attention layers are used and the result from each layer will be outputted after going through an additional normalization layer. The above-mentioned steps cover most of the progress in the vanilla transformer.

In the quantitative trading domain, some previous researchers tried to test the potential of transformer. [41] firstly tried to exploit transformer on trading sequences to classify stock price movements. Besides using a traditional transformer, other innovative methods of transformer are worth mentioning. [42] devoted to optimizing the efficiency of time complexity and memory usage of transformer on extremely long time series by informer. [43] takes the advantage of CNNs and transformers to model short-term and long-term dependencies in financial time series. They showed the advantage of the proposed approach on intraday stock price prediction of S&P 500 constituents. [44] proposed a new ConvLSTM model by combining convolutional transformer and

LSTM. The model was trained by stocks from S&P 500 from 2004-2021 and performs better than other models such as VaR and ARIMA.

Similar to previous work, [1] innovated the structure of a transformer, in the form of Adaptive Long-Short Pattern Transformer (ALSP-TF). Their model is structurally innovated for hierarchical representation and interaction of stock price series at different context scales. With the help of a learnable function, they make the self-attention aware of the weighted time intervals between patterns, to adaptively adjust their dependencies beyond similarity matching. In the end, they obtained more than 10% of annual return on average.

However, transformer has some disadvantages. [45] mentioned that the global selfattention module focuses on point-wise token similarities without contextual insights. As fluctuations of stocks are conditioned on composite signals over manifold periods, lacking pattern-wise interaction hinders the adequate discrimination of stock tendency and is susceptible to noise points. On the other hand, [46] claimed that the basic query-key matching paradigm is position agnostic. Although position embedding is inserted into the sequential inputs, it may not be optimal because of the inability to reveal precise distances.

3 Methodology

This section introduces the framework of the work and the steps of the establishment of the model, including the data processing, quantformer construction and prediction.

3.1 Framework overview

Figure 3 gives an overview of the structure. There are three major parts:

- (i) Data Initialization to align the time series of stocks into a regular matrix;
- (ii) Embedding the training dataset and training them by a quantformer with wordembedding layer replaced by linear layer and with no Mask(opt.) layer;
- (iii) Lastly, using the trained model to predict the possible trend of stocks.

3.2 Problem formulation

Inputs

Given the candidate stock set S^t for N stocks on the trading timestamp t:

$$S^t = \{s_1^t, s_2^t \dots s_N^t\}$$

 $S^t=\{s_1^t,s_2^t\dots s_N^t\}$ For a stock s_k^t in the stock set $S^t,$ where $k~\in~\{1,\dots,N\},$ consider the two-dimensional historical 1-time step sequence (such as one month):

$$\chi_k^t = [x_k^{t-20}, x_k^{t-19} \dots x_k^t] \in \mathbb{R}^{20 \times 2}$$

Each x_k^t contains two features. The first one is the accumulated daily profit rate during the time step, where p_i and p_{i-1} are the close price of the i^{th} and $(i-1)^{th}$ day, respectively.

$$r^t = \sum r_i = \sum \frac{p_i - p_{i-1}}{p_{i-1}}, \quad \sigma^t = \sum \sigma_i$$
 (1)

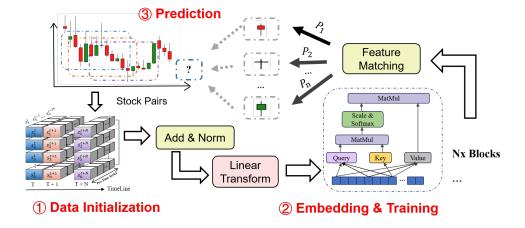


Figure 3: Overview of the work

The other feature is the accumulated daily turnover rate σ^t during the time step and the calculation method of σ^t is shown above. So each χ_k^t can be represented as:

$$\chi_k^t = \begin{bmatrix} r^{t-20} & r^{t-19} & \dots & r^t \\ \sigma^{t-20} & \sigma^{t-19} & \dots & \sigma^t \end{bmatrix} \in \mathbb{R}^{20 \times 2}$$

Outputs

For a stock set S^t on the trading timestamp t, each stock s_i^t has a profit rate r_i^{t+1} on the trading timestamp t+1, where the calculation method is the same as for r^t in the sequence of inputs shown in equation (1). Then the value in the list of next-time stamp's profit for N stocks in the timestamps t+1 can be represented as:

$$P^{t+1} = \{r_1^{t+1}, r_2^{t+1} \dots r_N^{t+1}\}$$

This list is then sorted and partitioned into q equal parts, where it is set to 3 or more. For example, set q=5; for the stocks s_k whose profit values ranked in the bottom 20%, middle 20%, and top 20% respectively. And the dimension of the outputs d_f is the number of selected quantiles in training. The value of d_f should be larger than 3 and not larger than q.

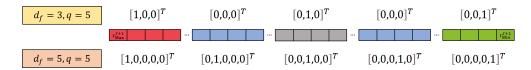


Figure 4: Training outputs remarked between different d_f

Both the dimensions of training and predicted outputs are the same, which is the d_f set at the beginning. For example, set q = 5; for the stocks s_k whose profit values ranked in the bottom 20%, middle 20%, and top 20% respectively, and the corresponding output of $d_f = 3$ is recorded, respectively, as

$$y_k^t = [1, 0, 0]^T, \quad y_k^t = [0, 1, 0]^T, \quad y_k^t = [0, 0, 1]^T, \quad y_k^t = [0, 0, 1]^T$$

The dimension of the output also can be 5, and in this case, the outputs of $d_f = 5$ are:

$$y_k^t = [1, 0, 0, 0, 0]^T, \quad y_k^t = [0, 0, 1, 0, 0]^T, \quad y_k^t = [0, 0, 0, 0, 1]^T$$

In this example, when $d_f = 3$, the output dimension will be 3 while the dimension will be 5 as d_f is set as 5.

3.3 Embedding initialization

Normalization

The next step is to normalize the input data for each time step by zero-mean, unit-variance normalization (Z-score), the normalization equation is shown in equation (2).

 $\tilde{x}_{k,i}^t$ represents the normalized value at i^{th} day of stock k at time t. $\mathbb{E}[x_i^t]$ and $\text{std}[x_i^t]$ are the mean and standard deviation of the variables x_i^t , respectively.

$$\tilde{x}_{k,i}^t = \frac{x_{k,i}^t - \mathbb{E}[x_i^t]}{\operatorname{std}[x_i^t]} \tag{2}$$

In this way, the input sequences are normalized with zero mean and unit variance, which aims to reduce the influence from outlying time points and allow different features to be comparable with each other [47].

3.4 Quantformer encoder

Then a quantformer encoder structure will be built in this subsection. The representation hierarchy consists of L blocks of multi-head self-attention layers. Taking initialized stock embedding sequences $\mathbf{P} \in \mathbb{R}^{N \times 20 \times 2}$ as input, the canonical self-attention in [10] can perform information exchange between every time points for each stock s_i .

To process both categorical and numerical data, the word embedding layer is replaced by a standard linear layer, utilizing linear transformations to substitute the process of word embedding. On the other side, in stock prediction, we aim to accurately forecast the return for a future period, thus the model's output is generally a single value representing the probability of price increase or decrease. Therefore, the decoder is simplified by removing the autoregressive prediction mechanism (in the decoder) and the masking operations.

More specifically, each $\mathbf{P}_i \in \mathbb{R}^{20 \times 2}$ is transformed into query, key, and value metrics, respectively:

$$\mathbf{Q}_{i,h} = \mathbf{P}_i \mathbf{W}_h^Q, \quad \mathbf{K}_{i,h} = \mathbf{P}_i \mathbf{W}_h^K, \quad \mathbf{V}_{i,h} = \mathbf{P}_i \mathbf{W}_h^V$$
(3)

where h = 1, ..., H is the head index, as well as trainable weights \mathbf{W}_h^Q , \mathbf{W}_h^Q , \mathbf{W}_h^Q , \mathbf{W}_h^Q $\in \mathbb{R}^{2 \times d_f}$. Then, the final layer is represented by the concatenation of all attention heads.

$$\mathbf{F}_{i} = \text{Multihead}(\mathbf{Q}_{i,h}, \mathbf{K}_{i,h}, \mathbf{V}_{i,h}) = \left(\left| \right|_{h=1}^{h=H} \text{Attention}(\mathbf{Q}_{i,h}, \mathbf{K}_{i,h}, \mathbf{V}_{i,h}) \right) \mathbf{W}^{O}$$
 (4)

where || represents the concatenation operator and d_f is the dimension of the projected feature space. After the attention computation is completed, the multi-head attention output is divided into different "heads". These outputs from the heads need to be recombined back into the original input dimension. $\mathbf{W}^O \in \mathbb{R}^{Hd_f \times 2}$ in equation 5 plays the role of combining these separate heads back into the original dimension. The attention head is shown below:

Attention(
$$\mathbf{Q}_{i,h}, \mathbf{K}_{i,h}, \mathbf{V}_{i,h}$$
) = softmax($\mathbf{Q}_{i,h}, \mathbf{K}_{i,h}^T / \sqrt{d_f}$) $\mathbf{V}_{i,h}$ (5)

In the end, all input sequences are represented in the form of:

$$\mathbf{F} = [\mathbf{F}_1; \mathbf{F}_2; \dots \mathbf{F}_N] \in \mathbb{R}^{N \times 20 \times Hd_f}$$

which are fed into feed-forward layers. From Section 3.2, the embedding output is denoted as:

$$\mathbf{Y}^t = \{y_1^t, y_2^t, \dots y_N^t\} \in \mathbb{R}^{N \times 1 \times d_f}$$

3.5 Output process

Eventually, the output is represented as:

$$\mathbf{Z}^t = \{z_1^t, z_2^t, \dots z_N^t\} \in \mathbb{R}^{N \times 1 \times d_f} \tag{6}$$

The output layer uses the softmax activation function, and for each z_i^t can be written

$$z_i^t = [z_{i,1}^t, \dots z_{i,m}^t, \dots z_{i,d_s}^t] \in \mathbb{R}^{1 \times d_f}$$

 $z_i^t = [z_{i,1}^t, \dots z_{i,m}^t, \dots z_{i,d_f}^t] \in \mathbb{R}^{1 \times d_f}$ $(m = 1, 2, \dots, n \text{ is the index number between } 1 \text{ and } n)$. The output probability can be represented as:

$$Y_o^t = [y_{o,1}^t, \dots y_{o,m}^t, \dots y_{o,d_f}^t]^T = \left[\frac{e^{z_1}}{\sum_{i=1}^n e^{z_i}}, \dots \frac{e^{z_m}}{\sum_{i=1}^n e^{z_i}}, \dots \frac{e^{z_n}}{\sum_{i=1}^n e^{z_{d_f}}}\right]$$
(7)

In equation (7), the $y_{o,i}^t$ take values between 0 and 1 and sum to 1, which means that they can be interpreted as the probability of the stock's performance in the slice m in the next timestamp

3.6 Prediction

The Mean Squared Error Loss (MSELoss) will be used to quantify the loss. MSE Loss is a widely used metric for assessing the discrepancy between a model's predictions and the actual values. It is defined as the average of the squares of the differences between the predicted value and the actual prices:

$$MSELoss = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$
 (8)

In equation (8), y_i is the actual value of the i^{th} observation, \hat{y}_i is the corresponding model prediction, and N is the total number of input samples. During each epoch, the MSE Loss is computed to guide the optimization process, to minimize this loss over successive iterations. A lower MSE indicates a closer alignment between the model's predictions and the actual stock prices, signifying an improvement in the model's learning and its ability to generalize from the training data.

4 Experiments

Based on the methodology in Section 3, in this section, the set of experiments is introduced, including the data resource, implementation details, trading strategy and metrics.

4.1 Dataset

The training data of the quantformer comes from the Chinese exchange market. The dataset is collected from the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE), which contains 4601 stocks that are listed or had been listed from January 2010 to May 2023. The data comes from AKShare¹ and Tushare², which are quantitative finance terminals. The training period is from January 2010 to December 2019 and the testing period starts from January 2020.

Closing price adjustments are used for the stock training price [48]. Closing price adjustments are essential in stock market analysis, particularly when analyzing historical data for long-term trends and patterns. This price takes into account factors such as dividends, stock splits, and other corporate actions that can affect a stock's price over time [49]. By adjusting for these events, the adjusted closing price provides a more accurate picture of a stock's value and performance, which is more appropriate for financial backtesting.

4.2 Timestamp

Data frequency concerns the number of data points within a specific unit of time, which may reflect different market characteristics [50]. To better test the performance of the factor, three frequencies are considered: monthly, weekly, and daily stock data.

In the first experiments, a timestamp was set as one month. So for a stock s_i from the stock set S^t , it details a feature sequence in which each item in the sequence contains the accumulated profit and accumulated turnover rate in a month. Both the accumulated profit and accumulated turnover rate are the sum of the trading day's

https://akshare.akfamily.xyz/

²https://www.tushare.pro/

Table 1: Detailed information of experiments

Strategy	Frequency	Output Dim	Training samples	Section	zero-output
Month_1	Monthly	3	85,490	100	w/o
Month_2	Monthly	3	142,409	100	w/
Month_3	Monthly	5	142,409	100	w/
$Week_{-1}$	Weekly	3	455,157	466	w/o
$Week_2$	Weekly	3	758,300	466	w/
Week_3	Weekly	5	758,300	466	w/
Day_{-1}	Daily	3	3,586,435	2,420	w/o
Day_2	Daily	3	$5,\!140,\!279$	2,420	w/
Day_3	Daily	5	$5,\!140,\!279$	2,420	w/

data in that month. In some cases, if one stock was first listed on the market or resumed trading in one month, the available data may not cover whole trading days, the data of the stock from that from would still be recorded. However, if there is a whole month during which the stock did not have any trading (perhaps due to stopped trading or not being listed in that month), this month's data will be recorded as "NaN". In the sequence χ_k^t , the sequence will not be used to train the model when there are missing values in the sequence.

Within the first experiments, three sub-experiments were set. The sub-experiments share the same inputs. For output data, outputs with different dimensions and different lengths but the same dimension are used. n=5 and n=7 are used in this experiments. In the group of n=5, the first one deleted the data with output such as $[0,0,0]^T$, and the second one used the origin dataset (zero-output).

Outliers of both accumulated profit and accumulated turnover rate will not be removed from the dataset these situations may happen in the future and they are expected to be predicted, though these incidents rarely happen.

In the second and third experiments, the inputs are in weekly and daily frequency, respectively. The sub-experiments under different groups are similar to the first one. All the accumulated number of parameters, the number of trained sections (such as 100 months from 2010 to 2019), and dimension are shown in Table 1.

4.3 Implementation details

The training process and model are implemented with PyTorch [51]. The parameters of the model are optimized by grid search, which is reliable in low dimensional spaces and simple to implement [52]. Here the input dimension is 2, and the dimension of the hidden feature space d_f is 16. The number of multi-head attention modules is 16, and the number of layers of encoder and decoder is 6. The model was trained on an NVIDIA GeForce RTX 2080 GPU and NVIDIA A100 Tensor Core GPU using the Adam optimizer [53] for 50 epochs, the learning rate is 0.001, and the batch size is 64.

4.4 Trading strategy

A trading strategy is used for the model and Algorithm 1 shows the pseudocode of the strategy. Before the first trade date of the timestamp t, all sequence $\chi_{i,k}^t$ from the

Algorithm 1 Trading Strategy

```
Require: The sequence x_{i,k}^t for each stock s_i in the set S^t and the amount of cash.
 1: run_monthly(trade, monthday=1, time='open')
 2: function OBTAIN_STOCKPOOL(x_{i,k}^t):
       stockpool = sort(model(x_k^t), key=lambda x : x[1], reverse=True)
 3:
 4:
 5: end function
   function TRADE
 6:
       stockpool = obtain\_stockpool(x_{i,k}^t)
 7:
       for stock in previous_stockpool do
 8:
           if stock not in stockpool then
 9:
              order(stock, 0)
                                                                               ⊳ sellout
10:
           end if
11:
       end for
12:
       for stock in stockpool do
13:
           if stock not in previous_stockpool then
14:
              order(stock, amount / len(stockpool))
                                                                                  ⊳ buy
15:
           end if
16:
       end for
17:
    end function
```

stock set S^t will be put in the model and obtain the list of outputs. Then, the stocks will be ranked according to the first element of the output and the first $\frac{1}{q}\%$ stocks will be added to the stock pool. If the stock already was in the stock pool on the last timestamp, it will be held; if the stock is in the predicted pool but not in the previous pool, it will be bought in with the same proportion of the whole account. Stocks that are not in the predicted pool will be sold out. The same method is run repeatedly during the subsequent periods. The backtest starts from January 2020, in other words, the result of the sequences from May 2018 to December 2019 will be used as the first stock pool to trade.

4.5 Metrics

Formally, the Sharpe Ratio (SR) and the α ratio will be used to test the performance of the strategy. The SR [3] is a measure of risk-adjusted return that describes the additional earnings an investor receives for each standard deviation unit increase, which is shown in equation (9), where R_p is the return of the portfolio and R_f is the risk-free rate is the rate of London Interbank Offered Rate (LIBOR) which calculated averaged from estimates submitted by banks in London. The risk-free rate in the backtest will be calculated under the average LIBOR rates during the test period.

$$SR = \frac{\mathbb{E}[R_p] - R_f}{\operatorname{std}[R_p]} \tag{9}$$

Alpha represents the excess return of an investment portfolio relative to its benchmark. It reflects the stock selection skills of an investment. A positive alpha indicates

that the investment portfolio has achieved a higher return than its benchmark after risk adjustment. Specifically, alpha is the excess return of the actual portfolio return over its expected theoretical return. Equation (10) shows the calculation method of the alpha rate, where $E(R_m)$ is the market return and β is the correlation between the portfolio and systemic risk.

$$Alpha = (R_p - R_f) - \beta(E[R_m] - R_f) \tag{10}$$

Besides the SR ratio and alpha rate, the annual return (AR) of the stock, the annual excess return (AER), the average turnover rate (TR) of the portfolio, and the win rate (WR) will also shown. The excess returns are returns achieved above and beyond the return of a proxy and the CSI 300 index is used as the basis when calculating the excess returns. The turnover rate is the average percentage of the portfolio adjusted daily in terms of market. The win rate is the percentage of trade days where the portfolio encounters a positive return overall trade days.

$$VaR = \mu + \sigma N^{-1}(X) \tag{11}$$

Value at risk (VaR) is a method to summarize the total risk in a portfolio [54]. Equation (11) shows the calculation of VaR, where μ is the mean and σ is the standard deviation of the portfolio, X is the confidence level and $N^{-1}(X)$ is the inverse cumulative normal distribution. In of the measurement of the portfolio, 99% VaR is used to estimate the maximum loss during the period under 99% of confidence.

5 Results and discussion

Building upon the analysis of individual strategies, this section presents an evaluation and discussion of the experimental outcomes. The discussion focuses on the comparative effectiveness of different timestamps (monthly, weekly, and daily) and different training scales. The results underscore the nuanced relationship between trading frequency and market performance, offering valuable insights for the development of robust quantitative trading strategies.

5.1 Overall performance

The result of the experiment is shown in Table 2. For the monthly group, Month_1 shows an annual return of 17.35% and an annual excess return of 19.43%, indicating a robust performance over that period. Conversely, Month_3 shows a diminished annual return and annual excess return of 7.37% and 9.91% respectively. The turnover rate is notably high in the second month at 51.69%. The win rate ranges from 43.1% to 57.3%, with the first month showing the highest win rate. The Sharpe Ratio and Alpha, vary across the strategies, with some periods showing negative values, suggesting underperformance relative to the risk taken, while others show positive values. In the comparison of 99% VaR, the strategies in monthly frequency perform better than others, where Month_1 and Month_3 are lower than 3%, which means the portfolio maximum loss 2.81% and 2.3% of return a day in 99% confidence.

Table 2: Result of experiments

Strategy	AR	AER	TR	WR	SR	Alpha	VaR
$Month_1$	17.35%	19.43%	26.09%	57.8%	0.915	$\bf 0.162$	2.81
$Month_{-2}$	9.91%	13.86%	51.69%	49.3%	0.289	0.102	3.61
Month_3	7.37%	9.91%	32.33%	51.6%	0.246	0.064	2.3
$Week_1$	-0.83%	1.31%	7.13%	46.4%	-0.236	-0.030	3.05
$Week_2$	7.49%	10.81%	1.18%	49.2%	0.160	0.085	3.73
Week_3	$\boldsymbol{12.3\%}$	12.73%	1.39%	54.4 %	0.372	0.116	3.77
Day_1	7.89%	11.4%	6.71%	43.1%	0.181	0.090	3.92
Day_2	$\boldsymbol{10.23\%}$	10.94%	6.51%	44.4%	0.279	0.097	3.91
Day_3	9.81%	10.03%	5.57%	44.6 %	0.281	0.092	4.02
CSI300	1.77%	\	\	\	-0.015	\	3.19%

In the weekly strategy results, Week_3 showed a remarkable annual return of 12.3% and an annual excess return of 12.73%, while Week_1 displayed a negative annual return. For the daily strategies, Day_2 had a return of 10.23% and an annual excess return of 10.94%. The turnover rate across the daily strategies showed lesser variation than the monthly or weekly, indicating a more consistent trading frequency. The win rate for the daily strategies remained fairly stable, hovering around the mid-40% mark. The Sharpe Ratio and Alpha for weekly and daily strategies show a mix of positive and negative values, reflecting the fluctuating nature of shorter-term trading efficacy.

To demonstrate the advantages of the quantformer factor over traditional factors, 100 price-volume type factors from JoinQuant 3 (one of China's largest financial quantitative platforms) were selected for backtesting under the same trading strategy (Algorithm 1). Price-volume factors were used because these are calculated based on stocks' prices, volumes, and turnover rates, which are similar to the training data used by quantformer factors (also used stock turnover rates and price data). The detailed performance of factors and benchmark is shown in Appendix A. On average, these factors achieved an annual return of -3.78%, an average excess return of -2.15%, and a Sharpe ratio of -0.36, where the benchmark return is -1.77%. The average maximum drawdown of the strategy was 44.88%, which means the potential worst-case scenario or the most extreme possible loss. The average volatility of the strategy (σ_p) was 0.26, with the benchmark at 0.197.

Among these factor-based strategies, the quantformer factor performed well. Except for the win rate, which was slightly lower than a few strategies, it excelled in terms of annual return, annual excess return, σ_p , Sharpe Ratio and sortino ratio ranking the best among the 101 factors. The 99% VaR of quantformer factor is in the quantile of the first 10% among all factors. Figure 5 illustrates the return curves of the quantformer (QF_Month_1) alongside the benchmark and some traditional factors. "25_week_rank" represents the current price's position over the past 25 weeks; "EMAC20" and "MAC20" are the 20-day index moving average and the stock's 20-day moving average respectively; "DAVOL20" and "VOL20" represent the ratio of the 20-day average turnover rate to the 120-day average turnover rate, and the mean of the stock's 20-day turnover rate; "ROC20" is the price rate of change over 20 days;

³https://www.joinquant.com/

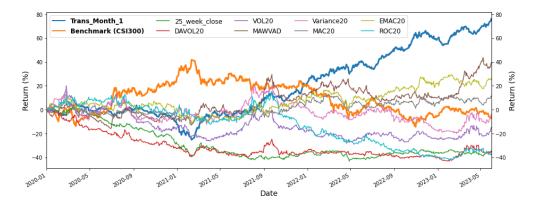


Figure 5: Backtest results based on different factors

"MAWVAD" is calculated as the product of the difference between the closing price and the opening price, divided by the range of the highest and lowest prices, all multiplied by the volume, accumulated over six days; "Variance20" is the variance of the stock's 20-day annualized returns. Most of these factors are compared based on a window of 20 timestamps, as the quantformer factor was also trained on 20 timestamps. In comparison with these factors, the quantformer factor (blue line) demonstrated a significantly better performance in terms of returns than the benchmark (orange line) and other factor strategies, expressing the improvement of the quantformer factor over traditional price-volume factors.

5.2 Half-life period test

To test the half-life period of the factor, another three portfolios based on $Month_3$ were conducted. The first one is the stock pool used in the next month; the second is using it in the month after the month; the last one is using it in the third month after the last feature of inputs. For instance, in the first strategy, the trade will start in January 2020; in the second, it will start in February 2020; in the second, it will start in March 2020. For the period from January 2020 to February 2022, the strategy achieved a total return (TotalR) of 65.29% and an annual return of 17.87%. The total excess return (TER) over this period was 66.39%, indicating a strong performance above a benchmark or risk-free rate. The Sharpe Ratio for this period was 0.863, which is a respectable figure that suggests a favorable risk-adjusted return. Additionally, the strategy generated an alpha of 0.164, demonstrating its ability to outperform the expected return on a risk-adjusted basis.

In the subsequent period from February 2020 to March 2023, the strategy yielded a slightly higher total return of 67.52% and an annual return of 18.21%. The excess return was 65.58%, with an improved Sharpe Ratio of 0.940, reflecting a better risk-adjusted return compared to the previous period. The alpha for this interval was 0.161, indicating the strategy's consistent performance in delivering additional returns.

Lastly, Table 3 shows the result of the backtest. From March 2020 to April 2023, the strategy's total return decreased to 56.41%, with an annual return of 15.63% and an excess return of 52.96%. The Sharpe Ratio also declined to 0.739, but it still represents a relatively efficient investment compared to the volatility of returns. The alpha reduced to 0.135, which, while lower than the other periods, still indicates that the strategy managed to provide returns above those predicted by its risk profile.

Comparing the results between monthly, weekly, and daily strategies provides further insights. The monthly strategies can deliver the highest returns, suggesting that longer-term signals better capture short-term trends. The weekly strategies underperform monthly ones but outperform the daily frequency overall. This indicates weekly data strikes a balance between filtering noise and responding swiftly to emerging patterns.

The daily frequency strategies perform lower annual returns and higher risk compared to others This highlights the challenge of making profitable trades at higher frequencies - noise and volatility make reliable signals more difficult. The distribution of returns also shows increased dispersion at the daily level. However, daily strategies achieve more consistent turnover rates around 5-7%. This allows for portfolio adjustments while avoiding excessive trading costs. In contrast, monthly strategies see a turnover rate above 50% in some cases. There is likely an optimal point between 1 week to 1 month where matches market regularly.

5.3 Training under different scales

Understanding data volume and data frequency is critical to designing infrastructure for processing data and model stability [55]. To test the ability of stock selection of the model, three other factors "QF_10%", "QF_5%", "QF_1%" are trained and tested (with "QF_Month_1%, named as "QF_20%"). The four groups are all trained under $d_f=3$, which include the first, middle, and tail 20%, 10%, 5%, and 1% of stocks in ranking, respectively. The backtest period and other settings are the same with 4.

Table 4 shows the result of the backtest. QF_10% strategy recorded an AR of 13.12% and an AER of 17.73%, with a slightly lower portfolio volatility of 0.159. This strategy had the highest WR at 61.8%. QF_5% strategy delivered 12.59% AR and 16.02% AW, with the lowest portfolio volatility at 0.136. It had the lowest VaR at 2.015%. QF_1% strategy outperformed the others, achieving the highest AR of 24.71% and the highest AER of 35.74%, though it had the highest volatility at 0.214. These four factors all perform better than CSI300 based on their return and risk. The result shows that the model takes the ability to select stocks under different training set and requirements.

Table 3: Result of the same strategy with different starting month

Strategy	TotalR	AR	TER	SR	Alpha	CSI300
2020/01-2022/02	65.29%	17.87%	66.39%	0.863	0.164	-0.66%
2020/02-2022/03	67.52%	18.21%	65.58%	0.940	0.161	1.17%
2020/03-2022/04	56.41%	15.63%	52.96%	0.739	0.135	2.26%

Table 4: Result of factors under different scales

Strategy	AR	AER	σ_p	WR	SR	Alpha	VaR
QF _20%	17.35%	19.43%	0.162	57.8%	0.915	0.162	2.81%
$QF_{-}10\%$	13.12%	17.73	0.159	$\boldsymbol{61.8\%}$	0.574	0.128	2.023%
$\mathrm{QF}_5\%$	12.59%	16.02%	0.136	61%	0.63	0.117	$\boldsymbol{2.015\%}$
QF_1%	$\boldsymbol{24.71\%}$	35.74%	0.214	53.3%	0.967	0.249	3.048%
CSI300	1.77%	\	0.197	\	-0.015	\	3.19%

6 Conclusion

This study proposed a new model, quantformer for quantitative stock prediction and trading. We addressed the need for handling numerical input data rather than text and adapting the model for forecasting tasks rather than sequence-to-sequence problems common in NLP. To enable direct processing of numerical time series data, we replaced the word embedding layer with a standard linear layer and removed the output masking operations. We also simplified the decoder to produce a probability distribution over future price movements rather than autoregressively generating token sequences.

Eventually, we tested the factor in the reality back test of the financial market and compared the factor with other 100 price-volume factors. Our experimental results demonstrate the promise of this approach. The model-based trading strategies were able to deliver substantial excess returns over the benchmark under a longer time period, with Sharpe Ratios indicating sound risk-adjusted performance. The positive alphas affirm the strategy's ability to outperform expected returns after accounting for risk factors.

There is further scope to enhance the framework, for instance by incorporating additional signals like news and fundamentals as auxiliary inputs. The self-attention mechanism could likely be improved to encode greater temporal context, or use transformer-based models such as GPT-4 [56] and Claude3 [57] to establish the strategy as these models are fine-tuned and may perform better for quantitative finance tasks.

Overall, our work illustrates the viability of quantformer for financial data modeling, provides a flexible framework to model the market from multiple perspectives of financial time series and develops profitable trading strategies that consider different variables. With further research to solve the above limitations, we believe such ML-based quantitative methods hold rich potential. The framework provides a flexible foundation for better understanding markets and developing profitable trading strategies.

The implementation code of quantformer is available at https://github.com/zhangmordred/QuantFormer.

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Appendix A Detailed backtest results between 100 factors and the quantformer factor

All the data of factors comes from JoinQuant⁴, which is one of the most common quantitative finance platforms. Detailed descriptions of the following factors are available at JoinQuant Factors.

Ten metrics are used to evaluate the performance of each factor:

- Annual Return (AR) and Annual Excess Return (AER) are two metrics to reflect
 the return of the portfolio directly. The excess returns are returns achieved above
 and beyond the return of a proxy and the CSI300 index is used as the basis when
 calculating the excess returns.
- Win Rate (**WR**) is the metric to evaluate the fraction between the action that makes a profit and all the actions.
- Sharpe Ratio (**SR**) is a measure of risk-adjusted return that describes the additional earnings an investor receives for each standard deviation unit increase, which is shown in equation (9).
- The **Alpha** measures the ability of a portfolio to generate returns above the market benchmark. A positive alpha indicates that the investment portfolio has achieved a higher return than its benchmark after risk adjustment, which is shown in equation (10).
- Beta is the correlation between the portfolio and systemic risk, reflecting the sensitivity of the strategy to the change in the market. For the daily return of the strategy, D_p , and the daily return of the benchmark D_m , the equation of beta is:

$$Beta = \beta_p = \frac{Cov(D_p, D_m)}{Var(D_m)}$$

where $Cov(D_p, D_m)$ is the correlation of between D_p and D_m , $Var(D_m)$ is the variance of daily return of benchmark.

• Max Drawdown (MD) means the potential worst-case scenario or the most extreme possible loss from the previous peak. For the trough value of a portfolio V_{trough} and the peak value of the portfolio V_{peak} , the MDD is calculated in the following way:

$$MDD = \frac{V_{peak} - V_{trough}}{V_{peak}}$$

• Portfolio volatility (σ_p) is the standard deviation of the portfolio returns. σ_p avoids the problem of negative deviations canceling with positive deviations and also penalizes larger deviations from the mean. It provides a kind of weighted average deviation in which large deviations carry more weight [58].

⁴https://www.joinquant.com/

- Sortino Ratio (STN) differentiates harmful volatility from total overall volatility by using the standard deviation of negative portfolio returns. This metric measures the performance of the investment relative to the downward risk.
- Value-at-Risk (VaR) estimates the potential loss in value of a risky investment, which is used to quantify the amount of potential loss and the likelihood of occurrence for that loss within a specified time frame, which is shown in equation (11). In the backtest, 99%VaR is used.

Factor	AR (%)	AER (%)	WR (%)	SR	Alpha	Beta	MD (%)	σ_p	VaR (%)	ST
ARBR	-1.47	0.32	54.7	-0.251	-0.002	0.914	34.46	0.221	3.74	-0.3
AR	-5.87	-4.37	53.7	-0.406	-0.048	0.981	47.84	0.260	3.94	0.6
ATR14	-2.12	-0.37	62.7	-0.250	0.006	1.160	46.55	0.250	4.51	-0.3
ATR6	-3.94	-2.31	61.2	-0.328	-0.014	1.175	50.11	0.253	4.48	-0.4
BBIC	1.17	3.14	50.9	-0.109	0.033	1.038	32.64	0.258	4.16	-0.1
BR	-6.91	-5.47	53.6	-0.467	-0.064	0.934	51.72	0.254	3.80	-0.7
CCI10	-18.65	-17.99	43.3	-1.402	-0.261	0.812	72.04	0.220	2.79	-2.0
CCI15	-17.70	-16.98	44.2	-1.293	-0.240	0.832	71.43	0.223	2.90	-1.8
CCI20	-15.52	-14.66	46.3	-1.051	-0.196	0.868	69.12	0.235	3.28	-1.5
CR20	-4.27	-2.67	54.8	-0.329	-0.032	0.927	49.92	0.263	4.26	-0.5
DAVOL10	-7.44	-6.04	54.1	-0.504	-0.071	0.920	45.45	0.248	3.38	-0.8
DAVOL20	-10.95	-9.78	54.4	-0.702	-0.119	0.919	48.96	0.246	2.86	-1.0
DAVOL5	-9.54	-8.28	51.8	-0.612	-0.097	0.950	46.41	0.250	3.17	-1.0
EMA5	2.77	4.85	48.3	-0.047	0.049	1.041	30.70	0.259	4.66	-0.0
EMAC10	0.27	2.17	50.6	-0.144	0.024	1.037	31.42	0.258	4.19	-0.2
EMAC12	1.58	3.57	50.6	-0.093	0.037	1.032	31.76	0.258	4.17	-0.1
EMAC20	6.01	8.29	54.1	0.069	0.079	1.044	32.43	0.260	4.32	0.1
EMAC26	3.83	5.97	54.1	-0.008	0.059	1.046	34.87	0.261	4.29	-0.0
EMAC120	1.74	3.75	48.3	-0.088	0.034	0.960	35.81	0.254	3.77	-0.1
Curtosis20	-2.96	-1.27	52.5	-0.395	-0.027	0.772	27.71	0.182	2.74	-
Curtosis60	-0.28	1.59	53.9	-0.240	-0.001	0.716	22.07	0.179	2.64	-0.3
Kurtosis120	-4.12	-2.51	49.0	-0.468	-0.043	0.708	28.28	0.182	2.44	-0.€
AC5	0.54	2.46	46.9	-0.134	0.026	1.035	30.03	0.257	4.29	-0.1
AC10	-1.20	0.61	49.6	-0.206	0.008	1.039	34.15	0.256	4.19	-0.2
AC20	2.47	4.52	53.5	-0.059	0.046	1.043	34.58	0.257	4.09	-0.0
AAC60	11.10	13.72	53.8	0.243	0.120	0.987	28.61	0.254	4.34	0.3
MAC120	3.11	5.21	47.7	-0.035	0.049	0.987	35.40	0.259	3.99	-0.0
ACDC	-11.12	-9.97	52.4	-0.674	-0.117	1.003	46.48	0.261	3.54	-1.0
ASS	-10.55	-9.35	51.0	-0.673	-0.115	0.886	48.34	0.249	6.19	-1.0
// AWVAD	7.29	9.67	55.9	0.119	0.082	0.891	36.54	0.248	4.19	0.1
AFI14	-6.21	-4.73	51.5	-0.456	-0.056	0.918	45.65	0.241	3.61	-0.6
PLRC6	-14.83	-13.92	47.8	-0.905	-0.178	0.960	66.24	0.259	3.85	-1.3
PLRC12	-7.28	-5.87	53.3	-0.452	-0.064	1.012	52.30	0.273	4.20	-0.6
PLRC24	-5.77	-4.26	58.1	-0.361	-0.044	1.034	53.28	0.289	4.88	-0.5
PSY	-9.11	-7.83	50.6	-0.660	-0.096	0.880	49.79	0.223	3.36	-0.9
Price1M	-13.55	-12.55	53.0	-0.760	-0.156	0.977	64.85	0.280	4.21	-1.1
Price3M	-6.69	-5.25	58.4	-0.380	-0.056	1.023	59.14	0.305	5.44	-0.5
Price1Y	1.55	3.54	66.8	-0.075	0.041	1.116	60.25	0.326	7.28	-0.1
ROC6	-16.13	-15.30	47.4	-0.982	-0.200	0.978	68.14	0.262	3.56	-1.7
ROC20	-11.63	-10.51	54.7	-0.628	-0.123	1.014	60.28	0.291	4.51	-0.9
ROC60	-6.86	-5.43	59.6	-0.382	-0.056	1.062	62.16	0.309	5.28	-0.5
ROC120	2.36	4.41	66.9	-0.051	0.049	1.117	56.36	0.319	6.79	-0.0
skewness20	-5.91	-4.41	50.8	-0.538	-0.058	0.820	40.65	0.197	3.04	0.8
skewness60	-6.47	-5.01	51.9	-0.595	-0.068	0.765	38.02	0.190	2.58	-0.9
kewness120	-4.37	-2.77	51.1	-0.459	0.044	0.743	36.01	0.192	2.69	-0.6
RIX5	-10.72	-9.54	52.5	-0.607	-0.110	1.009	56.07	0.280	4.16	-0.9
RIX10	-3.51	-1.85	58.4	-0.268	-0.019	1.008	52.92	0.292	5.14	-
VMA20	-1.92	-0.16	64.9	-0.209	0.014	1.268	44.66	0.288	4.63	-0
VMA6	-0.75	1.09	62.4	-0.166	0.026	1.259	39.46	0.288	4.76	-0.2
VSTD20	-1.83	-0.06	58.5	-0.214	0.012	1.218	35.89	0.277	4.03	-0.3
VSTD6	-3.77	-2.13	53.4	-0.297	-0.010	1.202	46.57	0.272	4.40	-0.4
/DEA	-3.05	-1.37	57.6	-0.305	-0.023	0.857	37.01	0.239	3.06	-0.4
DIFF	-7.93	-6.57	0.2	-0.533	-0.079	0.895	39.79	0.247	3.08	-0.8
/EMA5	-0.41	1.46	57.9	-0.186	0.006	0.850	37.31	0.237	3.33	-0.2
EMA10	0.95	2.91	58.9	-0.128	0.019	0.844	35.51	0.236	3.36	-0
EMA12	1.01	2.96	59.3	-0.126	0.020	0.840	35.17	0.235	3.35	-0.3
EMA26	2.41	4.46	59.3	-0.068	0.033	0.838	31.03	0.231	3.37	-
MACD	-1.03	0.79	50.5	-0.216	0.001	0.875	33.96	0.235	3.38	-0.3
OL5	-8.12	-6.76	55.9	-0.452	-0.066	1.155	53.86	0.296	4.48	-0.6
OL10	-7.07	-5.64	58.3	-0.404	-0.053	1.145	50.65	0.298	4.35	-0
OL20	-5.43	-3.89	58.6	-0.337	-0.032	1.156	50.19	0.298	4.33	-0.4
OL60	0.42	2.34	58.1	-0.125	0.032	1.145	38.35	0.286	4.71	-0.1
OL120	-1.88	-0.12	53.0	-0.213	0.007	1.136	42.09	0.281	4.64	-
/OL240	-5.51	-3.98	47.0	-0.382	-0.038	1.075	43.53	0.265	3.99	-0.5
OSC	-6.35	-4.88	51.2	-0.453	-0.056	0.944	40.40	0.246	3.44	-0.7
/ROC6	-16.30	-15.49	42.7	-1.179	-0.208	0.897	69.03	0.221	2.91	-1.7
VROC12	-11.47	-10.34	46.7	-0.793	-0.127	0.915	51.62	0.221	2.74	-1.2
/R	-8.43	-7.10	52.8	-0.566	-0.083	0.932	48.57	0.244	3.72	-0.8
	-0.43	-1.10	02.0			0.002	40.07	0.244		-0.0

Factor	AR (%)	AER (%)	WR (%)	$_{ m SR}$	Alpha	Beta	MD (%)	σ_p	VaR (%)	STN
VSTD10	-0.77	1.07	56.3	-0.205	0.001	0.843	37.75	0.234	3.19	-0.309
VSTD20	-1.60	0.19	53.7	-0.245	-0.007	0.844	37.31	0.232	3.01	-0.366
Variance20	-1.94	-0.18	59.9	-0.201	0.005	1.124	46.38	0.302	4.84	-0.301
Variance60	9.96	12.51	65.2	0.168	0.122	1.178	30.63	0.313	5.91	0.241
Variance120	5.40	7.65	60.8	0.040	0.083	1.193	39.54	0.312	5.93	0.058
Volume1M	-15.54	-14.68	20.7	-0.867	-0.189	0.991	63.68	0.285	3.61	-1.339
WVAD	-0.71	1.13	52.3	-0.199	0.002	0.836	42.38	0.238	3.67	-0.317
arron_down_25	-7.35	-5.94	48.3	-0.593	-0.072	0.880	42.63	0.209	2.84	-0.826
arron_up_25	-15.51	-14.65	46.4	-1.049	-0.195	0.870	66.73	0.235	3.19	-1.604
bear_power	-13.31	-12.30	50.8	-0.800	-0.154	0.934	59.58	0.261	3.61	-1.182
beta	10.30	12.87	62.4	0.168	0.134	1.344	35.96	0.328	6.76	0.252
book_to_price	1.87	3.86	58.5	-0.117	0.031	0.889	26.73	0.181	2.91	-0.162
bull_power	-14.81	-13.91	51.1	-0.844	-0.176	0.984	65.99	0.278	3.83	-1.285
earnings_yield	-2.41	-0.68	52.6	-0.348	-0.029	0.627	25.87	0.188	2.55	-0.55
growth	2.90	4.99	59.9	-0.045	0.052	1.068	37.35	0.244	4.50	-0.067
leverage	2.05	4.07	53.1	-0.089	0.023	0.719	22.57	0.217	3.22	-0.144
liquidity	-2.71	-1.00	56.7	-0.243	-0.002	1.137	41.28	0.284	4.56	-0.35
momentum	10.93	13.54	65.8	0.195	0.129	1.159	43.19	0.310	6.82	0.271
money_flow_20	-1.72	0.05	65.5	-0.202	0.016	1.269	44.10	0.288	4.63	-0.298
price_no_fq	6.83	9.17	76.1	0.095	0.092	1.132	44.86	0.267	6.20	0.131
pull-up	2.19	4.23	54.5	-0.068	0.044	1.062	33.09	0.265	3.92	-0.093
pull-down	-2.28	-0.54	47.6	-0.317	-0.015	0.831	34.46	0.203	3.87	-0.439
residual_volatility	4.13	6.30	62.3	0.003	0.062	1.048	41.34	0.269	5.25	0.004
sharpe_ratio_20	-11.88	-10.78	54.0	-0.663	-0.129	0.979	57.66	0.282	4.09	-1.019
sharpe_ratio_60	-7.42	-6.02	58.8	-0.417	-0.065	1.029	65.19	0.300	5.17	-0.583
sharpe_ratio_120	-0.32	1.55	65.7	-0.143	0.019	1.062	60.52	0.303	6.10	-0.2
size	-6.36	-4.89	51.8	-0.571	-0.058	0.906	36.00	0.196	2.64	-0.82
turnover_volatility	-10.80	-9.62	51.8	-0.624	-0.108	1.075	57.05	0.274	3.70	-0.905
1day_VPT	-16.45	-15.65	44.8	-1.062	-0.211	0.904	70.43	0.248	3.09	-1.553
1day_VPT_6	-6.36	-4.89	53.0	-0.416	-0.053	0.995	47.06	0.269	3.81	-0.82
1day_VPT_12	-0.07	1.82	57.9	-0.146	0.020	1.033	46.51	0.278	4.39	-0.22
25week_close	-11.51	-10.39	51.0	-0.859	-0.133	0.817	47.79	0.211	2.44	-0.684
QF_Month_1	17.35	19.43	57.8	0.915	0.162	0.588	18.35	0.161	2.81	0.946
QF_Month_2	9.91	13.53	49.3	0.289	0.102	0.684	26.77	0.205	3.61	0.372
QF_Month_3	7.37	10.4	51.6	0.246	0.064	0.483	17.33	0.137	2.3	0.309
QF_Week_1	-0.83	1.41	46.4	-0.236	-0.003	0.726	29.31	0.204	3.05	-0.291
QF_Week_2	7.49	10.55	49.2	0.16	0.085	0.792	29.08	0.219	3.73	0.206
QF_Week_3	12.3	12.4	54.4	0.372	0.116	0.793	29.86	0.223	3.77	0.48
QF_Day_1	7.89	11.4	43.1	0.181	0.09	0.834	29.15	0.196	3.92	0.245
QF_Day_2	10.23	10.68	44.4	0.279	0.097	0.819	30.02	0.223	3.91	0.361
QF_Day_3	9.81	10.03	44.6	0.284	0.098	0.801	30.1	0.223	1.02	0.367
QF_10%	13.12	17.73	61.8	0.754	0.128	0.594	18.32	0.159	2.02	0.714
QF_5%	12.59	16.02	61	0.63	0.117	0.504	13.3	0.136	2.01	0.796
QF_1%	24.71	35.34	53.3	0.967	0.249	0.667	23.28	0.214	3.35	1.299
Average	-2.92	-1.25	53.28	-0.32	-0.02	0.96	43.61	0.25	3.99	-0.467
CSI300	1.77		\	0.009	\	\	\	0.197	3.19	\

Appendix B Comparison between different quantformer strategies

In the provided scatter plot B1a, the QF_Month_1 factor exhibits notable performance in terms of annual return. Compared to other factors, QF_Month_1 offers

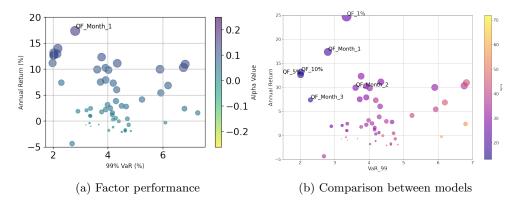


Figure B1: Comparison of factor performance and model performance

better returns. Regarding risk, as measured by the $Variance_Covariance_VaR_99$, the QF_Month_1 factor's data points are positioned in a moderately high range, indicating a balanced risk profile. The size and color intensity of the QF_Month_1 points, reflecting higher Alpha values, suggest a robust excess return or relative performance. Combining these observations, the QF_Month_1 factor likely provides a compelling investment opportunity by delivering robust returns while maintaining a moderate risk level, an attractive proposition for strategies aiming to optimize the trade-off between risk and return.

In scatter plot B1b, most of the factors based on quantformer perform better compared with the other 100 factors. The performance of quantformer factors which are trained under different scales shows ability in making profit and risk management.