Beyond Sentiment in Stock Price Prediction: Integrating News Sentiment and Investor Attention with Temporal Fusion Transformer *

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Abstract. News sentiment is attracting considerable interest in stock market prediction, given its crucial role in shaping stock prices. Previous research has mainly focused on improving prediction accuracy by exploiting news sentiment, without adequately considering the different levels of attention that individual news articles receive. Furthermore, despite the advanced predictive capabilities of deep learning models, there has been a lack of focus on the interpretability of these models, leading to predictions that are not transparent. This study presents an innovative prediction model that integrates a FinBERT-based analysis of news sentiment and investor attention metrics with an attention-based Temporal Fusion Transformer framework. This approach not only enables highly effective forecasting, but also provides insights into the temporal dynamics that influence the stock market. The effectiveness of the model is demonstrated by analyzing stock price data for 41 of the largest market capitalization companies over the period 2010 to 2021. The results confirm the superiority of the proposed model over existing deep learning approaches, and the attention analysis underscores the critical role of synthesizing news sentiment and attention metrics in predicting stock prices.

Keywords: Stock price · News sentiment · News attention · FinBERT · Temporal fusion transformer · Natural language.

1 Introduction

Predicting stock prices is a challenging task and has attracted the interest of researchers due to its complex and volatile nature, influenced by a range of factors from economic indicators to market sentiment. The challenge of predicting stock prices with even the most advanced deep learning models stems largely

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from the inherent complexity of financial markets. Factors such as the efficient market hypothesis, which suggests that stock prices already reflect all available information, make it difficult to identify patterns that could predict future price movements [1]. In addition, the non-stationary nature of financial data, together with high market volatility and the impact of unpredictable external events, further complicate forecasting efforts. These models also struggle with the high noise-to-signal ratio in financial data, leading to potential overfitting, where models learn from the 'noise' rather than the true underlying patterns [2]. Existing deep learning models for predicting stock prices, such as LSTM (long short-term memory) and GRU (gated recurrent units), offer good predictive capabilities, but often fall short in terms of interpretability. This shortcoming results in predictions that lack transparency, making it difficult to understand the reasoning behind the model's predictions.

Incorporating investor sentiment into stock price prediction models is a promising way to improve their accuracy [3]. Market-based sentiment reflects the prevailing mood among investors and traders, derived from actual market behaviour. It serves as a gauge of the market's response to all available information, not just news. However, market-based indicators tend to be reactive rather than predictive. They may also mirror herd behaviour and be swayed by factors not related to the underlying fundamentals or long-term sentiment [4]. In contrast, text-based sentiment analysis offers insights into the potential impact of news and public opinion on investor sentiment and, consequently, on stock prices. Sentiment analysis, which measures the general mood and attitudes of investors based on news articles, social media and other public communications, can provide valuable insights into collective market behaviour and expectations. This approach recognizes that market movements are not only driven by fundamental factors, but are also significantly influenced by the perceptions and reactions of market participants. However, accurately quantifying sentiment and incorporating it into predictive models remains a challenge. Indeed, effective sentiment analysis requires sophisticated natural language processing techniques to extract sentiment cues from vast amounts of textual data. In particular, language models trained on large corpora of financial texts, such as FinBERT (Financial Bidirectional Encoder Representations from Transformers), outperform general language models in financial predictions due their capacity to accurately interpret the unique language, jargon and numerical information found in financial discourse [5, 6]. This tailored approach also allows FinBERT to provide more accurate and contextually relevant sentiment scores [7].

Existing research on news-based sentiment analysis for stock price prediction has mainly focused on improving prediction accuracy by exploiting the sentiment conveyed in news articles [8, 9]. However, this body of literature overlooks the varying degrees of attention that specific news items receive, which can significantly influence their impact on stock prices, as has been shown for other financial assets. Moreover, previous research on investor attention has only focused on investors' Google search activity [10, 11]. Using Google search activity as a measure of investor attention to individual stocks has its limitations, primarily that it may not fully capture the nature of investor behaviour and interest. A key limitation is that the volume of searches can be influenced by broader market trends or major news events that may not be directly related to the underlying fundamentals or investor sentiment towards a particular stock, and thus provide an incomplete or misleading picture of investor attention. In addition, searches may not distinguish between positive and negative attention, making it difficult to interpret the sentiment behind the searches.

This study seeks to overcome these challenges by integrating news sentiment and attention metrics into a forecasting framework based on the temporal fusion transformer (TFT) architecture [12]. This integration facilitates accurate and interpretable multi-horizon quantile forecasts, allowing the study of persistent temporal patterns across different time scales. TFT was chosen for this study because it enables multi-horizon stock price prediction within a single model execution. It also features built-in interpretability mechanisms and effectively integrates both static and time-varying inputs into its predictions, unlike traditional recurrent neural network models. While the temporal convolutional network (TCN) also focuses on learning temporal patterns, the TFT extends this with attention mechanisms that allow dynamic weighting of different time steps, potentially capturing complex temporal relationships more effectively than the fixed convolutional filters in the TCN. The results of this study show that the TFT-based model outperforms conventional deep learning approaches in terms of predictive accuracy, while shedding light on the intricate ways in which news sentiment and attention affect stock price movements. In summary, the contributions of this paper are threefold:

- This paper introduces an innovative methodology for analyzing news sentiment, integrating a FinBERT-derived sentiment analysis framework with metrics of investor attention. This approach accounts for the impacts of news articles on investor behaviour and market dynamics.
- This research presents a novel TFT-based forecasting framework specifically designed for stock price prediction. It overcomes the inherent constraints of traditional recurrent neural network models within this field. The framework enables both precise and interpretable forecasts across multiple time horizons, representing a significant advancement in the predictive analysis of financial markets.
- Utilizing datasets encompassing a diverse portfolio of stocks, this study demonstrates that the proposed integrated model outperforms state-of-the-art neural network architectures in terms of predictive accuracy.

The rest of the paper is organized as follows. Section 2 reviews related literature on the use of news sentiment in stock market prediction. Section 3 outlines the model proposed for stock price prediction. Section 4 presents the data used for experimental validation. Section 5 shows the setting of the model and its experimental results, and compares the model with state-of-the-art approaches. Section 6 concludes and provides future research avenues.

2 Related Literature on Using News Sentiment in Stock Market Prediction

In their seminal work in the field, Schumaker et al. [13] showed that news articles characterized by negative sentiment were found to be particularly predictive of stock price direction for companies listed in the S&P 500. This suggests that negative news has a more pronounced effect on stock prices. The study also suggests that market traders may exhibit contrarian behaviour, responding to positive sentiment news by selling and to negative sentiment news by buying, as evidenced by the ability to predict price declines in positively sentient articles and price increases in negatively sentient articles. The fundamental information contained in company-specific news articles enhances investors' knowledge and influences their trading activities by providing valuable insights into company performance and prospects on the Hong Kong Stock Exchange [14]. The results of [15] suggests that increased uncertainty in news sentiment and a higher volume of news tend to have a negative impact on the US stock market (S&P 500 market).

Previous research has shown that combining news sentiment with stock price data improves prediction accuracy. For example, Li et al. [3] showed that a deep learning model incorporating both technical indicators derived from stock prices and sentiment vectors from news articles significantly outperforms models using only one type of data for the Hong Kong Stock Exchange. This highlights the complementary nature of market data and sentiment analysis in predicting stock movements. Xu et al. [16] constructed a monthly manager sentiment index derived from news sources, revealing that this sentiment indicator had significantly greater predictive accuracy during periods of high sentiment compared to periods of low sentiment for China's stock market. From an investment standpoint, this manager sentiment index proved to be highly economically valuable, offering substantial benefits to investors who utilized this index to optimize their stock portfolio strategies. The potential of multi-agent systems to improve portfolio management through intelligent analysis of financial news was also demonstrated by [17].

Deep learning models, such as LSTM neural networks, have been widely used to analyze the impact of news sentiment on stock prices. Mohan et al. [8] analyzed a large dataset of financial news articles using LSTM models to improve the accuracy of stock price predictions, suggesting the importance of large data in sentiment analysis. In addition, LSTM neural network showed superior performance in predicting stock price movements compared to traditional models such as ARIMA (autoregressive integrated moving average) and Facebook Prophet. Stacked-LSTM was used to predict the price movements of three major US companies, using sentiment analysis of COVID-19 news [18]. A hybrid approach has also been introduced that leverages the strengths of Bayesian structural modelling and LSTM neural networks, enhanced by the integration of news sentiment analysis [19]. The revised LSTM model, combined with investor sentiment analysis and the introduction of empirical modal decomposition, not only improved prediction accuracy, but also reduced the time lag between forecasts, making it more responsive to market changes [20]. Li et al. [21] used LSTM to address the challenges of using multimodal data, in particular fundamental and news information, for stock market forecasting.

The effectiveness of various sentiment analysis methods, including machine learning classifiers [22] and finance-specific sentiment dictionaries [23], has been investigated. Notably, customized sentiment analysis models for the financial sector have shown promising results in our previous efforts [23]. Models using dictionary-based sentiment analysis (both general and finance-specific) were found to outperform the traditional bag-of-words model in predicting stock prices [14]. Shah et al. [25] developed a sentiment analysis dictionary specifically for the financial sector and achieved excellent accuracy in predicting stock price trends based on news sentiment. The news sentiment indices developed using machine learning methods showed a strong correlation with contemporaneous business cycle indicators, indicating their effectiveness in capturing the prevailing economic mood as reflected in the news media [22]. Deep learning-based sentiment analysis was found to be significantly more accurate, effectively capturing the emotional tone of news headlines without neutral segments, unlike conventional VADER (valence aware dictionary and sentiment reasoner) and TextBlob sentiment analysis tools [9].

To summarize the above findings, the literature shows a strong correlation between news sentiment and stock market movements, with various studies demonstrating that incorporating sentiment analysis into prediction models improves their accuracy and reliability. Li et al. [26] found that the impact of the media on stock markets varies according to firm characteristics and the content of news articles, suggesting that not all news is equally influential. To account for these specific effects, this study combines a finance-specific BERT (bidirectional encoder representations from transformers) model with investor attention, expressed in terms of investor engagement through the number of comments on positive or negative news articles. In addition, by using TFT, some of the issues of previously used recurrent neural networks are addressed, in particular by using a built-in interpretability mechanism.

3 TFT-based Model for Predicting Stock Price

The proposed TFT-based model is depicted in Fig. 1.

Traditional recurrent neural network models face challenges, in particular their limited ability to capture long-term dependencies in data sequences. To address these shortcomings, recent research has focused on a more innovative architecture based on the attention mechanism [27]. Lim et al. [12] demonstrated that TFT excels in predictive performance in various financial forecasting tasks. TFT is purposefully designed to accommodate diverse inputs, including static covariates alongside time-varying inputs from both past and future timestamps. Unlike conventional deep learning methods for multi-horizon forecasting, TFT not only achieves outstanding predictive accuracy, but also provides valuable

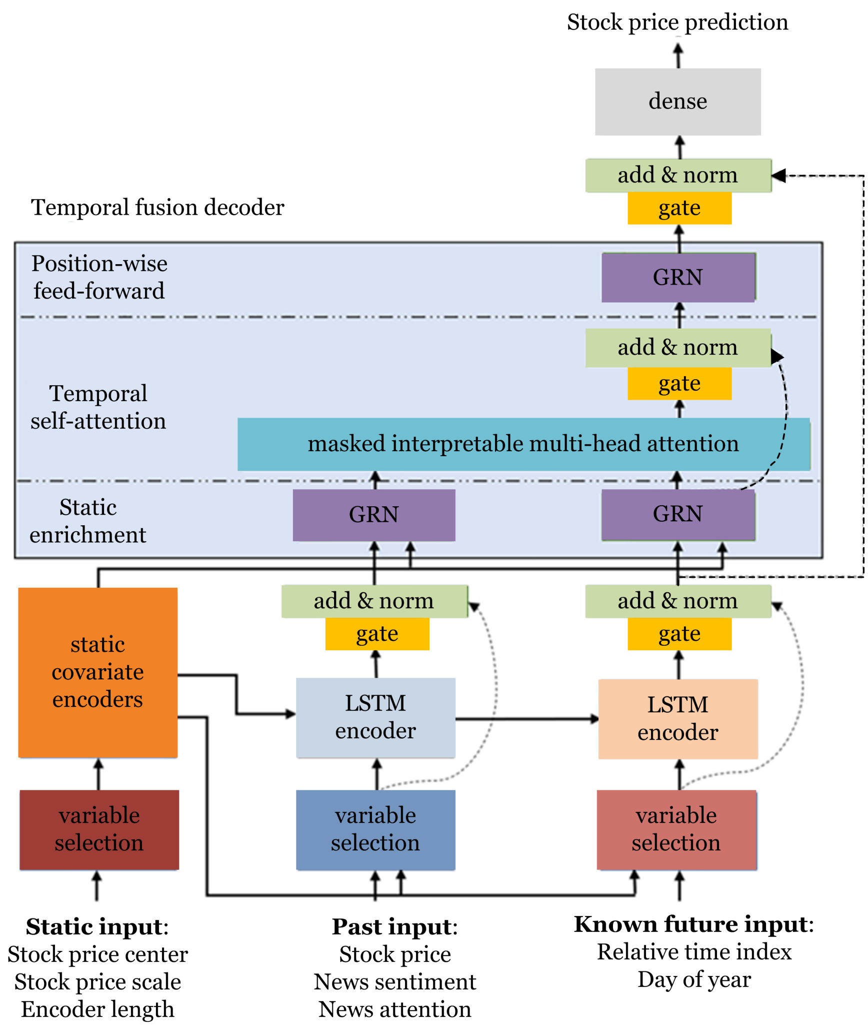

Fig. 1. TFT-based model for predicting stock price.

insights into temporal dynamics by interpreting attention patterns. A detailed description of the TFT architecture is given below.

To account for the complexity and non-linearity of the inputs, a gated residual network (GRN) performs gate control with the exponential linear unit (ELU) activation function:

$$GRN_{\omega}\left(p,c\right)=LayerNorm(p+GLU_{\omega}\left(\eta_{1}\right)), \tag{1}$$

where

$$\eta_{1}=W_{1,\omega}\eta_{2}+b_{1,\omega},\eta_{2}=ELU(W_{2,\omega}p+W_{3,\omega}c+b_{2,\omega}), \tag{2}$$

$$GLU_{\omega}\left(\gamma\right)=\sigma\left(W_{4,\omega}\gamma+b_{4,\omega}\right)\odot\ \left(W_{5,\omega}\gamma+b_{5,\omega}\right), \tag{3}$$

η_1 and η_2 represent the outputs of the intermediate layers; p and c are the primary and context information vectors, respectively; $W(.)$ denote weights, $b(.)$ are biases, and γ is the input.

The weights of the variables are given as follows:

$$v_{\chi_t}=softmax(GRN_{v_{\chi}}\left(\Xi_t,c_s\right)). \tag{4}$$

where c_s is the context vector of static covariates. The combination $\widetilde{\xi}_t$ of the GRN outputs $\xi_t^{(i)}$ is then obtained as:

$$\widetilde{\xi}_t=\sum_{i=1}^{m_x} v_{\chi_t}^{(i)}\widetilde{\xi}_t^{(i)},\widetilde{\xi}_t^{(i)}=GRN_{\widetilde{\xi}(i)}\left(\xi_t^{(i)}\right) \tag{5}$$

The mechanism of self-attention, which makes it possible to learn long-term relationships of any length in the TFT, is given in the following way:

$$Attention(Q,K,V)=A\left(Q,K\right)V,A(Q,K)=softmax(QK^T/\sqrt{d_{attn}}, \tag{6}$$

where $A(.)$ stands for a normalization function; d is the dimension of input variables; Q, K and V represent “query”, “key” and “value”, respectively. The multi-head attention is given as:

$$TFTMultiHead(Q,K,V)=\widetilde{H}W_H, \tag{7}$$

$$\widetilde{H}=\widetilde{A}\left(Q,K\right)VW_V=1/H\sum_{h=1}^{m_H}Attention(QW_Q^{(h)},KW_K^{(h)},VW_V^{(h)}). \tag{8}$$

In the proposed prediction model, past stock prices are combined with two variables, FinBERT-based news sentiment and news attention.

Among contextualized models, BERT has gained popularity due to its ability to capture both syntactic and semantic knowledge. BERT offers pre-trained representations that can be further fine-tuned for various tasks, including sentiment analysis. Given the unique characteristics of financial texts, it is advisable to conduct fine-tuning of BERT models on financial corpora. This approach ensures that the model captures relevant terminology specific to the financial domain. To this end, this study used the FinBERT model, which has been specifically trained on the TRC2 (text research collection) financial corpus, which consists of over 29 million words extracted from financial news articles. To fine-tune the FinBERT sentiment analysis model, we used a sample of approximately 5,000 sentences from financial news and company press releases, drawn from the Financial PhraseBank. This corpus is annotated by financial experts with respect to its potential effect on stock prices. Following the experimental setup outlined in [7], we configured the fine-tuning process with a maximum sequence length of 64 tokens, six training epochs, and a learning rate of 2e-5, while progressively unfreezing layers for training. Subsequently, the fine-tuned FinBERT model was applied to label the collected news headlines related to the companies in the sample.

This study proposes to use the number of investor comments on online news articles as a measure of investor attention and engagement for several reasons. First, comments represent real-time engagement with the content, with investors actively interacting, indicating a higher level of interest compared to passive readers. Second, a high number of comments can indicate an engaged community of investors around the topic or news, suggesting that the article has generated discussion among investors, which can further contribute to the dissemination of information [28]. Moreover, a large number of comments can be a signal to other investors that the article is worth a read. The number of comments can therefore be used as an indicator of which news items are attracting the attention of investors.

4 Data

This study covered the 41 US companies listed in the New York Stock Exchange with the largest market capitalization over the period from 2010 to 2021. Note that the effect of common risk factors on stock prices is reduced by selecting companies with large market capitalization [23].

To compile the news corpus on the companies, 83,912 news headlines were collected from the SeekingAlpha news service. Each headline was accompanied by the number of investor comments, which served as an indicator of investor attention. Using the FinBERT model, specifically refined for sentiment analysis, the sentiment tone of these headlines was assessed, categorizing them as positive, neutral or negative. The aggregate sentiment for each company was calculated by subtracting the number of negative headlines from the number of positive headlines and then dividing this difference by the total number of headlines within the sample period [23]. These sentiment data were then integrated with the corresponding stock price data from Yahoo Finance and measures of investor attention (averaged per day). For the purposes of model training and evaluation, the dataset was partitioned using sequential validation, with an 80:20 split between training and test datasets.

The descriptive statistics in Table 1 suggest that the news sentiment was moderately positive for all companies, with AAPL (Apple) and MSFT (Microsoft) having the highest average news sentiment of 0.062 and 0.061, respectively. The highest attention of investors was paid to the reports of TSLA (Tesla) (207.13) and AAPL (81.42) companies, while TMO's (Thermo Fisher Scientific) news received the least attention. The most volatile stock prices were observed for NVDA (Nvidia) (st.dev. 1.33) and TSLA (1.32), while KO (Coca-Cola) had the lowest volatility (0.18).

Table 1. Descriptive statistics (mean±st.dev.) of the data.

company	# news articles	sentiment	attention	ln close price
AAPL	7500	0.062±0.381	81.42±147.49	3.371±0.706
ABBV	1218	0.054±0.320	13.05±44.92	4.246±0.286
ABT	722	0.017±0.223	2.95±23.31	3.824±0.469
ADBE	462	0.022±0.200	1.12±10.80	4.564±0.939
AMZN	5294	0.057±0.339	47.43±103.80	3.389±1.004
...	...	...	...	...
XOM	3201	0.000±0.352	31.16±78.30	4.333±0.227

5 Experimental Results

The Optuna hyperparameter optimization framework was employed to determine the optimal values for the parameters of the TFT model. The chosen parameter values were as follows: learning rate = 0.003, dropout = 0.16, attention head size = 4, hidden continuous size = 38, hidden size = 54, and gradient clipping value = 0.89. Hyperparameter optimization was conducted over specified ranges: learning rate = (0.001, 0.1), dropout = (0.1, 0.3), attention head size = (1, 4), hidden continuous size = (4, 128), hidden size = (4, 128), and gradient clipping value = (0.01, 1.0). Additionally, various maximum encoder lengths were experimented with, ultimately determining 180 days to be the optimal choice. Moreover, in keeping with Chen and Hao [29], the maximum prediction length was fixed at 20 days. The model implementation was realized within the PyTorch Forecasting library. This study employed three widely recognized error metrics to evaluate the prediction performance of the TFT model: root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), following prior related research [8].

This research chose the GRU [30], LSTM [21], the BiLSTM [31], and TCN [32] models for comparison due to their renowned efficacy and widespread acceptance in predicting stock markets. We also explored varying unit counts in the hidden layers, consisting of two layers each of GRU/LSTM/BiLSTM followed by a single dense layer, to determine the most effective architectures for these deep learning models. The Adam optimizer was employed to train the models over 100 epochs.

The superior accuracy of the TFT model is demonstrated by the results in Table 2.

Furthermore, an ablation study was conducted to demonstrate the impact of integrating news sentiment and attention mechanisms on the predictive performance of the TFT model. Table 2 illustrates that error rates rose significantly when news sentiment and attention were excluded.

Table 2. Results of stock price prediction (average of 41 companies and forecasting horizons from 1 to 20 days).

model	MAE	MAPE	RMSE
LSTM	0.075	2.589	0.140
BiLSTM	0.076	3.127	0.142
GRU	0.057	1.845	0.116
TCN	0.043	0.920	0.033
TFT	**0.024**	**0.636**	**0.018**
TFT w/o Attent.	**0.026**	0.885	0.033
TFT w/o Sent.	0.028	0.935	0.025
TFT w/o Sent. and Attent.	0.041	1.574	0.051

Significantly lower values are in bold (using the nonparametric Wilcoxon signed-rank test at $p < 0.05$), w/o Sent. and w/o Attent. are TFT models trained without news sentiment and attention, respectively.

To determine the importance of static, encoder and decoder variables, patterns were compiled from the time series data. Fig. 2 reveals that among the static variables, the most significant weights are assigned to those identifying the encoder length and the scale of stock prices. Regarding past inputs, the day of the year and previous stock price values play pivotal roles. For future inputs, the day of the year exerts the most substantial influence on stock price predictions. Additionally, the results corroborate the critical influence of news attention and sentiment on stock price forecasts.

To explore temporal relationships within the data, a technique that leverages the attention weights within the TFT decoder's self-attention layer was adopted. Analyzing these weight patterns enables us to identify key historical time steps that impact the TFT model. This approach stands in contrast to conventional and machine learning methods for time series analysis, which typically depend on predefined models for examining lags. Instead, the TFT model discerns these patterns from the raw training data. Significant shifts in attention patterns are observed during periods of falling stock prices, which coincide with negative investor sentiment and heightened attention. These variations in temporal dynamics align with the increases in attention depicted in Fig. 3. Fig. 3 additionally presents seven distinct quantiles, illustrating considerable uncertainty in the forecasted outcomes for AMZN and META, especially in terms of potential upside risks.

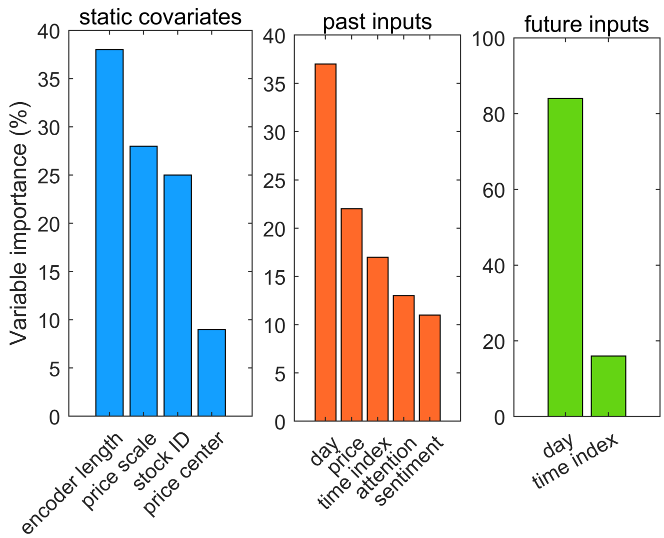

Fig. 2. Variable importance in TFT stock price prediction.

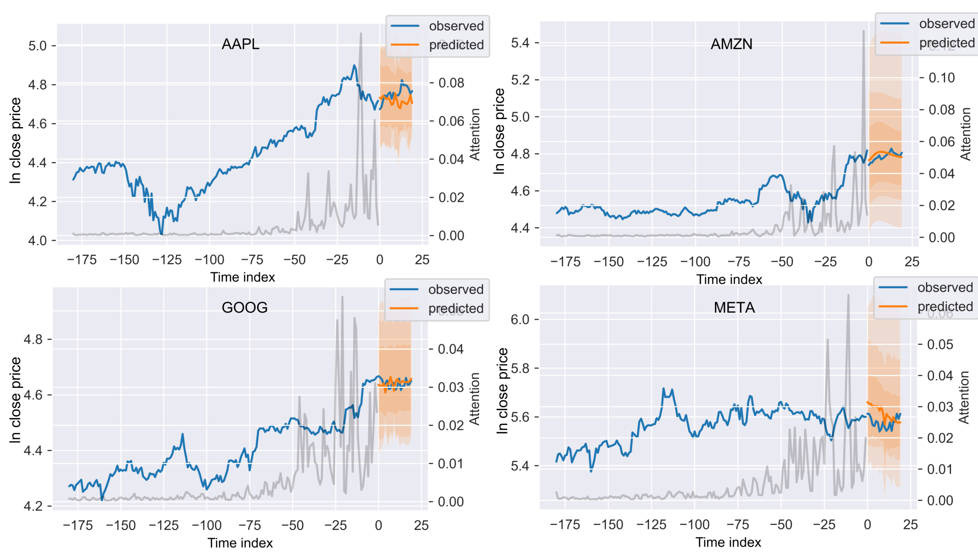

Fig. 3. Quantile predictions for selected companies with attention mechanism showing persistent temporal patterns in 2021.

6 Conclusion

This study used an attention-based TFT deep learning model to predict the price of stocks. It enabled us to effectively capture temporal relationships, incorporate news sentiment and attention, select relevant features, and provide probabilistic forecasts across various prediction horizons. It was shown that by incorporating news sentiment and attention into the prediction model, the prediction performance can be improved within an appropriate deep learning-based architecture. These findings can provide investors with helpful decisional assistance.

The primary limitation of this study lies in its reliance solely on historical stock prices, news sentiment, and attention as past inputs. In future studies, we aim to incorporate a broader range of factors influencing stock prices, including technical indicators, market trends, and fundamental indicators. Moreover, we plan to explore alternative indices of investor sentiment, such as those based on stock market development and social media [33]. Another avenue for future research is the use of news affect (emotion) indicators [34] and the application of news sentiment analysis using various large language models [35].

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