Journal of Econometrics and Statistics
Vol. 1, Issue 2, 2021, pp. 169-181

URL : www.arfjournals.com/jes

FORECASTING FINANCIAL MARKETS WITH PREDICTIVE ANALYTICS: ON THE IMPACT OF THE TRADING VOLUME

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Article History
Received : 28 August 2021
Revised : 25 September 2021
Accepted : 30 October 2021
Published : 30 December 2021

To cite this paper
Alroomi, A., & Nikolopoulos, K. (2021). Forecasting Financial Markets with Predictive Analytics: On the Impact of the Trading Volume. *Journal of Econometrics and Statistics.* 1(2), 169-181.

Abstract: This paper introduces the trading volume of the share price into the neural network in an attempt to test if an exogenous variable, in the form of trading volume, can produce more accurate results compared to only having the closing price fed into the neural network. By feeding the volume into the neural network we can understand if human behaviour and action can affect the future of that share price and the significance of its effect on the future price. By feeding the volume into the network, we can also compare how a greater number of trading days, weeks, months, quarters and years affect the future share price. This may clarify whether higher or lower volumes of trading result in better forecasting accuracy. Comparisons can also be drawn for when the trading volume is being fed into the network and when it is not.

Keywords: Neural Networks; Forecasting; Prediction; Trading;

Introduction

The existing literature suggests that the relationship between returns and trade volume is of undisputable interest to financial markets. The daily trading volume represents the number of shares traded on any particular day (Tangmongkillert & Suwanna, 2016). Many of the published studies clearly provide support for the existence of a positive relationship between trading volume and stock price changes, a factor that depends primarily on the company's closing share price. A consensus seems to exist supporting the assumption that the relationship between trading activity, which includes trading volume, and closing share price changes is critical because trading activity tends to be thin whereas price volatility is quite high. This blueprint provides a comprehensive review of the issues relating to the relationships between share prices, trading volume, volatility, and returns as documented in the existing empirical studies.

Literature Review

In today's international financial markets, volatility is a critical risk factor, with portfolio allocation methods and asset pricing models relying upon the precision of its estimates. Consistent with a study carried out by Tangmongkillert & Suwanna (2016), Sabbaghi (2011) sought to examine the relationship between asymmetric volatility and trading volume, based on their evidence from the G5 countries. Specifically, the researcher used national equity indices and performed an EGARCH analysis to explicate the asymmetric volatility-trading volume relationship. Findings from this study proved to be quite captivating. After performing the EGARCH analysis, the researcher established that trading volume is a critical variable in explaining conditional volatility. Just like Tangmongkillert & Suwanna (2016), Sabbaghi (2011) also found that the presence of trading volume did not cause the persistence levels of volatility to decrease. Gebka & Wohar (2013), in a similar light, endeavoured to examine the causality that exists between index returns and trading volume in the Pacific Basin countries. While ordinary least squares regression did not show any causal relationships between trading volume and index returns, applying a quantile regression method did reveal strong nonlinear causality that was negative for low return quantiles and positive for high return quantiles at both long-term and short-term horizons.

Caginalp & DeSantis (2017) endeavoured to examine whether price efficiency increases with trading volume, testing this relationship using 124,236 daily observations of 68 large and liquid exchange traded funds (ETFs) in the US equity markets. The main advantage of ETFs, according to Caginalp & DeSantis (2017) and Samonas (2015), is that the forecasters can measure efficiency in terms of deviation between the trading price and the underlying net asset value reported each day. Data for a study by Caginalp & DeSantis (2017) came from the Bloomberg terminal and the findings from this inquiry suggested that the relationship between efficiency and trading volume is nonlinear, with the efficiency increasing as trading volume increases from low to moderately high levels and, in turn, the closing share price increases, but efficiency decreases subsequently as the volume increases even further. The researchers speculated that, as the volume increases even further, it leads to increased speculation that ignores valuation and thus decreases efficiency. In the long-term, this leads to a decline in the closing share price.

Considerable publications have also delved into the relationship between search intensity and trading volume. One such inquiry was by Takeda & Wakao (2014), who tested the relationship between Google search intensity and returns as well as trading volume in Japanese stocks. The scholars measured the search intensity according to the search volume of names of companies listed in Google. Takeda & Wakao (2014) used a sample consisting of 189 Japanese stocks searched in the period between 2008 and 2011. After performing regression analyses, the researchers established that correlations with search intensity were weakly positive for stock returns and strongly positive for trading volume. The rationale behind this trend was that the increase in search activity had a direct association with increases in trading activity, which subsequently increased the share price at the closing time. In their study, Caginalp & DeSantis (2017) refuted the claims by Takeda

& Wakao (2014) through asserting that increases in trading activity had a low probability of leading to increases in stock prices.

The relationship between trading volume and returns in financial markets has continued to attract notable attention from not only academicians but also from practitioners. Chen, Qiu, Jiang, Zhong & Wu (2015), similar to studies conducted by many other researchers, also endeavoured to gauge the manner in which trading volume responds to price returns in financial dynamics. The researchers based their analysis on daily data of the United States and the Chinese stock markets. For the United States, analysed datasets came from the Dow Jones Industrial Average (DJIA) and the S&P 500 whereas datasets for the Chinese stock market came from the Shenzhen Composite Index and the Shanghai Composite Index. After deploying a retarded herding model, results from this inquiry differed in various aspects from those conducted by Boonvorachote & Lakmas (2016) and Samonas (2015). Specifically, Chen *et al.* (2015) observed a positive correlation between trading volume and returns in the Chinese stock markets, but for the United States stock markets they observed a transition from the positive to the negative correlation. They attributed the changes to the differences in financial dynamics between mature or developed markets (e.g. US) and emerging markets (e.g. China).

Following a methodological approach similar to that favoured by Chen (2012), Gupta, Das, Hasim & Tiwari (2018) likewise revisited the dynamic relationship between trading volume and stock returns. Differently, Gupta *et al.* (2018) relied upon a maximum overlap discrete wavelet transform (MODWT) approach to revisit the relationship in a time-frequency domain. The researchers utilised almost concurrent data of over 15 years from the emerging stock markets of India and China. To examine the dynamic relationship, Gupta *et al.* (2018) first applied the MODWT for the purposes of decomposing the level series. They then applied VAR to the decomposed data in order to obtain a richer picture of the causality between stock returns and trading volume for different time-scale horizons. According to Samonas (2015), the VAR methodology is beneficial for gauging horizon-based investor behaviour and ascertaining whether the stock returns are responsible for predicting trading volume or vice-versa. Gupta *et al.* (2018), after deploying the MODWT-VAR approach, found that the examined markets work according to an efficient market hypothesis in the short-term horizon, and in the long-term horizon they reach a stage of market inefficiency, a factor that may lead to low closing share prices.

A number of empirical studies have affirmed the possibility of an additional foreign market presence having a direct effect on trading volume. This is especially true for cross-listed forms. Ghadhab (2016) rolled out a study geared towards addressing the question of the effects that additional foreign market presence can have on the trading volume of cross-listed firms and, consequently, their closing share prices. The researcher relied upon a comprehensive and unique sample of 235 firms from 32 nations with 788 foreign listings over the period spanning from the year 1980 to 2013. Just like Dodd, Louca & Paudyal (2015),Ghadhab (2016) made a clever observation by reiterating that extant literature shows that cross-listing can enhance the value of the firm but the source of such increment remains elusive, although corporate managers often attribute the value addition to increases in stocks' liquidity. In his study, Ghadhab (2016) found that, compared with the decline in trading volume after the first cross-listing/trading, additional foreign listings resulted in more shares being traded on the stock. Furthermore, the researcher found that the effect of additional cross-listing/trading was more important for high orders.

Dodd *et al.* (2015), in a similar study, seemed to contradict the findings arrived at by Ghadhab (2016). The researchers explored the determinants of the foreign trading volume with a particular emphasis on European stocks listed in multiple markets. Unlike Ghadhab (2016), who found that additional foreign listings resulted in more shares being traded on the stock, the results by Dodd *et al.* (2015) contradicted these findings. Their results suggested that stocks that cross-list in markets that have greater liquidity and are larger than their home markets, and stocks for which foreign investors can obtain information at a lower cost, tend to experience higher trade volumes in foreign destinations. As Dodd *et al.* (2015) vividly pointed out, this is the reason why stocks cross-listed in the US stock market are usually more attractive to foreign traders compared to stocks cross-listed in European markets. Among the fundamental motives to trade, the researchers added that stock risk and diversification benefit are more important for investors aspiring to trade in American markets while for investors in European markets, the difference in trading costs is more critical. Samonas (2015) also echoed similar sentiments, adding that informational motives to trade are also significant determinants of trading in US markets but not in European markets.

Contrary to many other studies, Alvez-Albelo (2012) initiated an investigation designed to examine whether importing growth via trade volume or via terms of trade matters when determining the extent of competition in the export sector. In order to illustrate their arguments, the researchers constructed two simple growth models that represented a small open economy using its export revenues to import capital goods and enjoying strong export market power. In the second model that specifically tested whether trade volume increases mattered when determining the degree of export sector competition, Alvez-Albelo (2012) proposed that growth directly depended upon externalities associated with the trade volume or the number of shares traded. Results from this study indicated that importing growth via both trade volume increases and terms of trade was relevant for determining the extent of competition in the export sector. They concluded that when growth relies on externalities associated with the trade volume, "more competition is required in the export sector" (Alvez-Albelo, 2012, p. 8). This supported the empirical evidence of Samonas (2015), which showed that high closing share price is responsible for increasing competition in the export market.

Meanwhile, Magkonis & Tsouknidis (2017) examined spillover effects that were evident across petroleum-based commodities and among trading volume, spot-futures volatilities, and open interest from 2341 observations. To accomplish this goal, they looked at daily time-series of closing spot prices, futures total volume, futures prices, and futures open interest using RVs of spot-futures markets as inputs for estimating a VAR model and distinguishing dynamic spillovers in total as well as net effects. When examined pairwise, the results revealed the existence of time-varying and large spillovers across the petroleum-based commodities and among spot-futures volatilities. Furthermore, the researchers found that hedging pressure, as reflected by open interest, and speculative pressures, as reflected by the futures trading volume, transmitted persistent and large spillovers to the futures and spot volatilities of heating oil gasoline and crude oil markets respectively (Magkonis & Tsouknidis, 2017).

Boonvorachote & Lakmas (2016) similarly based their study on commodity markets, although their specific focus was on futures exchanges, unlike Magkonis & Tsouknidis (2017) who explored petroleum-based commodities. The primary objective in the study by Boonvorachote & Lakmas (2016) was to investigate the impact that trading activity, including open interest and trading volume, had on price volatility on futures exchanges in Asian economies. Their study utilised three different definitions of volatility. The first was daily volatility, which they measured according to close-to-close returns. The other two were trading volatility measured via open-to-close returns and non-trading volatility measured according to close-to-open returns. Boonvorachote & Lakmas (2016) subsequently divided volume and open interest into unexpected and expected components, after which they employed an augmented GARCH model using these components as explanatory variables. Findings were consistent with those of Chan, Fung & Leung (2004), with Boonvorachote & Lakmas (2016) suggesting that while open interest was able to mitigate volatility, a positive contemporaneous relationship on the contrary existed between daily volatility as measured via close-to-close returns and unexpected and expected trading volume. Chan *et al.* (2004), in their empirical investigation that centred on volatility behaviour in the Chinese market, went on to add that hedging activities, as substituted by open interest, tended to stabilise the market while speculative activities, as substituted by the volumes, tended to increase the futures volatility.

Wang, Qian & Wang (2017) endeavoured to examine the dynamic relationship between trade volume and stock returns. The researchers held the view that the popularisation of high-frequency, high-speed trading over the past two decades, which is a conspicuous aspect of financial markets, has attracted increasing attention with regard to the relationship between trading volume and stock return from both practitioners and academicians. In conducting their study, Wang *et al.* (2017) looked at the relationship from the perspective of out-of-sample stock return predictability. They believed that for the purposes of risk management and real-time predictions, focusing on the dynamic relationship between returns and volume is perhaps more informative than the often elusive contemporaneous causality. Wang *et al.* (2017) in their study found that in certain markets including the United States, higher stock returns do indeed follow higher trading volume, whether measured by high volume return premiums or by aggregate time-series of turnover, a sentiment also echoed by Dodd *et al.* (2015). However, Wang *et al.* (2017) acknowledged that forecasters and academicians should interpret such predictive power with caution because the associated economic gain is quantitatively minimal for the market as a whole.

It is important to mention that, whereas many of the reviewed studies have explicitly examined the relationship between trading volume and returns, others have gone a step further to explore the mediating role of trading volume on volatility of financial markets. For instance, Shahzad, Hernandez, Hanif & Kayani (2018) aspired to investigate the dynamics of long memory and efficiency, as mediated by trading volume, on the volatilities and efficiency of returns of four major traded global currencies (GBP, EUR, JPY, and CHF). The researchers, in a similar light to Tabak & Cajueiro (2006), affirmed that the issue of efficiency in financial markets is of critical importance since it relates to the absence or existence of arbitrage opportunities that can, in turn, enhance or diminish the probability of earning above-average market returns and thus affect the closing share price positively or negatively. Shahzad *et al.* (2018) in their investigation used a quantile-on-quantile (QQ) approach while simultaneously implementing full sample and rolling window MF-DFA in order to test the mediating role of trading volume and employed high-frequency data (5-minute interval) spanning from 2007 to 2016. After deploying the QQ approach for analysis, the scholars found evidence of higher levels of efficiency in the CHF and JPY currency markets, with further analysis revealing that the trading volumes' impact on efficiency was only significant in these two currencies. The least efficient currency in the investigation appeared to be the GBP, closely followed by the EUR, both of which experienced substantial declines in their closing share prices over the study duration.

Overall, the portion of the literature reviewed above has revealed that the relationship between trade volume and returns, while taking into account factors such as volatility and closing share price, is of significant interest to financial markets. In many of the studies explored, it became apparent that trading volume positively affects returns, with factors such as volatility, uncertainty, market structure, and cross-listing in foreign markets serving as mediators to the degree of the relationship. Gaining a heightened understanding of the relationships between the aforementioned variables can help corporate investors, forecasters, and other concerned stakeholders to make informed decisions that are beneficial for their investment ambitions.

Like many other researchers, Wang (2001) also centred his study on the neural network approach to input-output analysis, albeit focusing exclusively on economic systems. The researcher contended that conventional input-output analytic methods are becoming less attractive for various reasons. The first of these reasons pertains to the assumption of a constant linear relationship between the input and output. For the Chinese economy, Wang (2001) affirmed that this assumption is incorrect because of various factors such as the introduction of modern technologies, the introduction of massive amounts of FDI due to the "open door" policy, fast-growing demand from both the government and consumers, as well as unbalanced development in different regions. Hence, as the scholar averred, in conventional input–output analysis, the linear input coefficient matrix calculated based upon the statistics of the previous years would be unacceptably erroneous for the current year.

Consistent with Wang (2001), Claveria, Monte & Torra (2015) in their systematic review also highlighted another shortcoming of the conventional input-output analysis in neural networks. The researcher affirmed that another major shortcoming stems from the reality that all conventional input-output neural network analysis assumes that exogenous sectors (final demands) are given. The alternative neural network input-output analysis model developed by Wang (2001), which was a layered neural network model, had many advantages over traditional or conventional mathematical models, including high adaptive capacity and the advantage of nonlinearity. Nevertheless, the researcher also affirmed that the model had little capability of modelling oscillatory economic systems such as the stock market.

Shi (2000) offered an interesting perspective on reducing prediction error through transforming input data for neural networks. According to the researcher, the primary goal of data transformation is modifying the distribution of input variables so that they can match the outputs better. The three prevalent methods of data transformation are linear transformation, mathematical functions, and statistical standardization. Shi (2000) presented another method of data transformation using cumulative distribution functions, merely addressed as distribution transformation. The researcher contended that this method has the potential to transform a stream of any data distributed in any range of data points that are uniformly distributed on [0, 1]. Therefore, "all neural networks input variables can be transformed to the same ground-uniform distributions on [0, 1] (Shi, 2000, p.109).

Methodology

Table 1

Methods		*Description*
1.	*Nymphy_Close_Volume*	Neural Network with Close and Volume share price

Nymphy_Close_Volumeis the method used in this paper.

Table 2: Classifications of Time Series

	Companies	*Methods*	*Error Matrices*	*Horizons*	*Index*
Daily	18	1	6	22	FTSE 100
Weekly	18	1	6	12	FTSE 100
Monthly	18	1	6	18	FTSE 100
Quarterly	18	1	6	12	FTSE 100
Yearly	18	1	6	4	FTSE 100

The table above shows the structure of the methodology.

Results

Table 3: Daily Ape

METHOD	*HORIZON*								
	1	*2*	*3*	*4*	*5*	*10*	*22*	*1-10*	*1-22*
CLOSE_VOLUME	0.024027	0.024026	0.024025	0.024024	0.024022	0.024015	0.024003	0.024021	0.024015
CLOSE_HIGH	**0.016707**	**0.016708**	**0.016708**	**0.016708**	**0.016708**	**0.016708**	**0.016702**	**0.016708**	**0.016706**
_LOW	*0.021847*	*0.021847*	*0.021847*	*0.021848*	*0.021848*	*0.021847*	*0.021843*	*0.021848*	*0.021847*
SES	**0.013289**	**0.018832**	**0.022836**	**0.026175**	**0.029162**	**0.040821**	**0.059134**	**0.029275**	**0.041303**
	0.013383	*0.018959*	*0.023048*	*0.026486*	*0.029591*	*0.042036*	*0.062275*	*0.031007*	*0.045043*
	(AUTOARIMA_ FOURIER)								

Discussion

The close_volume here does not perform stronger than method carried over from paper 3 but compares well with the method carried over from paper 2, even performing stronger in the latter stages of the horizon.

Table 4: Weekly Ape

	HORIZON							
	1	*2*	*3*	*4*	*6*	*12*	*1-6*	*1-12*
CLOSE_VOLUME	0.01235	0.012375	0.012398	0.012423	0.012474	0.012642	0.012411	0.012490
CLOSE	0.010104	0.010125	0.010146	0.010168	0.010213	0.010354	0.010157	0.010226
	0.016593	0.016617	0.016631	0.016643	0.016688	0.016781	0.016639	0.016693
AUTOARIMA_	0.029086	0.040883	0.049625	0.056642	0.069163	0.098690	0.051387	0.069353
FOURIER	0.025839	0.037228	0.051038 (SES)	0.058677 (SES)	0.072259	0.104405	0.054858	0.075354

Discussion

The method from paper 2 here shows significant strength compared to the other two winning methods.

Table 5

MONTHLY	*ape*							
	HORIZON							
	1	*2*	*3*	*4*	*9*	*18*	*1-9*	*1-18*
CLOSE_VOLUME	0.111967	0.111374	0.110548	0.109767	0.105142	0.099356	0.014732	0.015132
CLOSE_HIGH_LOW	**0.043350**	**0.043355**	**0.043174**	**0.042933**	**0.042019**	**0.041146**	**0.042735**	**0.042062**

	0.048346	*0.048161*	*0.047784*	*0.047416*	*0.045705*	*0.043429*	*0.047049*	*0.045658*
AUTOARIMA_ FOURIER	**0.056734** *0.059492*	**0.081133** *0.086376*	**0.100575** *0.108120* **(NAÏVE)**	**0.118678** *0.129480*	**0.199235** *0.230741*	**0.349945** *0.442083*	**0.133154** *0.150454*	**0.206680** *0.242198*

Discussion

Akin to the weekly results, the winning method from paper 3 is the most accurate.

Table 6

QUARTERLY	ape			HORIZON				
	1	2	3	4	8	12	1-8	1-12
CLOSE_VOLUME	0.262950	0.262968	0.263902	0.265588	0.270850	0.289465	0.265962	0.270890
CLOSE_HIGH_LOW	**0.164642** *0.285519*	**0.165393** *0.286098*	**0.166231** *0.286737*	**0.167947** *0.289040*	**0.174909** *0.298342*	**0.183577** *0.312349*	**0.167552** *0.288737*	**0.172817** *0.296064*
AUTOARIMA_ FOURIER	**0.108245** *0.120869*	**0.164416** *0.190705*	**0.213086** *0.252326*	**0.262497** *0.321027*	**0.538682** *0.628008*	**0.508976** *0.832367* **(SES_THETAF)**	**0.239539** *0.286677*	**0.441059** *0.565188*

Discussion

Akin to the weekly and monthly results, the winning method from paper 3 is the most accurate.

Table 7

Yearly	*ape*		*HORIZON*			
	1	*2*	*3*	*4*	*1-2*	*1-4*
CLOSE_VOLUME	0.251166	0.240078	0.252682	0.279575	0.245622	0.255875
CLOSE_HIGH_LOW	**0.164094** *0.252530*	**0.166871** *0.250952*	**0.179122** *0.262187*	**0.196443** *0.282098*	**0.165483** *0.251741*	**0.176632** *0.261942*
THETAF_YEARLY	**0.238219** *0.451838*	**0.324738** *0.558452*	**0.428134** *0.936784* **(NNET_ THETAF)**	**0.422913** *1.294401* **(NNET_ THETAF)**	**0.281478** *0.505145*	**0.400210** *0.747618*

Discussion

Akin to the weekly, monthly and yearly results, the winning method from paper 3 is the most accurate.

Table 8

daily METHOD	mse 1	2	3	4	HORIZON 5	10	22	1-10	1-22
CLOSE_VOLUME	856	856	857	857	858	862	869	858	863
CLOSE_HIGH	**1788**	**1791**	**1794**	**1798**	**1801**	**1821**	**1858**	**1804**	**1825**
	2020	*2024*	2029	2035	2041	2073	2130	2045	2080
SES	**1058**	**1977**	**2839**	**3673**	**4526**	**8521**	**16861**	**4882**	**9405**
	1061	*1985*	*2851*	*3687*	*4545*	*8566*	17010	*4904*	*9469*

Discussion

Where on our APE results the introduction of trading volume did not produce more accurate results, on the MSE daily data the volume was very effective in terms of producing the most accurate result.

Table 9

weekly METHOD	mse 1	2	3	4	HORIZON 6	12	1-6	1-12
CLOSE_VOLUME	981	991	1003	1014	1035	1111	1008	1043
CLOSE	**1137**	**1149**	**1161**	**1175**	**1200**	**1278**	**1169**	**1206**
	1968	*1979*	*1986*	*1991*	*2011*	*2052*	*1989*	*2012*
NAIVE	**4503**	**8556**	**12343**	**15871**	**22293**	**42137**	**13771**	**23799**
	4538	*8599*	*12419*	*15959*	*22510*	*42850*	*13875* **(SES)**	*24094* **(SES)**

Discussion

Akin to the daily results, the winning method from paper 4 is the most accurate.

Table 10

monthly METHOD	mse 1	2	3	4	HORIZON 9	18	1-9	1-18
CLOSE_VOLUME	32593	33262	33814	34445	38439	48093	35309	39313
CLOSE_HIGH_LOW	**7953**	**8079**	**8116**	**8143**	**8630**	**9429**	**8236**	**8658**
	8748	*8831*	*8850*	*8873*			*8943*	
THETAF	**14628**	**28570**	**44750**	**61296**	**136167**	**265066**	**75360**	**142695**
	*15758***(AUTO ARIMA_ FOU RIER)**	*31659* **(NAÏVE)**	*49450* **(AUTO ARIMA_ FOURIER)**	*68644* **(AUTO ARIMA_ FOURIER)**	*159636*	*305858*	*86973*	*170078*

Discussion

The close_volume does lose pace when we reach the monthly frequency where the method from paper 3 is the most accurate.

Table 11

quarterly	*mse*							
METHOD					*HORIZON*			
	1	*2*	*3*	*4*	*8*	*12*	*1-6*	*1-12*
CLOSE_VOLUME	136033	145783	156900	169513	220089	281896	163671	203033
CLOSE_HIGH_LOW	**18465**	**19647**	**20943**	**21924**	**27318**	**34928**	**21291**	**25807**
	25223	*25518*	26152	27359	32977	38312	27237	31107
NAIVE	**54706**	**108625**	**153372**	**197683**	**344889**	**547139**	**169837**	**293670**
	61860	*140296*	*239579*	*326865*	*449253*	*644036*	*271532*	*387320*

Discussion

Akin to the monthly results, the method from paper 3 is the most accurate.

Table 12

yearly	mse					
METHOD			HORIZON			
	1	2	3	4	1-2	1-4
CLOSE_VOLUME	175727	220196	293567	398809	197961	272075
CLOSE_HIGH_LOW	**69173**	**80559**	**101363**	**121866**	**74866**	**93240**
	88165	*96818*	*118893*	*142911*	*92492*	*111697*
DSHW	**251580**	**369859**	**591059**	**933826**	**285997**	**530783**
	276596	*387370*	*591059*	*933826*	*329866*	*563602*
					(THETAF)	**(THETAF)**

Discussion

Akin to the monthly and quarterly results, the method from paper 3 is the most accurate.

Conclusion

Analysis & Evaluation

The introduction of the trading volume into the neural network tested whether trading volume would make the model produce more accurate results. This proved to be consistent with our predictions as some days in the financial market there is high trading volume, meaning high liquidity and some days the market is quiet, due to investors and traders waiting for an event or as a result of their fear of market volatility.

In our test, we were able to observe some significant results where the introduction of the trading volume variable showed great robustness and beat all other methods that had won the previous papers and were carried over to this test. This variable also showed more accuracy as the horizons increased. If we take into consideration the models from paper 2, the close_volume model showed greater accuracy in most frequencies and horizons. Nevertheless, the models from paper 2 did produce better accuracy on the first horizon of some of the frequencies. However, overall the model from paper 4 showed greater power than the model from paper 2. It also beat the close_high_low model from paper 3 in some cases, however the close_high_low model performed better than the close_volume model.

Other important variables that affect the relationship between share price, trading volume, and returns include volatility, uncertainty, market efficiency, and listing of stocks in multiple foreign countries.

The MSE results for close_volume did not show great strength against its counterparts in higher frequencies, however it did show accurate results on lesser frequencies.

Future Research

After testing the trading volume in this paper, future research will test other exogenous variables including changes in inflation, interest rate and consumer price index (CPI) and test how these variables affect the volume of trading in the market and how that eventually affects the share price. The share price of some companies would react differently to different exogenous variables depending on the industry they are in and/or the service they provide.

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