

Large Language Models for Time Series: an Application for Single Stocks and Statistical Arbitrage

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Abstract

Large Language Models (LLMs) have been adapted for time series prediction with significant success in pattern recognition. However, the common belief is that these models are not suitable for predicting financial market returns, which are known to be almost random. We aim to challenge this misconception through a counterexample. Specifically, we utilize the Chronos model from Ansari et al. (2024) and test both pretrained configurations and fine-tuned supervised forecasts on the largest American single stocks using data from Guijarro-Ordonnez et al. (2021). We construct a long/short portfolio, and the performance simulation indicates that LLMs can in reality handle time series that are nearly indistinguishable from noise, demonstrating an ability to identify inefficiencies amidst randomness and generate alpha. Finally, we compare these results with benchmark models, highlighting significant room for improvement in LLM performance to further enhance their predictive capabilities.

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1 Introduction

Large Language Models (LLMs) gained widespread popularity when ChatGPT convinced many that machines were intelligent enough to reason like humans, even though the underlying techniques merely determine the most likely sequences of words that could respond to a prompt. Besides, with regards to the integration of generative AI in the financial industry, Citadel CEO Ken Griffin says "the tech hasn't done much for hedge funds where it matters most— beating the market"¹. This study challenges this view by applying for the first time a LLM to a large portfolio of U.S stocks. Recently, the introduction of the transformer architecture by Vaswani et al. (2017) was a key development, as it enabled fast training on large datasets. LLMs are composed of many layers of transformers and have around a billion parameters. For instance, the T5 (Text-To-Text Transfer Transformer) architecture was introduced by Raffel et al. (2023), and further advanced the field from T5-small size with 60 million of parameters to T6-11B with 11 billion of parameters). Amatrianin (2023) describes the catalog of LLMs models from Albert to ChatGPT and classifies T5 among others.

The incorporation of Transformers into trading, risk, and the portfolio management industry is on the verge of transforming the financial landscape due to the oncoming technological gap. The reason is straightforward: They are reaching the state-of-the-art performance of learning from time series in many domains including Traffic, Climate, Energy, and recently, Finance. The transformer is indeed a deep learning architecture that enhances considerably the analysis and processing of huge volume of diverse and complex data that are valuable for businesses and decision-makers on a real time basis. For instance, it helps making timely decision of buying and selling securities or of optimizing portfolio with risk prediction. LLMs, such like Generative Pre-Trained Transformers, are designed for specific tasks useful in the financial industry like real time translation or sentiment analysis. Still, the most challenging, crucial and valuable task remains the time series forecasting. Time series in finance are difficult to predict because they are modeled as random walk process based on a sequence of random observations generated by a stochastic process over time. In addition, financial time series are subject to noise, temporal dependence, non-stationarity and sometimes missing values. In an efficient market it should be nearly impossible

¹<https://blinks.bloomberg.com/news/stories/T48R8PBQ99TS>

to do prediction. In the real world, there exist thousands of financial time series since several decades, but most of them are not liquid enough to be included in a sample for prediction. For example, small capitalization shares or penny stocks could be subject to less frequent or stale quotes. Econometrics models (e.g. ARIMA) are well suited for predicting financial future outcomes because they provide a clear representation of the system, which is very useful in an industry where regulators require explanations. Unfortunately, they suffer from limitations when it comes to handling large and complex data structure. Significant advancements were made from the machine learning models (e.g. Nearest-Neighbor methods, Shrinkage methods, Tree-based methods and Boosting, Support Vector Machines classifiers, Neural Networks approaches) that proved successful in capturing complex data set. On top of that, deep learning models (e.g. Long Short-Term Memory) went even further through modelling heterogeneous and long-term data to extract patterns from complex data structure, which enhances forecasting accuracy. However, they are exposed to a sort of performance saturation because they are relatively small models with hundreds of parameters. Transformers address this limitation allowing for billions of parameters to be estimated on large scale dataset (please see Wen et al. 2024 for a survey on transformers on time series). They are reshaping the field of time series forecasting given their empirical success in the so-called “one-model-for-all-datasets” (Wu et al. (2025)). The vanilla Transformer is built on the encoder-decoder structure where the model architecture is based on an attention mechanism to draw global dependencies between inputs and outputs (see Vaswani et al. (2017)). This encoder-decoder architecture has become a promising tool for predicting complex multivariate time series. LLMs share the same architecture with transformers. LLMs for time series (e.g. BERT) are able to perform time series forecasting across a variety of datasets and are capable of incorporating missing data (Gruver et al. (2023)). The application of such LLMs for time series prediction is an emerging field that excels in predicting time series with clear patterns (Tang et al. (2025)).

Garza et al. (2023) introduce TimeGPT, the first foundation model for time series, capable of generating accurate predictions for diverse datasets not seen during training. They evaluate their pre-trained model against established statistical, machine learning, and deep learning methods, demonstrating that TimeGPT zero-shot inference excels in performance. Ansari et al. (2024) also sought to adapt these highly efficient LLMs to time series forecasting. Their approach involved representing real numbers in differ-

ent bins (using a vocabulary of 4096 tokens) and training a T5 architecture on a wide range of time series data (around 90 billion observations). They produced several pretrained models of varying sizes, ranging from tiny (11 millions of parameters) to large. TimesFM (Time Series Foundation Model) is another pretrained time-series foundation model developed by Das et al. (2024). Rasul et al. (2024) uses a lagged features for tokenization. Nie et al. (2023) build a transformer model for multivariate time series forecasting by using segmentation of time series into subseries-level patches that served as input tokens to the Transformer and also by using channel-independence for which each channel contains a unique time series that shares the same Transformer weights through all the series. Ekambaran et al. (2023) develop a neural architecture exclusively composed of multi-layer perceptron modules for multivariate forecasting and representation learning on patched time series. This novel MLP-Mixer is also patching-based and it exploits various time-series features for multivariate forecasting. Motivated by recent advances in Large Language Models for Natural Language Processing, Ansari et al. (2024); Das et al. (2024) designed a time-series foundation model for forecasting whose out-of-the-box zero-shot performance on a variety of public datasets comes close to the accuracy of state-of-the-art supervised forecasting models for each individual dataset. Their models are based on pretraining a patched-decoder style attention model on a large time-series corpus, and can work well across different forecasting history lengths, prediction lengths and temporal granularities.

Deep learning has become very popular among researchers in finance, both for asset pricing and systematic strategies: Brugiere and Turinici (2024) tested transformers for financial time series and showed that the algorithm cannot predict returns, but can only predict squared returns. Konigstein (2024) stated that LLMs present challenges, but also opportunities, particularly for long-term financial time series forecasting. Guijarro-Ordonnez et al. (2021) implemented transformers (with only 769 parameters) but coupled them with convolutional layers and tested them on quantitative trading strategies applied to single stocks. Their results, without accounting for trading costs, were encouraging. They applied deep learning algorithms to residual daily returns after removing common factors using techniques such as Principal Component Analysis (PCA), Fama-French factors, or Instrumental Principal Component Analysis (IPCA), implementing the methodology from Kelly et al. (2019), who used financial data to constrain the eigenvectors. This approach was also developed and justified by Valeyre (2019). Trans-

formers have also been used by Jiang et al. (2023) to identify patterns in images for financial price time series. Wood et al. (2022) applied deep learning techniques with only a few parameters to identify the most effective trend-following indicators enhancing and timing trend-following strategies. Transformers have also been used to extract common returns, as demonstrated by Gu et al. (2021). Qyrana (2024) applied a simple Short Term Reversal factor fed by residual returns using an autoencoder-based factor model, subsequently generating a highly profitable trading strategy (i.e. through buying losing stocks based on residual returns and shorting winner stocks). Chen et al. (2021) used a deep learning technique to identify anomalies in asset pricing.

However the question remains whether a Large Language Model optimized for time series outside the field of finance is sufficiently intelligent and sensitive to capture inefficiencies and market anomalies. Despite the burgeoning literature, there are still no papers that apply a deep learning technique with millions of parameters to financial forecasting while this is the natural number of parameters to consider in the context of LLMs. Studies such as Chen et al. (2021), Jiang et al. (2023), Wood et al. (2022), Guijarro-Ordonez et al. (2021), and Brugiere and Turinici (2024) utilized models with at most a few hundred parameters so their models were not real deep learning models. This limitation was due to their inability to pre-train models with millions of parameters using large datasets from outside the financial industry. This study fills the gap by implementing deep learning algorithms with more than 11 million parameters for forecasting financial returns. This methodological approach attempts to solve the problem to what extent LLMs are intelligent enough to predict financial returns. Therefore, the contribution of this paper is to be the first that use LLMs for financial time series forecasting.

The employed methodology is two-fold. First, we conduct a zero-shot evaluation of the predictions from pretrained and fine-tuned supervised time series foundation LLMs Chronos by Ansari et al. (2024), which were pre-trained on 13 datasets that do not include single stock data or stock indices, using the datasets of the residual returns of American single stocks published by Guijarro-Ordonez et al. (2021). The interest in using only zero-shot evaluation is that it provides more convincing results, as overfitting is less likely in this case. Indeed overfitting is a major concern in machine learning when applied to trading, which often makes honest results appear suspect. Another interesting aspect is demonstrating how the algorithm can adapt and display 'intelligence' in trading without being specifically trained for that

purpose. We simulate a portfolio that goes long the stocks whose predicted next return is positive and short the stocks whose predicted next return is negative. Secondly, we compare these results with the well-known standard Short Term Reversal (STR) or trend-following approaches, as described in Jegadeesh (1990); Jegadeesh and Titman (1993). The main finding reveals that LLMs optimized on non-financial time series are still capable of producing significant forecasts for financial time series.

2 The methodology of our empirical backtest

2.1 Chronos as the LLM model

Our objective is to assess whether one LLM-based time series model could capture inefficiencies or market anomalies in financial markets.

We limited our test to the Chronos model because it stands out as a best-in-class LLM for time series forecasting, delivering robust performance, particularly in zero-shot and long-horizon forecasting tasks. Its adaptability and scalability make it a valuable tool across a wide range of forecasting applications. The model used was "amazon/chronos-t5-tiny" version of the chronos which was pretrained by Ansari et al. (2024) on 14 datasets (Brazilian cities temperatures, Mexico city bikes, Solar, Spanish energy and weather, Taxi, USHCN, weatherbench, wiki daily, wind farms) but not on financial time series. The model has 11 millions of parameters. Chronos was presented by Konigstein (2024). Her thorough comparative examination includes several LLM models, such as Lag-Llama from Meta (Rasul et al. (2024)), PatchTST from IBM (Nie et al. (2023)), and TSMixer from IBM (Ekambaram et al. (2023)). According to Konigstein (2024), Chronos was both the easiest to implement and the most effective among the models tested, based on internal evaluations across a variety of models: local models, task-specific models, in-domain pretrained models, and out-of-domain pretrained models. We do not claim that it is optimal or superior to simpler models without pretraining, especially given that out-of-sample results in quantitative finance papers sometimes lack of reliability and sometimes are not confirmed once the paper is published as mentioned by McLean et al. (2016) and Harvey et al. (2016). That is why we limited our investigation to two well established and very simple benchmarks such as both the Short Term Reversal (STR) and ARIMA, while including the machine learning model of Guijarro-Ordonez

et al. (2021) as we used their data. We used a ‘context’ period of 100 days so that Chronos guess the next day, knowing only the previous 100 days. We focused only on the next day return forecast. We used 100 days as a compromise to avoid running out of memory while giving Chronos a chance to capture some patterns. Additionally, we decided to limit the study to predicting the next daily returns. While forecasting weekly or monthly returns was a possible alternative, we considered that Chronos would be more effective at identifying patterns over a shorter time horizon.

We used both the zero-shot pretrained and fine-tuned versions of Chronos. To implement the fine-tuned version, we adjusted the 11 million weights of the ‘amazon/chronos-t5-tiny’ model by training it on our dataset, setting τ —the maximum number of training steps and one of Chronos’s key parameters—to 5, 15, or 40. Training was conducted daily during the backtest, using the data available on each respective date and starting from the weights of the previous day. The details of the parameters used for both the pretrained and fine-tuned cases are provided in Sections 2.3.1 and 2.3.2, with additional information and the corresponding Python code available in Appendices B.1 and B.2.

2.2 Dataset description

We use the datasets from Guijarro-Ordonnez et al. (2021), who restricted their analysis to the most liquid stocks to mitigate trading and friction issues. Specifically, they considered stocks whose market capitalization in the prior month exceeded 0.01% of the total market capitalization of that month, resulting in a selection of approximately the largest 550 stocks on average. This portfolio of the most liquid U.S. stocks over such a long period appears as the most appropriate sample for a deep learning application. The total number of stocks exceeds 550 because the composition changes daily and we have a total of 9483 different stocks in the whole period. It is very common in financial studies to test strategies on the largest 500 U.S. stocks. Indeed evaluating investment strategies or identifying market anomalies often involves testing on large-cap U.S. stocks, particularly those in the S&P 500 index. This practice is prevalent due to the S&P 500’s representation of a substantial portion of the U.S. equity market and the availability of high-quality data: Hou et al. (2020) examines 452 documented anomalies in finance. The authors construct a vast data library and apply rigorous replication tests, emphasizing the use of NYSE breakpoints and value-weighted

returns to mitigate the influence of microcap stocks. Their methodology underscores the importance of focusing on larger, more liquid stocks, such as those in the S&P 500, to ensure robustness in empirical findings. It is worth noting that Gu et al. (2021), in their effort to gather sufficient data to train their 500,000²-parameter models, explicitly stated that, "unlike the existing literature", they did not exclude micro-cap stocks. They applied no filters, resulting in an average of over 6,200 stocks per day in their dataset. Also as we mainly use the pretrained case of Chronos, we did not need a larger dataset for the zeros shot version or the fine tuned one.

The three different datasets of daily residual returns (IPCA, PCA and FF) provided by Guijarro-Ordonnez et al. (2021) are all based on the same raw universe of securities from the CRSP dataset spanning January 1978 to the end of 2016, but obtained using different methods for extracting the residuals. Guijarro-Ordonnez et al. (2021) released their datasets of residual returns on GitHub. We utilized their three datasets whose statistics are displayed in Tab. 1, each corresponding to their standard parameters with the number of factors, K , equal to five:

- IPCA factors with a rolling windows of 240 months with the details described in Kelly et al. (2019). We report the following summary statistics for daily residual returns: a mean of 4.35×10^{-6} and a standard deviation of 0.0066.
- PCA factors with a rolling windows of 252 days. We report the following summary statistics for daily residual returns: a mean of 2.31×10^{-6} and a standard deviation of 0.0059.
- FF factors (Fama-French market, value, size, investment and profitability factors) with a rolling windows of 60 days. We report the following summary statistics for daily residual returns: a mean of 2.95×10^{-6} and a standard deviation of 0.0068.

$K = 5$ appears to be the optimal hyper parameter according to Guijarro-Ordonnez et al. (2021) when applying their convolution and transformer

²The figure of 660,000 parameters for their simple version is our own estimation, based on the code released at <https://github.com/dkyol/Asset-Pricing-Model>. However, this implementation does not appear to be officially validated by Gu et al. (2021) and may not be fully appropriate, as it assigns different weights to each stock, whereas one would typically expect a shared parameter structure across stocks

Dataset	Mean	SD	Skewness	Kurtosis	Total number of residual returns
IPCA	4.35×10^{-6}	0.0066	1.38	583	4079040
PCA	2.31×10^{-6}	0.0059	1.16	594	4079040
FF	2.95×10^{-6}	0.0068	1.16	504	4079040

Table 1: Statistics of the daily residual returns of single stocks included in the 3 datasets provided by Guijarro-Ordonnez et al. (2021)

process with a performance measure, the gross sharpe ratio, of 3.21 for Fama-French, 3.36 for the PCA and 4.16 for the IPCA. Nevertheless the sharpe ratio in net appears to be significant only before 2006. Using residual returns allows for a less correlated dataset, which is crucial for deep learning. It is worth noting that Gu et al. (2021) also used IPCA, PCA and FF as benchmarks to compare the performance of the residuals produced by their autoencoder asset pricing model.

2.3 Description of the different simulated strategies

Our experiment is organized in three parts. We began by testing the zero-shot version of Chronos, then we implement the fine-tuned version, and finally compared the results against three different benchmarks. We used exactly the same evaluation procedure, described in Section 2.3.1, which constructs the portfolio based on the forecasts generated by each method. Only Guijarro-Ordonnez et al. (2021), which in one of the benchmarks, directly determined the portfolio without going through a separate forecasting step.

2.3.1 Zero-shot version

First, we implemented a "zero-shot evaluation", which means without any fine-tuning (or training). The weights of Chronos were not trained on financial data. Our experiment consists of, for each day, from 2001-12-26 to 2016-12-30, and for each dataset (IPCA, PCA, FF):

- Computing $\hat{\chi}_{d,i}$, the Chronos average prediction of the next residual daily return, derived in the Eq 2 conditioned to a rolling window of the last 100 days. In Eq 2 we used the average of different "equiweight" scenarii χ computed by Chronos of the forecasted residual return, \hat{r}_{d+1} , knowing only $r_{d,i} \dots r_{d-99,i}$. We used two possible inputs for Chronos:

- Either the last 100 residual daily returns $r_{d,i} \dots r_{d-99,i}$ of the single stock i .
- or the last $\hat{r}_{d,i} \dots \hat{r}_{d-99,i}$ the exponential moving average of the last 100 residual daily returns derived in Eq 1 with $\alpha > 0$. In fact, the second possibility is merely a more general case of the first, which corresponds to the particular case where $\alpha = 0$ in Eq 1. We tested α values of 0.1, 0.2, 0.3, 0.4, 0.5, and 0.8, all different from zero. This option allows the model to account for the well-known weak negative autocorrelation of daily returns, potentially improving its forecasting ability. However, in this case, the model must outperform the Short-Term Reversal strategy described in Eq. 10 as Eq. 1 is close to Eq. 10.
- Predicting of the next residual returns with $\tilde{\chi}_{d,i}$ which is derived in Eq 3.
- Calculating the weights of the portfolio $\hat{\omega}$ derived in Eq 6 which uses ω_d^χ derived in Eq 4 which ranks through $\Re = \text{ArgSort}$ every day d the different the forecasted residual return $\tilde{\chi}_{d,i}$ from Eq 3. In this method, in Eq 4, the median rank is withdrawn through $\frac{N}{2}$ where N is the number of stocks. A normalization of the weights is derived in Eq 6 to target a gross investment of 1. This process ensures that the portfolio is 50% long and 50% short every day, with weights proportional to the distance in ranking from the median stock according to the forecasted residual returns $\tilde{\chi}$ derived in Eq 3. Valeyre (2019) proved that this approach is the mathematically optimal method and better than just buying the top quintile and short the bottom quintile as it is invested on a larger number of stocks with a better diversification. A 'resized' version to manage better risk through reducing weights on volatile stocks is also tested when the weights are also inversely proportional to the volatility as derived in Eq 5 where σ are the standard deviation of the daily returns on the previous 100 days and \mathbf{M} is the median.
- Simulating the performance of the portfolio determined by the weights in Eq 6: We derived \mathcal{P}_{d+1} , the performance of the portfolio for the next day through Eq 8. We then reconstructed the cumulative returns and calculated the gross Sharpe ratio, excluding any trading costs. We also simulate $[\mathcal{P}_{d+1}]$ for the resized version through Eq 9 which used weights derived in Eq 5.

$$\hat{r}_{d+1,i} = \alpha \hat{r}_{d,i} + r_{d+1,i} \quad (1)$$

$$\hat{\chi}_{d,i} = \mathbf{E} [\chi (\hat{r}_{d+1,i} | \hat{r}_{d,i} \dots \hat{r}_{d-99,i})] \quad (2)$$

$$\tilde{\chi}_{d,i} = \hat{\chi}_{d,i} - \alpha \hat{r}_{d,i} \quad (3)$$

$$\omega_d^\chi = \Re[\Re(\tilde{\chi}_d)] - \frac{N}{2} \quad (4)$$

$$[\omega_d^\chi]^r = \left(\Re[\Re(\tilde{\chi}_d)] - \frac{N}{2} \right) \frac{\mathbf{M}(\sigma_0 \dots \sigma_N)}{\max(\sigma, \mathbf{M}(\sigma_0 \dots \sigma_N))} \quad (5)$$

$$\hat{\omega}_{d,i}^\chi = \frac{\omega_{d,i}^\chi}{\sum_j |\omega_{d,j}^\chi|} \quad (6)$$

$$[\hat{\omega}_{d,i}^\chi]^r = \frac{[\omega_{d,i}^\chi]^r}{\sum_j |[\omega_{d,j}^\chi]^r|} \quad (7)$$

$$\mathcal{P}_{d+1} = \sum_i \hat{\omega}_{d,i}^\chi \times r_{d+1,i} \quad (8)$$

$$[\mathcal{P}_{d+1}] = \sum_i [\hat{\omega}_{d,i}^\chi] \times r_{d+1,i} \quad (9)$$

2.3.2 Fine-tuned version

Secondly, we employed a very naive approach to fine-tuning from the pre-trained weights, which can be highly challenging and unstable in practice Goodfellow et al. (2013). Thanks to that feed, Chronos can adapt its weights according to the properties of the financial time series. We trained Chronos which was initiated at the beginning of the backtest with the pretrained weights. The training was realized on a daily basis during the backtest using the available residual returns data starting on every day with the weights of the previous day. On every day d , we provided as input to Chronos the updated time series available at day d using the the previous 100 days. We test 5 and 15 as values for τ , the maximal number of steps in the iteration process. τ is a critical parameter of the algorithm, detailed in Appendix B.2, governing the daily training process. If τ is set too high, Chronos may completely forget its pretrained knowledge, leading to severe overfitting—especially given the relatively small size of our dataset compared to the model’s 11 million parameters. Moreover, even a moderate value such as $\tau = 15$ is already highly computationally demanding: it required approximately one week of

computation on our setup, which includes 22 Intel(R) Core(TM) i7-14700KF 3.40GHz processors, two NVIDIA GeForce RTX 4060 Ti GPUs with 80 GB of combined VRAM, and 128 GB of RAM. We also used different values of the parameter α in Eq 1 which adjusts the input of Chronos. The continuous training led to Chronos model to update its weights for each day of the backtest leading to a continuous outsample result. We then determined the portfolio weights based on the predictions using the fine-tuned weights instead of the pretrained ones.

We do not claim that our methodology for fine tuning is optimal to empirically determine other approaches by controlling overfitting and the loss of the pretrained weights through the analysis of the statistics of the eigenvalues derived from the millions of weights (Martin (2019, 2024)). However, this falls outside the scope of our current study. For instance, the drawback of our methodology is that the pretraining weights are gradually forgotten over time, which is not an ideal solution. We give more detail of the methodology we used for fine tuning in Section B.2 of the Appendix.

We did perform an analysis using WeightWatcher (Martin (2024)) on both the pretrained and fine-tuned models, and found no signs of overfitting or underfitting. The results of this analysis (Fig 2 in Sec B.3 of the Appendix) which is distribution of the power law coefficient of the eigenvalues distributions layer per layer are included in the appendix and show that the power-law exponents fall within the range of 2 to 6 in the fine-tuned case, indicating no risk of overfitting (which would be suggested by exponents below 2) or underfitting (suggested by exponents above 6). The statistics from the fine-tuned model are even more favorable than those of the pretrained model, which shows some exponents above 6, suggesting a minor risk of underfitting.

2.3.3 Comparison

Third, we compare the results of Chronos to those obtained by replicating the machine learning model with a small number of 169 parameters of Guijarro-Ordonez et al. (2021), who used a CNN Transformers model. Their number of paramaters is small compared with the 11 million of the Chronos one. They used a CNN Transformers model. We also include the results achieved using standard autoARIMA from the statsforecast package (<https://pypi.org/project/statsforecast/>) as it is a standard benchmark in Machine Learning, as well as the Short Term Reversal (STR) described in Jegadeesh (1990); Jegadeesh and Titman (1993) which is a well-documented

market anomaly that was first noted by Fama (1965) as the same anomaly is captured by Chronos.

Both AutoARIMA and Short Term Reversal (STR) appear to be well-suited benchmarks, as they capture anomalies that are very similar to those detected by Chronos within our framework. Guijarro-Ordonnez et al. (2021) captures also Short Term Reversal (STR). The returns between their portfolios are correlated.

The Autoregressive integrated moving average (ARIMA) specification is part of the ARMA statistical models that typically predict future values based on explicit past values. The class of ARIMA models has been widely applied through Box and Jenkins (1970) methodology and has proved fruitful for time series modeling according to Engle (1978). They are made with three components: First, an Auto-Regressive (AR) component based on a number of lagged values with order (p). Second, a Moving Average (MA) component based on the number of lagged residual terms. Third, an Integrated (q) component based a number of differencing orders used to make the data stationary on a degree (d). The auto-ARIMA specification use information criteria such like AIC or BIC to determine optimally the ARIMA parameters (p,d,q), where the best ARIMA model for the time series is one with the smallest AIC or BIC. The AutoARIMA was also fit in a continuous way every day during the backtest using the previous $100 \text{ days} \times N$ observations and yielded to forecasts \mathbf{A}_d and the portfolio weights $\omega_d^{\mathbf{A}}$ were also derived with the same methodology Eq 12.

Short Term Reversal (STR) financial strategy has been a market anomaly that was first observed by Fama (1965) and first documented by Jegadeesh (1990). It belongs to the category of price trend-following strategies in the industry of portfolio management and it captures the Short Term mean-reversion behavior. In practice this dynamic strategy requires sorting stocks into deciles according to their past-month returns in order to buy losers (stocks in the bottom decile) and sell winners (stocks in the top decile). It is a dynamic strategy because it is rebalanced on a monthly basis. It is also a robust and statistically significant strategy because Jegadeesh (1990) unveil a monthly extra return of 2% (see for a detailed discussion, see e.g. Da et al. (2014)). The Short Term Reversal (STR) strategy was implemented using an exponential moving average of residual returns, as defined in Equation 10, with two parameter settings: $\beta = 1 - \frac{1}{5}$ and $\beta = 1 - \frac{1}{20}$. The portfolio of the STR is then derived in Eq 11 with $\omega_d^{\varsigma_d}$, the weights of the portfolios, using the same methodology as for the Chronos forecast where N is the number of

single stocks.

$$\tilde{r}_{d+1,i} = \beta \times \tilde{r}_{d,i} + r_{d+1,i} \quad (10)$$

$$\omega_d^\zeta = \Re[\Re(-\tilde{r}_d)] - \frac{N}{2} \quad (11)$$

$$\omega_d^A = \Re(\Re(A_d)) - \frac{N}{2} \quad (12)$$

2.4 Performance measures

We based our results on the gross Sharpe ratio metric of the portfolio which corresponds to the outsample annualized average of daily returns of the portfolio divided by the annualized standard deviation of daily returns, meaning that we do not consider slippage and trading costs. This metric is standard in the portfolio management literature and can be associated with the t-statistic by multiplying it by the square root of 15, corresponding to the 15 years in our sample period. If the Sharpe ratio of the portfolio is positive and the associated t-statistic exceeds 3, we can consider that the prediction methodology has succeeded in capturing some market anomalies through its forecasts. Fama and French (2015) typically assess anomalies by comparing the performance of portfolios formed on different quantiles (e.g., quintiles) of a given factor. They consider an anomaly to exist if the return spread between extreme portfolios is statistically different from zero, based on a t-statistic. In this sense, our use of the Sharpe ratio—or its associated t-statistic—is closely related to their methodology. The Sharpe ratio is particularly relevant as it provides an aggregate performance measure across the entire universe and is a simple yet widely used metric in asset management to evaluate whether a strategy is efficiently generating profits. A net Sharpe ratio of 1 is already considered excellent from the perspective of a final investor.

3 Empirical results

We can see that resizing the weights of the portfolio inversely proportional to the volatility improves the Sharpe ratio for Chronos slightly, as well as for the benchmarks so that we chose to report only the results obtained from this version for all methods.

We observe that the pre-trained Chronos model with the autoregressive coefficient $\alpha = 0.3$ effectively identifies opportunities in the financial market (see Table 2), achieving a Sharpe ratio above 3.17 for PCA over a 15-year period, which corresponds to a t-statistic of $3.17\sqrt{15} = 12.27$. However, trading costs are prohibitive, as including a 3 basis point slippage³ cost per trade results in negative net Sharpe ratios. Additionally, we note a decline in profitability over time, suggesting that markets may be becoming more efficient or that opportunities are increasingly challenging to capture or that returns used to be more negatively autocorrelated before 2008 (see Figure 1). However, at least until 2007, it was easier for AI to capture inefficiencies.

α	0	0.1	0.2	0.3	0.4	0.5	0.8
FF	0.07	1.27	1.80	1.84	1.39	1.39	-0.24
PCA	0.04	2.08	2.75	3.17	3.25	2.71	0.07
IPCA	-0.47	0.68	1.19	1.34	1.42	1.18	-0.81

Table 2: Simulation of the Gross sharpe ratio of the strategy with the resized version (ie. Eq 5) to reduce risk on volatiles stocks based on the zero-shot pretrained prediction of Chronos when using as input the exponential moving average of daily residual returns through using either the IPCA, the PCA or FF. α is the parameter of the EMA from Eq 1. The period is 2002-2016.

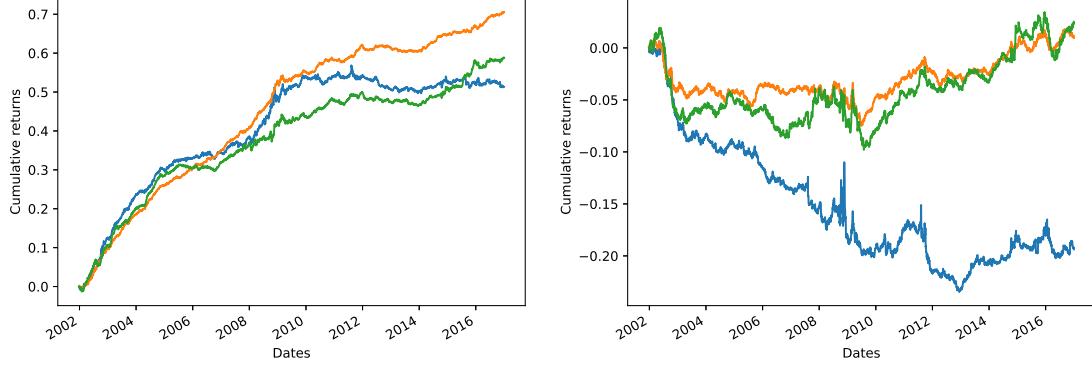
It is particularly interesting to observe that the pre-trained version with $\alpha = 0$ is ineffective until 2007 but seems to work after 2008 (see Figure 1). In our interpretation, Chronos is pre-trained on data where ‘trend’ serves as an efficient indicator, whereas in our dataset, residual returns tend to be negatively autocorrelated in the short term. We believe that $\alpha = 0.3$ is optimal, as it offsets this effect, helping Chronos to overcome biases from its trend-oriented training dataset. Setting $\alpha = 0.3$ artificially helps Chronos. However, it ultimately gets very correlated to the Short-Term Reverseal (STR) strategy with $\beta = 0.3$ but fails to outperform it . In other words, when Chronos is fed with the Exponential Moving Average (EMA), its performance does not exceed that of a zero forecast. Nevertheless, it avoids being affected by detrimental noise, which is already a positive outcome.

³A transaction cost of 3 basis points per trade is consistent with the average market impact—typically between 2 and 3 basis points for very small orders—and brokerage fees of approximately 1 basis point. With $\alpha = 0.3$, the gross Sharpe ratio for PCA is 3.17, but it drops to -1.49 after accounting for a 3 basis point trading cost.

	FF	PCA	IPCA
pretrained Chronos $\alpha = 0.2$	1.80	2.75	1.19
trained Chronos $\alpha = 0 \tau = 15$		0.24	
trained Chronos $\alpha = 0.3 \tau = 5$	2.12	3.90	2.29
trained Chronos $\alpha = 0.3 \tau = 15$		3.97	
resized trained Chronos $\alpha = 0.3 \tau = 15$		4.21	
trained Chronos $\alpha = 0.3 \tau = 40$		3.80	
CNN Transformer	3.15	5.01	4.29
STR $\beta = 0.2$	2.23	4.16	2.31
STR $\beta = 0.3$	2.16	4.03	2.31
resized STR $\beta = 0.3$	2.31	4.27	2.32
STR $\beta = 0.8$	1.24	2.42	1.76
STR $\beta = 0.95$	0.98	1.38	1.20
autoARIMA	1.43	2.10	1.22

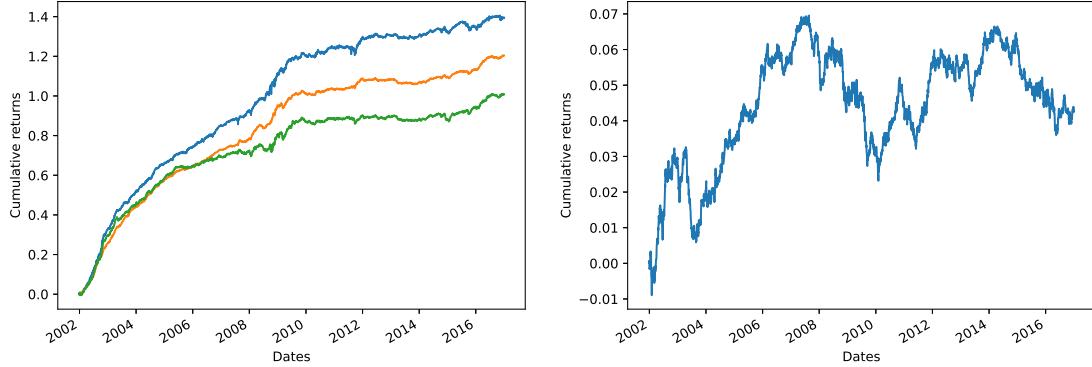
Table 3: Simulation of the Gross sharpe ratio of different strategies using the resized version (ie. Eq 5) to reduce risk on volatiles stocks. α is the parameter of the EMA in Eq 1. β is the parameter of the EMA in Eq 10. τ is 'max steps' input in the fine-tuned version of Chronos. The period is 2002-2016.

Table 3 presents the Sharpe ratios for the fine-tuning case as well as for the benchmarks. When setting $\alpha = 0$, Chronos requires fine-tuning with $\tau = 15$, which is the number of iterations of the algorithm, to achieve a Sharpe ratio of $0.24\sqrt{15} = 0.92$. It appears to work well until 2008 (see Figure 1), but after that, the pre-trained configuration may have been completely forgotten due to the numerous fine-tuning processes performed since 2002. It might be interesting to test a version where there is a regular reinforcement of the pre-trained configuration to ensure it remains in memory. Additionally, the correlation with the STR strategy is not significant when $\alpha = 0$ and $\tau = 15$. In contrast, the CNN-Transformer appears to be primarily a linear combination of STR strategies at different time scales based on its empirical correlation with such a basket. This suggests that the opportunities captured by Chronos may be more complex than those driven by basic mean reversion process. We also observe that



(a) zero-shot pretrained prediction of Chronos. $\alpha = 0.3$. The orange is for pca, the green for FF, the blue for ipca.

(b) zero-shot pretrained prediction of Chronos. $\alpha = 0$. The orange is for pca, the blue for ipca, the green for FF.



(c) STR $\beta = 0.8$. The blue is for ipca, the orange for pca, the green for FF.

(d) fined tuned Chronos. $\alpha = 0$ and $\tau = 15$. the blue for pca.

Figure 1: Simulation of the strategy. α is the parameter of the EMA in Eq 1. β is the parameter of the EMA in Eq 10. τ is 'max steps' input in the fine-tuned version of Chronos.

the autoARIMA model, which is a classical benchmark in Machine Learning

underperforms the STR model, demonstrating that fitting a model is particularly challenging when the data are nearly random and contain significant noise. This results in underperformance compared to more rigid models like STR. Finally, it is interesting to note that the optimal τ for training appears to be 15. When $\tau = 40$, the Sharpe ratio decreases, suggesting that Chronos may lose some of its pre-trained intelligence.

4 Conclusion

Our results show that AI, specifically LLMs, can be trained on large datasets that exclude financial time series and still exhibit enough intelligence to identify opportunities in the financial market, previously considered too challenging for AI, without the risk of overfitting. Currently, AI lacks the “intelligence” to find opportunities that remain profitable when factoring in trading costs, but we can anticipate that advancements in AI may eventually make this feasible.

Nevertheless, the specialized models, which theoretically capture well-established opportunities in an optimal way, will always prove more efficient, while AI could serve as a valuable tool for identifying more complex opportunities. That assertion is supported by the case of the strong outperformance of the STR compared to AutoARIMA, which can capture more complexity but whose noisy fit makes it suboptimal and overly erratic.

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A Data

The datasets provided by Guijarro-Ordonnez et al. (2021) are released at <https://github.com/gregzanotti/dlsa-public/tree/main/residuals>

B Parameters of Chronos

We downloaded the python package:

```
1 !pip install git+https://github.com/amazon-science/  
    chronos-forecasting.git
```

B.1 Parameters of pretrained version of Chronos

We used the version "amazon/chronos-t5-tiny" with the following parameters in python:

```
1 ChronosPipeline.from_pretrained( "amazon/chronos-t5-tiny"  
    ,device_map="cuda" , torch_dtype=torch.bfloat16)  
  
1 load_model(  
2     model_id="google/t5-efficient-tiny" ,  
3     model_type="seq2seq" ,  
4     vocab_size=4096 ,  
5     random_init=False ,  
6     tie_embeddings=False ,  
7     pad_token_id=0 ,  
8     eos_token_id=1)  
  
1 forecast = pipeline.predict(batch_context , 1)
```

```

1 predictions = np.mean(forecast.numpy(), axis=1) -
    alpha_chronos*np.reshape(data_train_t[-1, group *
    size_group_chronos:(group+1)*size_group_chronos], (np.
    shape(data_train_t[-1, group*size_group_chronos:(group
    +1)*size_group_chronos])[0], 1)) # -all_timeseries
    [-1, :])#np.quantile(forecast.numpy(), 0.5, axis=1)
2 eline.predict(batch_context, 1)

```

B.2 Parameters of Fine tuned version of Chronos

Starting from the initial pretrained weights at the beginning of the backtest period, we updated the Chronos model’s weights daily throughout the backtest. Each day, this update was performed by running the training procedure on 10 subgroups of the asset universe, using the previous 100 days of data. For each subgroup, training was conducted with τ iterations per day, corresponding to the ”max steps” parameter in the ”TrainingArguments” configuration of the ”trainer.train()” method. In other words, τ successive weight updates were applied using the ’AdamW Torch Fused’ gradient optimization algorithm. We tested τ values of 5, 15, and 40. The specific Python training parameters used are listed below:

```

1 chronos.ChronosConfig(
2     tokenizer_class='MeanScaleUniformBins',
3     tokenizer_kwargs={'low_limit': -15.0, 'high_limit':
4         15.0},
5     n_tokens=4096,
6     n_special_tokens=2,
7     pad_token_id=0,
8     eos_token_id=1,
9     use_eos_token=True,
10    model_type="seq2seq",
11    context_length=length_training_chronos-1,
12    prediction_length=1,
13    num_samples=20,
14    temperature=1,
15    top_k=50,
16    top_p=1,
)

```

```

1 TrainingArguments(
2     output_dir=str("./output/"),
3     per_device_train_batch_size=32,
4     learning_rate=1e-3,
5     lr_scheduler_type="linear",
6     warmup_ratio=0,
7     optim="adamw_torch_fused",
8     logging_dir=str("./output/logs"),
9     logging_strategy="steps",
10    logging_steps=500,
11    save_strategy="steps",
12    save_steps=500,
13    report_to=["tensorboard"],
14    max_steps=5,#200000,
15    gradient_accumulation_steps=2,
16    dataloader_num_workers=0,#len(loader),
17    tf32=True, # remove this if not using Ampere GPUs (e.g
18        .., A100)
19    torch_compile=True,
20    ddp_find_unused_parameters=False,
21    remove_unused_columns=False,)
```

```

1 shuffled_train_dataset = tch.ChrnosDataset(
2     datasets=(tch.create_gluonts_dataset(all_timeseries,
3         daily_dates[length_training_chronos+:
4             length_training_chronos+t+1])), #list(tch.
5         create_gluonts_dataset2(loader))
6     probabilities=[1.0 / len(all_timeseries)] * len(
7         all_timeseries),
8     tokenizer=chronos_config.create_tokenizer(),
9     context_length=length_training_chronos-1,
10    prediction_length=1,
11    min_past=50,
12    model_type="seq2seq",
13    imputation_method= None,
14    mode="training",
15    ).shuffle(shuffle_buffer_length=100)
```

```
1 trainer = Trainer(
```

```

2 |     model=model,
3 |     args=training_args,
4 |     train_dataset=shuffled_train_dataset,)

1 | trainer.train()

```

B.3 Analysis by WeightWatcher

We assessed the quality of both the pretraining and fine-tuning of Chronos using the analysis method described at <https://weightwatcher.ai/>. Fig 2 shows that the power-law exponents fall within the range of 2 to 6 in the fine-tuned case, indicating no risk of overfitting (which would be suggested by exponents below 2) or underfitting (suggested by exponents above 6). The statistics from the fine-tuned model are even more favorable than those of the pretrained model, which shows some exponents above 6, suggesting a minor risk of underfitting.

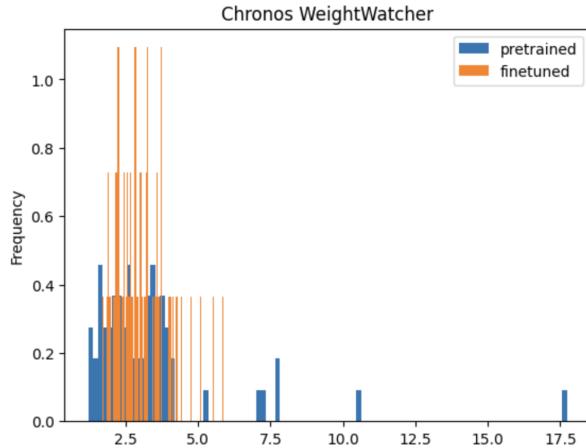


Figure 2: Analysis of the Weightwatcher (Martin (2024)) of the distribution of eigenvalues shows that there is no overfitting nor underfitting in both pretrained and finetuned case.

C Parameters of the CNN Transformers strategy

We used the following major parameters provided by Guijarro-Ordonnez et al. (2021) we did not change from <https://github.com/gregzanotti/dlsa-public/tree/main/config>

```
1      # Major parameters
2      mode: "test" # can be 'test' or 'estimate'
3      results_tag: "" # optional; try not to use
4          underscores in this tag, use dashes instead
5      debug: False # set to True to turn on debug
6          logging and file naming
7      # Model parameters
8      model_name: "CNNTransformer" # name of a class
9          defined in models folder and initialized in
10         model folder's __init__.py
11     model: { # contains parameter settings for
12         __init__() function of class with name '
13         model_name'
14         lookback: 30, # number of days of
15             preprocessed residual time series to
16             feed into model
17         dropout: 0.25,
18         filter_numbers: [1,8],
19         filter_size: 2,
20         attention_heads: 4,
21         hidden_units_factor: 2, # multiplicand
22             of last item in 'filter_numbers';
23             determines number of hidden units (e.
24             g. 2*8 = 16)
25         # hidden_units: 16, # use either
26             hidden_units or hidden_units_factor,
27             but not both
28         normalization_conv: True, # normalize
29             convolutions or not
30         use_transformer: True,
31         use_convolution: True,
32     }
33     # Data parameters
```

```

20     preprocess_func: "preprocess_cumsum" # name of
21         a function defined in preprocess.py
22     use_residual_weights: False # use residual
23         composition matrix to compute turnover, short
24         proportion, etc.
25     cap_proportion: 0.01 # defines asset universe:
26         0.01 corresponds to a residual data set
27     factor_models: { # number of factors per
28         residual time series to test, for each factor
29         model
30             "IPCA": [5],
31             "PCA": [5],
32             "FamaFrench": [5],
33         }
34     perturbation: { # perturbation of residual time
35         series by noise is optional, leave empty or
36         comment out entirely to disable
37             # "noise_type" : "gaussian",
38             # "noise_mean" : 0.0,
39             # "noise_std_pct" : 2,
40             # "noise_only" : False,
41             # "per_residual" : True,
42         }
43     # Training parameters
44     num_epochs: 100
45     optimizer_name: "Adam" # see PyTorch docs for
46         potential optimizers
47     optimizer_opts: { # see PyTorch docs for
48         optimizer options
49             lr: 0.001
50         }
51     batch_size: 125
52     retrain_freq: 125 # if mode=='estimate', this
53         is the number of obs used to form a test set
54         (chronologically after the training set)
55     rolling_retrain: True # set to False for no
56         rolling retraining (i.e. train once, test for
57         all data past training set)
58     force_retrain: True # force the model to be
59         trained, even if existing weights for the

```

```
        model are saved on disk
45    length_training: 1000 # size of rolling
        training window in trading days
46    early_stopping: False # employ early stopping
        or not
47    objective: "sharpe" # objective function: '
        'sharpe' or 'meanvar' or 'sqrtMeanSharpe'
48    # Market frictions parameters
49    market_frictions: False # enable or disable
50    trans_cost: 0 # cost in bps per txn side per
        equity, e.g. 0.0005
51    hold_cost: 0 # cost in bps for short positions
        per equity per day, e.g. 0.0001
```