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The wisdom of the Twitter crowd in the stock market: Evidence from a fragile state

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Abstract

The classical finance theory postulates that markets are informationally efficient and that the actions of arbitrageurs always bring stock prices to their correct values. Behavioural finance, on the other hand, emphasises the role of investor sentiment in the formulation of asset prices. In this study, we provide insights into the relationship between textual sentiment extracted from Twitter and stock returns in the fragile market of Zimbabwe between 24 February 2019 and 22 June 2020. Wavelet analysis is used to find the linkages between sentiment and returns in a frequency-time domain. The results from this study show that coherence is persistent and significant in highly volatile periods characterised by increasing inflation as well as during the time COVID-19 was declared a global pandemic. The findings also show that macroeconomic instability, especially hyperinflation, induces fear in investors while the onslaught of black swan events like the COVID-19 pandemic leads to greed in the financial markets as investors become uncertain about the future. The government could, therefore, prioritise macroeconomic stability as the high coherence between sentiment and returns during a crisis like the COVID-19 pandemic may lead to a crashing of the stock market. Classical finance theory, therefore, falls short in explaining the stock market returns as the evidence in the study shows that investors are susceptible to investor sentiment.

Keywords: Twitter sentiment; Zimbabwe Stock Exchange; Old Mutual Implied Rate: wavelet analysis; behavioural finance.

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1. Introduction

Elon Musk, the Chief Executive Officer of Tesla Inc. recently initiated a Twitter poll proposing to sell a tenth of his Tesla shareholding if users of the social media network approved[1]. After almost 60% of the people who voted in the poll approved the plan, the Tesla stock tumbled by close to 5% within hours and accounted for over 10% of all trading in U.S. companies. This story challenges the classical finance theory which postulates that markets are informationally efficient and as a result, it is not possible for investors to sustainably get returns above the risk-adjusted returns (Fama, 1965). According to this school of thought, asset prices only respond when new information is filtered into the market. Indeed, behavioural economists (e.g., Shiller, 2000) give evidence of the stock market crises like the internet bubble of 2000, the subprime mortgage crisis of 2008 and various other stock market anomalies as proof that the stock market is not informationally efficient. Black (1986) argues that noise traders are known for trading on sentiment since limits to arbitrage prevent arbitrageurs from driving asset prices to their 'correct prices'. Thus, sentiment plays an important role in the formation of asset prices in financial markets.

A growing strand of literature points to the increasing role that investor sentiment extracted from stock microblogs is playing in financial markets. The Fourth Industrial Revolution has brought with it increased internet penetration which has, in turn, increased stock market discussions on stock microblogs. Various social media platforms are being used by naïve investors to solicit advice as well as recommendations from other market participants. Twitter is being used by many investors because of its conciseness (less than 280 characters) and the use of cashtags (stock ticker symbols that are prefixed with a dollar sign) to reduce the amount of noise in the messages (Kearney & Liu, 2014).

These recent developments raise several questions. Can social media sentiment be used to predict stock returns? Should governments regulate the posting of significant information by company insiders that can influence the stock market? Should professional asset managers use social media sentiment for their strategic asset allocations?. Several studies have been done to establish the nexus between sentiment extracted from stock microblogs but these studies have been concentrated in developed countries like the USA, Germany and the United Kingdom (Ranco *et al*., 2015; Dimpfl & Kleiman, 2019; Audrino *et*

[1] https://www.theguardian.com/technology/2021/nov/08/will-elon-musk-abide-by-twitter-poll-and-sell-10-of-his-tesla-shares

*a*l., 2020), emerging markets like China (Huang *et al*., 2019) and South Africa (Johnston & Maree, 2015) as well as frontier markets like Ghana (Nti et al., 2020). To the best of our knowledge, no study has been done on the nexus between sentiment and returns in a fragile market using social media and this study seeks to fill this gap. The definition of a fragile market in this study is motivated by the Fund For Peace Initiative (FFPI) which publishes the Fragile State Index. The index is calculated from the following indicators; cohesion indicators, economic indicators, political indicators, social indicators as well as cross-cutting indicators. Countries of the world are ranked on a scale of 1 to 179; 1 represents the most fragile state and 179 represents the least fragile state of all the countries. The current rankings of the Fragile States Index place Zimbabwe on number 10, which means that there are only 9 other countries that are more fragile than Zimbabwe on a global scale. These countries consist mainly of nations that are in the midst of or have been recently affected by war and include the Democratic Republic of Congo, South Sudan and Chad. Investigating the experiences of fragile markets, which are less researched because of lack of data and being shunned by international investors, helps to further advance financial economics and expand our appreciation of African economies.

Four additional reasons make this study timely. Firstly, many investors are diversifying their investments and increasingly investing in fragile markets since these markets are less correlated with the developed markets (Berger *et al*., 2011; Guney *et al*., 2016). Secondly, even though currently marginalised, the Zimbabwean economic managers have a wealth of experience. At one point, it was only they who ran Africa's first stock exchange denominated in the US dollar (USD). Thirdly, Zimbabwe has launched another stock exchange specifically for dual-listed companies and is denominated in the USD and therefore offers stability and opportunities for diversification for investors. Finally, investor sentiments are important in fragile markets since most stocks in these markets are difficult to value. Compared to the Johannesburg Stock Exchange, the Zimbabwe Stock Exchange has a market capitalisation of less than 15 billion US dollars[2] (JSE has over 1 trillion USD), average daily traded volume in the last 12 months[3] is less than 10,000 (JSE has more than 200,000 average daily trades), but this relatively small size gives insights on whether investor sentiment is important in smaller markets also.

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[2] Conversion to USD is based on the official auction rate which is not reflective of the true market value of the ZWL

Old Mutual Limited Zimbabwe (OMLZ) is used in this study for several reasons. Firstly, it is a company that receives the most attention on stock microblogs and therefore contains enough data for the purposes of analysis. Secondly, the OMLZ stock has been used as the barometer of the economic situation in Zimbabwe through the Old Mutual Implied Rate (details of the implied rate are given in Section 2) and it is one of the most liquid stocks on the Zimbabwe Stock Exchange (ZSE). This approach of separating one company to determine how it is affected by investor sentiment has been used successfully in previous studies (such as Cornell & Damodaran, 2014), so it is adopted in this paper to analyse average sentiment extracted from *tweets* about OMLZ on the Twitter platform. Wavelet coherency analysis based on the continuous wavelet transform is used to determine the lead-lag dynamic relationship between average sentiment and returns. We show that coherency between sentiment on microblogs and the OMLZ stock is not always significant, particularly at lower frequencies.

While fragile markets are expected to have significant and persistent coherence between investor sentiment and stock returns, the results from this study show that coherence is persistent and significant in highly volatile periods characterised by increasing inflation as well as the time COVID-19 was declared as a global pandemic. This inconsistent coherence between sentiment and returns can be explained by the low participation of retail investors on the ZSE because of high unemployment and low financial literacy in Zimbabwe. Retail investors are known for trading on sentiment compared to smart investors who trade on fundamental information.

The study proceeds as follows: Section 2 gives background to the Old Mutual Implied Rate, Section 3 outlines empirical evidence on the relationship between textual sentiment and returns, Section 4 outlines the methodology used in the study, Section 5 presents the findings from the study, and Section 6 concludes.

2. Old Mutual Zimbabwe and the Old Mutual Implied Rate

Old Mutual is a diversified international financial services group listed on the stock exchanges of London, South Africa, Malawi, Namibia and Zimbabwe. Old Mutual Zimbabwe offers its services to its Zimbabwe-based clients through a wide range of products including life assurance, asset management, unit trusts, property development and management, short term insurance as well as banking services. Its clientele base includes a host of large corporations

[3] Last twelve month from the time the study was done (October 2021).

as well as multinational companies and the company has been operating in Zimbabwe for more than 100 years.

Zimbabwe experienced its worst inflation between 2007 and 2008 and during that time the central bank of the country failed to report any meaningful macroeconomic data including inflation. This inspired researchers to design alternative ways of measuring reliable macroeconomic data for Zimbabwe, including the Old Mutual Implied Rate. Table 1 shows the trends in the inflation rate in Zimbabwe between 2007 and 2008.

TABLE 1: EVOLUTION OF ZIMBABWE'S INFLATION, 2007-2008

Date	**M-O-M inflation (%)**	**Y-O-Y inflation (%)**
March 2007	50.54	2,200.20
April 2007	100.70	3,713.90
May 2007	55.40	4,530.00
June 2007	86.20	7,251.10
July 2007	31.60	7,634.80
August 2007	11.80	6,592.80
September 2007	38.70	7,982.10
October 2007	135.62	14,840.65
November 2007	131.42	26,470.78
December 2007	240.06	66,212.30
January 2008	120.83	100,580.16
February 2008	125.86	164,900.29
March 2008	281.29	417,823.13
April 2008	212.54	650,599.00
May 2008	433.40	2,233,713.43
June 2008	839.30	11,268,758.90
July 2008	2,600.24	231,150,888.87
August 2008	3,190.00	9,690,000,000,000
September 2008	12,400.00	471,000,000,000.00
October 2008	690,000,000.00	3,840,000,000,000,0000,000.00
14 November 2008	79,600,000,000,000.00	87,700,000,000,000,000,000,00

Source: Hanke and Kwok (2009).

To augment the information gap left by the government in reporting reliable macroeconomic data, Hanke and Kwok (2009) devised a proxy for the inflation rate using the Purchasing Power Parity (PPP) theory and utilising the Old Mutual share prices. Old Mutual shares are listed both on the London Stock Exchange

(LSE) and the Zimbabwe Stock Exchange. Each Old Mutual share is entitled to the same claim on the company's earnings and assets irrespective of where the share is traded (Hanke & Kwok, 2009). The only difference arises because the Old Mutual shares traded on the LSE are denominated in the British Pound and those traded on the ZSE are denominated in the Zimbabwean dollar (ZWL).

If price arbitrage works and PPP holds, the ratio of the Old Mutual share price on the ZSE to that on the LSE equals the Zimbabwe dollar/sterling exchange rate. To convert the resulting Zimbabwe dollar/sterling exchange rate to a Zimbabwe dollar/U.S dollar rate, also called the Old Mutual Implied Rate (OMIR), Hanke and Kwok (2009) multiplied the Zimbabwe dollar/sterling exchange rate by the sterling/U.S. dollar rate. The U.S. dollar rather than the pound sterling was used as the basis for the calculations because the U.S. dollar circulated widely and was the currency of choice in Zimbabwe during the dollarised period. Once the OMIR was obtained, it was used to estimate the inflation rate in Zimbabwe. A lot of companies in Zimbabwe, therefore, used the OMIR as a proxy for the exchange rate between the USD and the ZWL as well as estimating the inflation rate. Because of its linkage to the OMIR, an analysis using the Old Mutual Zimbabwe stock provides interesting avenues of research which can be generalised to the entire economy.

3. Textual sentiment and stock returns

The Efficient Market Hypothesis (EMH) emphasises the rationality of investors in explaining stock price dynamics. According to the EMH, in an efficient market, the prices of financial assets can only be affected by the arrival of new information into financial markets. On the other hand, the arrival of new information into the financial markets is presumed to be random which makes the effect of the new information on stock prices unpredictable. Another school of thought emphasises the existence of certain phenomena in capital markets-e.g excess volatility, the weekend effect and financial crises – as evidence of cognitive biases and investor sentiment (De Long *et al*., 1990). Various studies have been done to determine the connection between investor sentiment and financial markets and various proxies for investor sentiment have been used including retail investor trades (Baker & Wurgler, 2007), mutual fund flows (Brown & Cliff, 2005) and dividend premiums (Baker & Wurgler, 2007). These proxies of investor sentiment have been criticised in contemporary literature because of their measurement at low frequencies as well as their failure to measure asset-specific sentiment (McGurk *et al*., 2020). As a result, textual sentiment has evolved in recent literature to ameliorate some of the above-mentioned metrics.

The notion of textual sentiment from social media is an emerging form of investor sentiment which is text-based and portrays the level of positivity and negativity in texts from social media platforms, news articles or message microblogs (Li *et al*., 2018). Twitter and StockTwits have emerged as some of the most used platforms from which researchers are extracting sentiment from texts. Several studies have been done to examine the link between textual sentiment and stock returns and these studies have largely produced evidence showing the importance of textual sentiment in predicting financial markets. Bartov *et al*. (2018) find that their Twitter sentiment can predict a stock's return prior to earnings announcements. Ranco *et al*. (2015) create an investor sentiment index for 30 stocks in the Dow Jones Industrial Average (DJIA) using Twitter and test if large tweet sentiment increases relate to future abnormal returns. The authors find that estimated negative and positive sentiment Granger cause abnormal returns. McGurk *et al*. (2020) utilise Bloomberg News to determine if changes in the news sentiment index can predict intraday stock returns. The study finds that while the investor sentiment measure is statistically significant, it is not economically significant.

The studies discussed assume that the causal relationship between textual sentiment and stock returns is constant. Recent studies have digressed from this approach as there is evidence that posts on social media have structural changes and the connection between sentiment and stock returns is therefore dynamic. Several studies have investigated this time-varying causal relationship between sentiment and stock returns using various methods. Xu et al. (2017) suggest that the relationship between Weibo (a Twitter-like platform in China) sentiment and the stock market changes over time and across frequencies and detailed sentiments contain more information regarding the stock market than polarity sentiments. Abdelhedi and Boujelbène-Abbes (2019) use the BEKK GARCH model as well as wavelet analysis to examine the dynamic relationship between investor sentiment and stock returns. The study found that the association between sentiment and stock returns is time-varying and that the coherence between the variables increases during crises periods. This study uses wavelet analysis to examine the time-varying nature of the lead-lag linkage between sentiment and stock returns in the context of a fragile market.

4. Methodology

4.1. Data

The study uses data for the OMLZ stock for the period 24 February 2019 to

22 June 2020. The starting period is chosen because it is the earliest date at which Bloomberg Inc. started incorporating sentiment data for the stock. Old Mutual Zimbabwe was suspended from the ZSE on 22 June 2020 in preparation for its relisting on a secondary US dollar-denominated stock exchange after suspicions that it was being used to manipulate the exchange rate. Thus, data for the returns and sentiment for OMLZ are only available up to 22 June 2020. As explained earlier, the OMLZ stock is chosen ahead of other stocks for various reasons including its liquidity and availability of sentiment data. Additionally, the Old Mutual Zimbabwe stock has been used as a barometer to gauge the state of the Zimbabwean economy and has been unofficially used as a proxy for determining the exchange rate between the Zimbabwean dollar and the American dollar.

Return (R_t) for the OMLZ stock at time t is calculated from the closing prices extracted from the Bloomberg terminal and calculated as follows:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where P_t stands for the closing price at time interval t and $P_{t\text{-}1}$ stands for the closing price at time t–1. Continuously compounded returns are used instead of discrete returns since stock returns are assumed to be lognormally distributed (Brooks, 2019). For holidays when there is no trading, missing values are imputed following Nguyen and Huynh (2020) using Multiple Imputations by Chained Equations (MICE). This is not expected to significantly affect the results since holidays constitute less than 5% of the trading days on the ZSE.

Average sentiment for the purposes of this study is extracted from Bloomberg Inc. The process of calculating the average sentiment used by Bloomberg Inc. starts with manually analysing large datasets of *tweets* using human experts. Labels are then assigned to each *tweet* and categorised into positive, negative and neutral labels using the following question;

> "*If an investor having a long position in the security mentioned were to read this tweet, would he/she be bullish, bearish or neutral on her holdings?*"

The manually classified feeds are then fed into machine learning models that are taught to imitate language experts in analysing text messages. The completed machine learning models are subsequently used to scrutinise new *tweets* tagged with tickers and assign each tweet a story-level sentiment score ranging from -1 to +1 in real-time. Bloomberg does not, however, disclose the details of the models used to determine the sentiment scores because of their proprietary nature. The average firm-level daily sentiment is then extracted from the weighted average story-level sentiment scores in the last 24 hours collected from Twitter and StockTwits and updated every day 10 minutes before the ZSE opens and is calculated as:

$$A_{i,t} = \frac{\sum k \in P(i,T) S_i^k C_i^k}{N_{i,T}}, \qquad T \in [t - 24h \tag{2}$$

Where:

S^k_i is the sentiment polarity score for *tweet k* that references firm *i*,

C^k_i is the confidence of *tweet k* that references firm *i*,

$P(i,T)$ is the set of all non-neutral *tweet* feeds that reference firm *i* in the 24-hour period *T*,

Ni,t is firm *i's* total number of positive or negative *tweets* during period *T*.

Ai,t ranges from -1, the most negative sentiment to +1, the most positive sentiment. This means that an average sentiment score of 0 denotes neutral sentiment.

4.2. Wavelet analysis

The wavelet analysis method is increasingly used in financial economics to establish the coherence between time series data. The wavelet transform is a method that is used for signal conversion and processing which has its origins in Fourier analysis. In comparison to the conventional econometric methods, the utilisation of wavelets in finance allows the analysis of the correlation and coherence patterns between time series during different regimes without splitting the sample (Nguyen & He, 2015). Thus, the method mitigates sample selection bias. The use of wavelets also necessitates the use of a three-dimensional approach where the time and frequency domains as well as the strength of the correlation between the time series can be considered simultaneously (In & Kim, 2012). The aforementioned advantages of the use of wavelets compared to traditional econometric methods like Pearson Correlations and Granger causality tests led to the adoption of wavelets for the purposes of analysing the coherence between investor sentiment and stock returns for this study. Specifically, the Continuous Wavelet Transform (CWT) was used to decompose the investor sentiment and stock return series.

CWT is found by adding a basis wavelet which is attained from the translation and dilation of the mother wavelet, thereby transforming the initial time series into a two-dimensional plane of time and frequency. The continuous wavelet transform (CWT) $Wx(\tau,s)$ for a given time series X(T) corresponding to its mother wavelet $\psi(t)$ is obtained by projecting the mother wavelet into examined time series, where the mother wavelet is defined as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{3}$$

Where and τ and s are the location parameter and scale dilation parameter of the wavelet respectively. Given a mother wavelet, the CWT is then defined as:

$$W_x(\tau,s) = \int_{-\infty}^{\infty} x(t)\psi_{\tau,s}{}^{*}(t)dt \tag{4}$$

Where $\psi_{\tau,s}{}^{*}(t)$ represents the complex conjugate of the basis wavelet $\psi_{\tau,s}(t)$. For the purposes of this study, in line with Xu *et al*. (2017), the Morlet wavelet is used in analysing the data on both amplitude and phase. The Morlet wavelet is a complex sine wave within a Gaussian envelope:

$$\psi_{\omega 0}(t) = \pi^{-1/4}\left(e^{i\omega 0t} - e^{-\omega_0{}^2/2}\right)e^{-t^2/2} \tag{5}$$

Where $\pi^{-1/4}$ guarantees that the wavelet function has unit energy and $e^{-\omega_0{}^2/2}$ guarantees the admissibility condition of a mother wavelet. The wavelet power spectrum of a time series is the modulus of the CWT ($|W_x(\tau,s)|^2$) which recovers the relative contribution at each time and each scale to the time series variance. The wavelet power spectrum can be obtained using the following equation, and can be integrated across the τ *and* s to recover the total variance in the investigated series:

$$\tau_x{}^2 = \frac{1}{C_\psi}\int_0^{+\infty}\int_{-\infty}^{+\infty} |W_x(\tau,s)|^2 \frac{d\tau ds}{s^2}, with\ 0 < C_\psi = \int_0^{+\infty} \frac{\left|\hat{\psi}(\omega)\right|^2}{\omega} d\omega < \infty \tag{6}$$

Where $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$. The cross-wavelet transform of two time series $x(t)$ *and* $y(t)$ is defined as $W_{xy}(\tau,s) = W_x(\tau,s)\, W_y^{*}(\tau,s)$. The cross wavelet spectrum wavelet is correspondingly defined as $|W_{xy}(\tau,s)^2| = |W_x(\tau,s)^2||W_y(\tau,s)|^2$, implying the local comovement between $x(t)$ and $y(t)$. The wavelet coherence is used to measure the local strength of the association between two time series over time and across frequencies. It ranges from 0 to 1 with the former denoting low coherence and the latter denoting high coherence. The wavelet coherence coefficients are estimated using the following formula:

$$R^2(\tau,s) = \frac{\left|S\left(s^{-1}W_{x,y}(\tau,s)\right)\right|^2}{S\left(s^{-1}|W_x(\tau,s)|^2\right)S\left(s^{-1}\left|W_y(\tau,s)\right|^2\right)}, with\ R^2(\tau,s)\ \in [0,1] \quad (7)$$

Where S(.) is the smooth factor in time and scale. The interpretation of the lead-lag coherence relationship is interpreted using Table 2:

TABLE 2: INTERPRETATION OF THE COHERENCE RELATIONSHIPS

Direction	**Implication**
→	$x(t)$ *and* $y(t)$ are positively related
←	$x(t)$ *and* $y(t)$ are negatively related
↗ or ↙	$x(t)$ *leads* $y(t)$
↘ or ↖	$y(t)$ *leads* $x(t)$

Where $x(t)$ represents the exogenous variable Twitter sentiment and $y(t)$ is the dependent variable, returns.

5. Results

5.1. Descriptive statistics

Table 3 shows the summary statistics of the variables used in this study. The mean, median, minimum value, maximum value and the standard deviation for Average sentiment, ZWL-denominated returns, USD-denominated returns and number of daily *tweets* are shown. The sentiment scores extracted from Bloomberg Inc. came from 10 997 stock-related Twitter messages spanning 485 trading days from 24 February 2019 to 22 June 2020. The Average Sentiment score was -0.003 while the minimum and maximum scores were -0.5 and 0.17 respectively, showing that over the sample period, prospects about the OMZL stock were generally negative, which reflects the fragile state of the Zimbabwean economy in the period.

TABLE 3: DESCRIPTIVE STATISTICS

	Mean	**Median**	**Min**	**Max**	**S.D**
Average sentiment	-0.003	0.000	-0.50	0.17	0.04
Return (ZWL)	0.005	0.000	-0.34	0.16	0.04
Return (USD)	-0.002	-0.002	-0.15	0.15	0.027
Daily tweets	18.33	13.50	1.00	353	24.57

Notes: Min, Max and S.D represent the minimum value, maximum value and standard deviation respectively.

Source: Authors' estimates.

From Table 3, it can also be seen that the mean of the ZWL-denominated returns was higher than the USD-denominated returns, which shows that the latter could have been driven by inflation. Table 4 shows the Pearson correlation matrix of the variables used in the study:

TABLE 4: PEARSON CORRELATIONS

	Average Sentiment	**Returns (ZWL)**	**Return (USD)**
Average sentiment	1.000	0.0814*	-0.0111
Return (ZWL)	0.0814*	1.000	-0.0448
Return (USD)	-0.0111	-0.0448	1.000

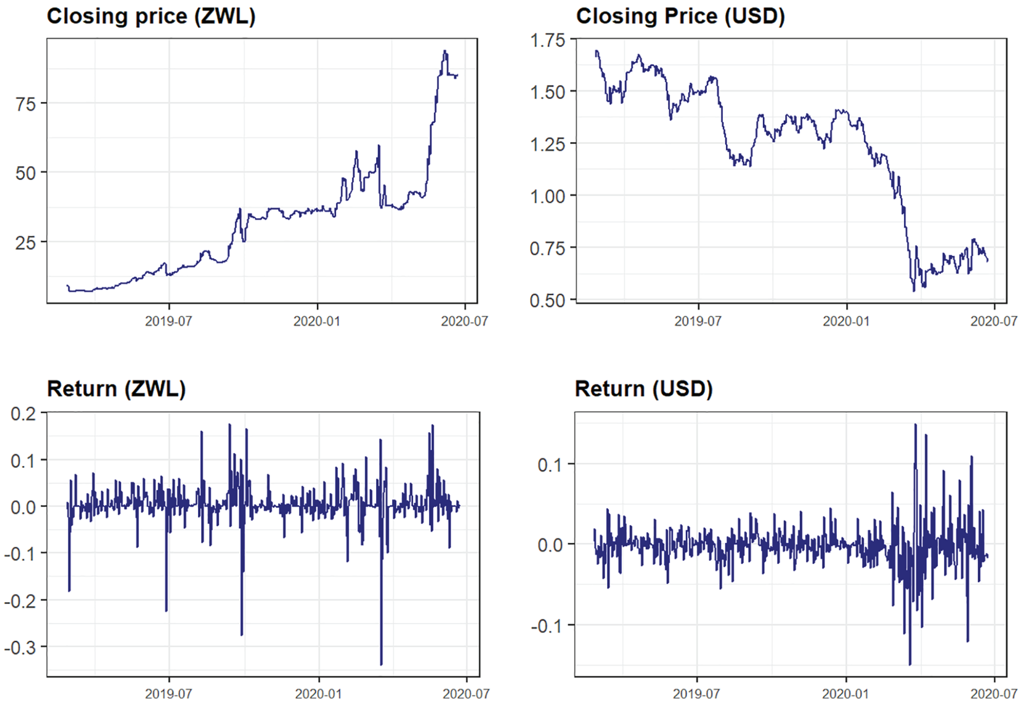
Notes: * shows p<0.1
Source: Authors' estimates.

Table 4 shows that Average sentiment is significantly correlated with ZWL-denominated returns while the relationship with the USD-denominated returns is not statistically significant. Finally, Figure 1 shows visualisations of the closing price of the Old Mutual Zimbabwe stock denominated in ZWL and the USD together with the associated returns. Figure 1 shows that the closing price of the OMLZ stock was increasing in ZWL terms while in USD terms, the stock's price was on a downward trend from the highest price of USD1.70 realised at the beginning of the sample period to prices below 1USD seen for most of 2020. The return series also shows that the ZWL returns fluctuated widely for the duration of the sample period while significant fluctuations in USD terms can be seen after the beginning of 2020, which can be attributed to the onslaught of the COVID-19 pandemic.

5.2. Morlet wavelet power spectra

Figure 2 and 3 shows the power spectra diagrams of the OMLZ stock returns in ZWL and the Average Twitter Sentiment (ATS) respectively. The $y - axes$ of the diagrams show the different wavelet transform periods while the $x - axes$ depicts the calendar time which is shown at monthly intervals. Consistent with Tweneboah, Junior and Oseifuah (2019), the wavelet scales are used to interpret the findings from the study as shown in Table 5.

Figure 1: ZWL and USD Closing Prices and Returns



Source: Authors' estimates.

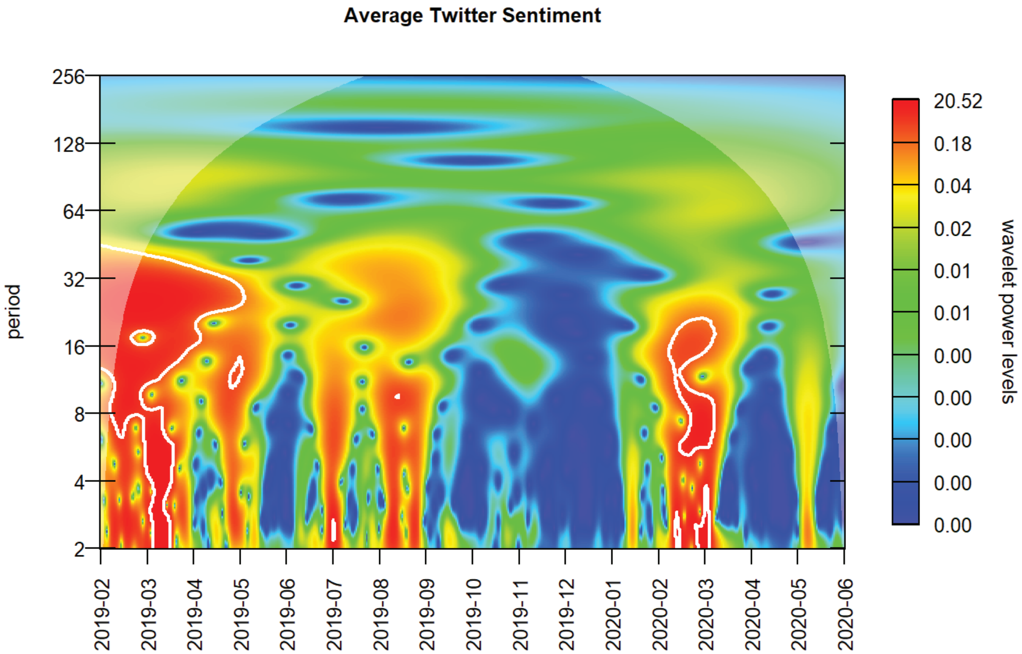
Table 5: Interpretation of Wavelet Scales

Frequency	Scale	Interpretation
W_{i1}	2-4	Intraweek
W_{i2}	4-8	Week
W_{i3}	8-16	Fortnight
W_{i4}	16-32	Month
W_{i5}	32-64	Month to quarter
W_{i6}	64-128	Quarter to biannual
W_{i7}	128-256	Biannual to annual

Source: Tweneboah, Junior and Oseifuah (2019).

In Figures 2 and 3, the white contour areas represent statistical significance at the 95% confidence level. Based on 1000 simulations, the *p-values* of the variance were computed using white noise as the method of generation of surrogates to represent the null hypothesis. The wavelet power levels for the power spectrums are shown on the $z - axes$ and the colour codes range from blue, denoting low power to red, denoting high power. The high power areas shown by the significantly warmer areas show the impacts from events showing that the variable fluctuates significantly. The cone of influence (COI) which shows the area affected by edge effects is shown in the greyed area.

FIGURE 2: MORLET WAVELET POWER SPECTRUM OF AVERAGE SENTIMENT

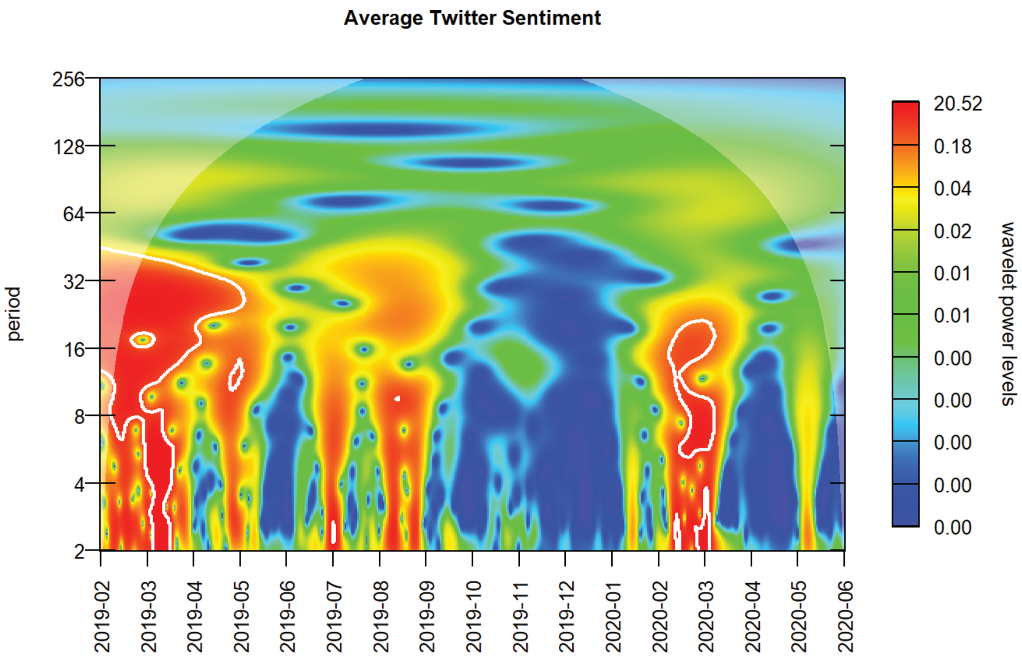


Source: Authors' estimates.

As shown in Figure 2, for average Twitter sentiment, most of the high-power spectrum regions appear at the beginning of 2019 and the beginning of 2020. Thus, the Average Twitter Sentiment shows significant fluctuations from intraweek frequencies right up to monthly frequencies. This corroborates the average sentiment time-series graph in Figure 1 which shows intense cyclical oscillations around the first few months of 2019 and 2020 respectively. The significant fluctuations at the beginning of 2019 coincide with a major currency reform instituted by the Government of Zimbabwe. In February 2019, the Government of Zimbabwe abandoned the multi-currency regime which had been operational since 2009 for a local currency, Real Time Gross Settlement (RTGS) dollar. This policy promulgation meant that all transactions, including transactions on the Zimbabwe Stock Exchange, were to be denominated in the local currency with foreign currencies only reserved for offshore transactions. This could have led to the increased mentioning of the OMLZ stock on stock microblogs as people started using the OMIR to convert their local currency holdings into US dollar terms. Initially, the ZWL was pegged to the USD and economic agents relied on the OMIR as the pegged value was not reflective of the real value of the ZWL.

For the remainder of 2019, the Average Twitter Sentiment for the OMLZ stock remains stable and only starts fluctuating again around February and March of 2020. The fluctuations in the Average Twitter Sentiment coincide with the time the COVID-19 disease was officially declared a global pandemic[4] and several countries started instituting COVID-induced national and regional lockdowns. There were lots of discussions on stock microblogs around this time because of the uncertainty that the disease had brought to financial markets. Many novice traders entered the stock market while others liquidated their holdings to protect themselves against this uncertainty and this could have led to the wide fluctuations in the Average Twitter Sentiment score. While the currency reform introduced in 2019 led to immediate significant fluctuations in the Average Twitter Sentiment as shown in Figure 2, this did not immediately lead to significant fluctuations in the returns of the OMLZ stock as shown in Figure 3.

Figure 3: Morlet Wavelet Power Spectra of ZWL Returns

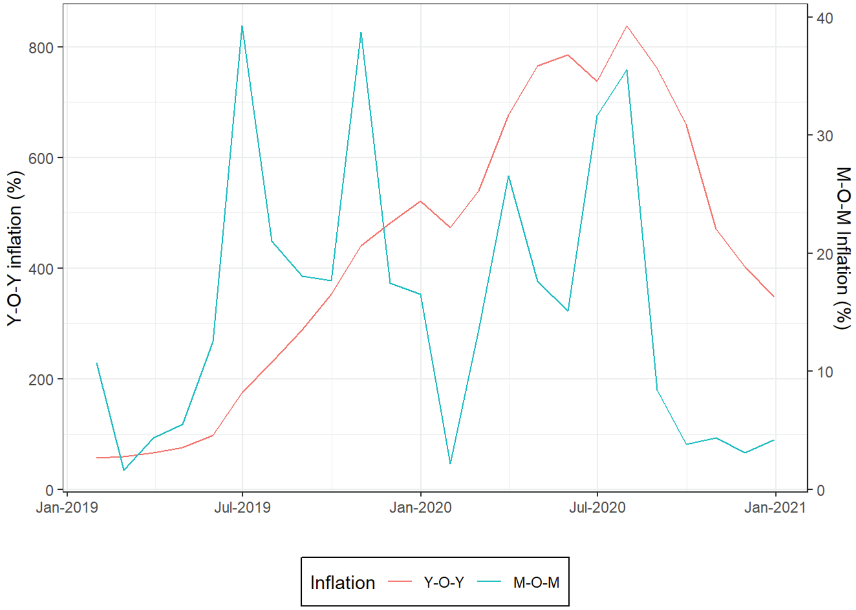


Source: Authors' estimates.

[4] The WHO declared COVID-19 a public health emergency of international concern on 30 January and a pandemic on 11 March 2020, following which much discussion has ensured about COVID-19 and African economies (see, for example, Obeng-Odoom, 2020).

As seen in Figure 3, significant fluctuations of the ZWL-denominated returns begin to be seen from June 2019 until September 2019. This could have been driven by investors flocking the stock market and snapping up the Old Mutual stock to hedge against inflation as inflation started increasing during that time as shown in Figure 4. Month-on-month and year-on-year inflation start increasing steeply from June 2019 as the ZWL/USD exchange rate started floating freely.

FIGURE 4: MONTH-ON-MONTH AND YEAR-ON-YEAR INFLATION



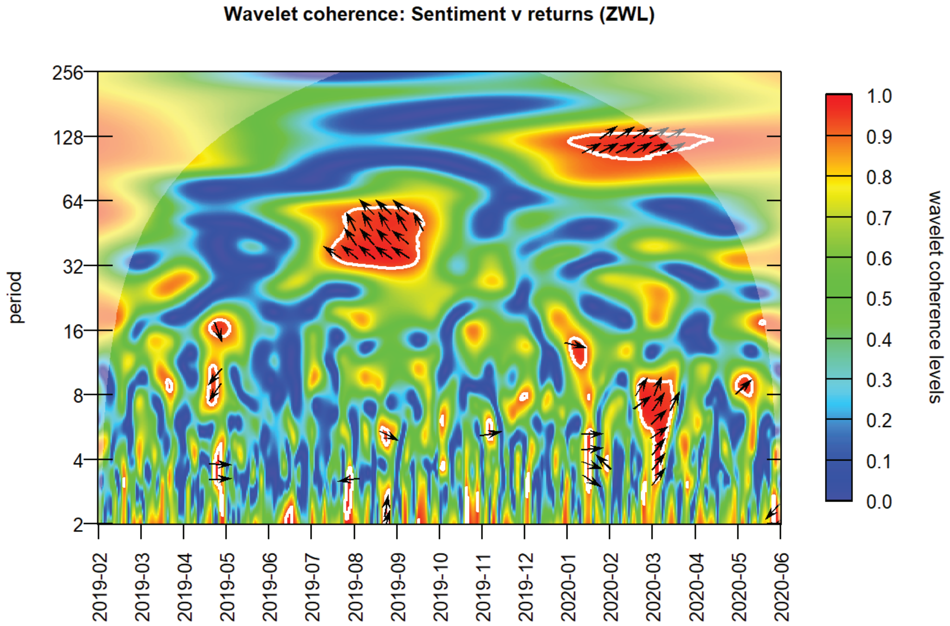
Notes: Y-O-Y and M-O-M represent year-on-year and month-on-month inflation respectively.
Source: Authors' estimates from the Reserve Bank of Zimbabwe data.

Another wave of significant fluctuations in the stock returns denominated in ZWL starts at the beginning of the year 2020 and this could have been driven by the uncertainties of the COVID-19 pandemic. What can be seen from the power spectra of both the Average Twitter Sentiment and ZWL-denominated stock returns of the OMLZ stock is that the significant fluctuations are only restricted to frequencies of less than 64 days. Thus, at lower frequencies (frequencies above 64 days) there are no significant fluctuations in the average sentiment and stock return series.

5.3. Coherence analysis

The Morlet wavelet coherence spectra of average Twitter sentiment and the OMLZ stock return is shown in Figure 5. The wavelet coherence levels are shown in the legend to the right of Figure 5 ($y - axis$) and range from 0 (lowest coherence) to 1 (highest coherence). The colour code ranges from blue, denoting low coherence to red, denoting high coherence. The white contours show the 5% significance level estimated from a Monte Carlo simulation of the wavelet coherence between 1000 sets of two white noise time series with the same length as the average Twitter sentiment and OMLZ return series. The black arrows in Figure 5 show the phase difference (see Equation 7) between the series, with the interpretation of the direction of the arrows done in accordance with Table 2.

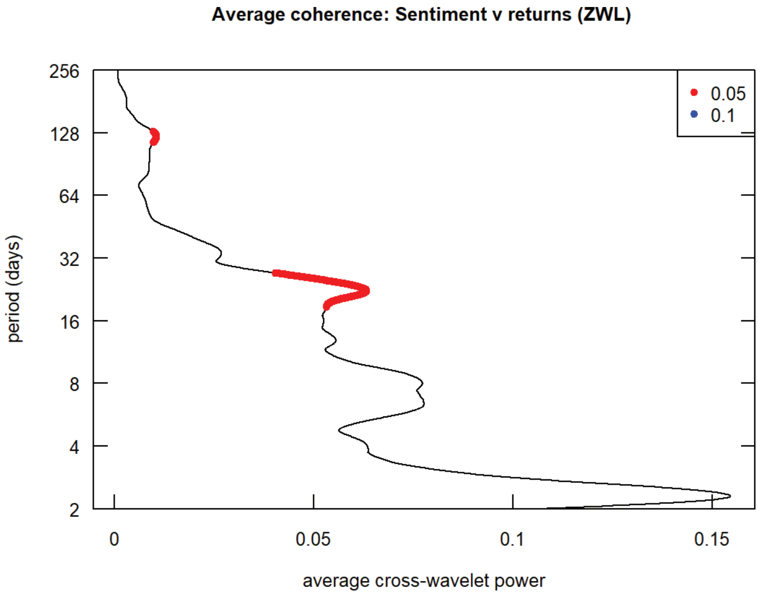
Figure 5: Coherence Spectra of Sentiments and ZWL Return



Source: Authors' estimates.

Several points can be deduced from the coherence and lead-lag patterns shown in Figure 5. Firstly, the significant regions at higher frequencies (0-32 days) are short-lived and can be ascribed to statistical fluctuations and noise (Xu, Liu, Zhao & Su, 2017). Sustained coherence between average sentiment and return series occur in the July 2019-October 2019 period as well as the March 2020 period. The significant coherent regions occur in the 32-64 as well as the 64-128 day time scales respectively. For the lead-lag relationship, the stock return leads the average sentiment anti-phase in the July 2019-October 2019 period while the Average Twitter Sentiment leads stock return in-phase in the March 2020 period. In the July 2019-October 2019 period, an increase (decrease) in stock return leads to a decrease (increase) in Average Twitter Sentiment. This is a period during which ZWL-denominated returns on the ZSE were being driven by inflationary pressures in the economy. Further increases in returns therefore induced fear in investors which led to a decrease in sentiment as investors feared that inflation would spiral out of control especially given past episodes of hyperinflation that took place around 2008. On the other hand, a fall in returns signalled a fall in inflation and therefore led to an increase in investor sentiment as this improved investors' prospects about the future. The March 2020 period which coincides with the official declaration of the COVID-19 as a global pandemic, shows a positive relationship between average sentiment and stock return and sentiment leading returns. In terms of average coherence, Figure 6 shows that the most significant region is the period characterised by increased inflationary pressures between July and October 2019 which is characterised by fear in the financial market. Figure 6 shows that the average coherence is significant at 5% levels in the 16-32 day periods and close to 128 days.

Figure 6: Average Coherence between Sentiment and ZWL Returns



Notes: Areas marked in red show significant average cross wavelet power at the 5% level of significance.

Figure 6 shows that the average coherence between sentiment and stock returns is significant at mid and long term intervals while at higher frequency intervals the average comovements are insignificant. However, as expected, the absolute value of the average cross wavelet power decreases as the period increases.

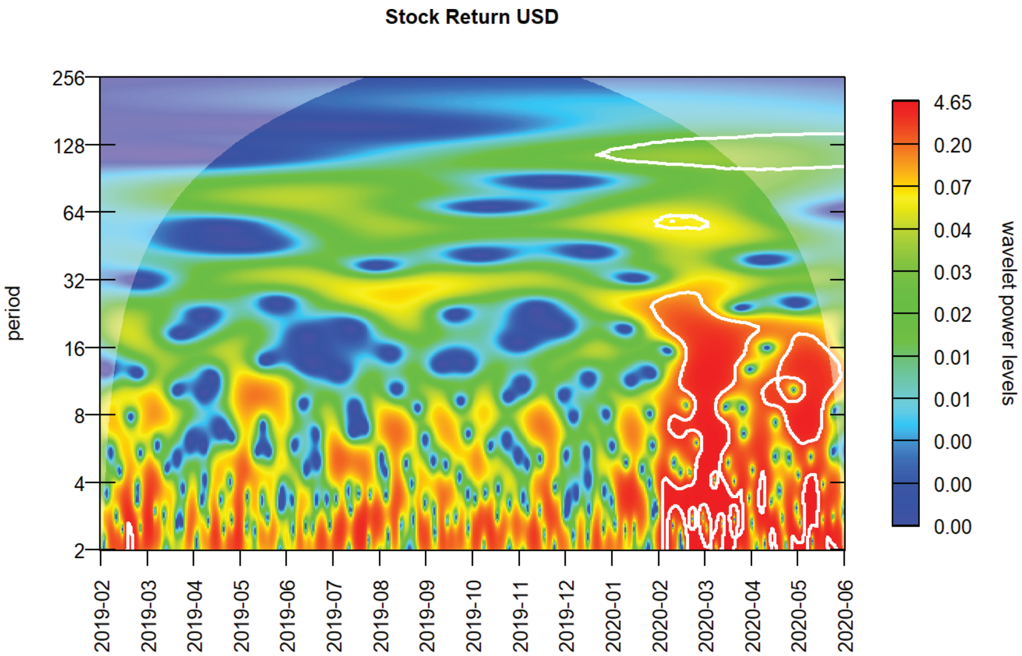
5.4. Robustness

Though the stock prices on the Zimbabwe Stock Exchange are denominated in the ZWL, most of the transactions in the informal market remain denominated in the USD. Formally, the Government of Zimbabwe has not fully de-dollarised as seen by some sections of the economy which are still allowed to charge for services using the USD. This includes payment for electricity (Ndlovu, 2020), fuel (Sibanda, 2020) as well as tariffs on imports and a host of other services in the informal market. In such an environment, many investors invest in ZWL dollar-denominated assets with prospects of getting positive USD-denominated gains. It is therefore of paramount importance to establish the co-movement and coherence patterns of Average Twitter Sentiment and USD-denominated returns.

Many investors and economic agents in Zimbabwe have been using the Old Mutual Implied Rate as a proxy of the exchange rate. Figure 7 shows the power spectrum diagram of the stock returns denominated in the USD using the OMIR as the exchange rate. What can be seen from the diagram is that the OMLZ stock return in USD terms does not fluctuate from the beginning of 2019. The significant fluctuation of the stock return starts at the beginning of 2020 around February. The significant fluctuations continue until 22 June when the OMLZ was suspended from the ZSE on suspicions that investors were abusing the OMIR by using it as a proxy for the exchange rate between the Zimbabwean dollar and the US dollar and thereby fuelling inflation as companies were using it in their pricing decisions (Reuters, 2020). This can be seen from Figure 7 as the OMLZ stock return in US dollar terms is stable throughout 2019 and starts to fluctuate significantly beginning in February 2020 up to the end of June 2020 when OMLZ is suspended from the ZSE. The move by the Government led to the stabilisation of the exchange rate as well as the plummeting of the month-on-month as well as the year-on-year inflation after July 2019 as shown in the inflation statistics in Figure 4. Figure 4 shows the month-on-month and year-on-year inflation rates plummeting in the aftermath of the suspension of the OLMZ stock.

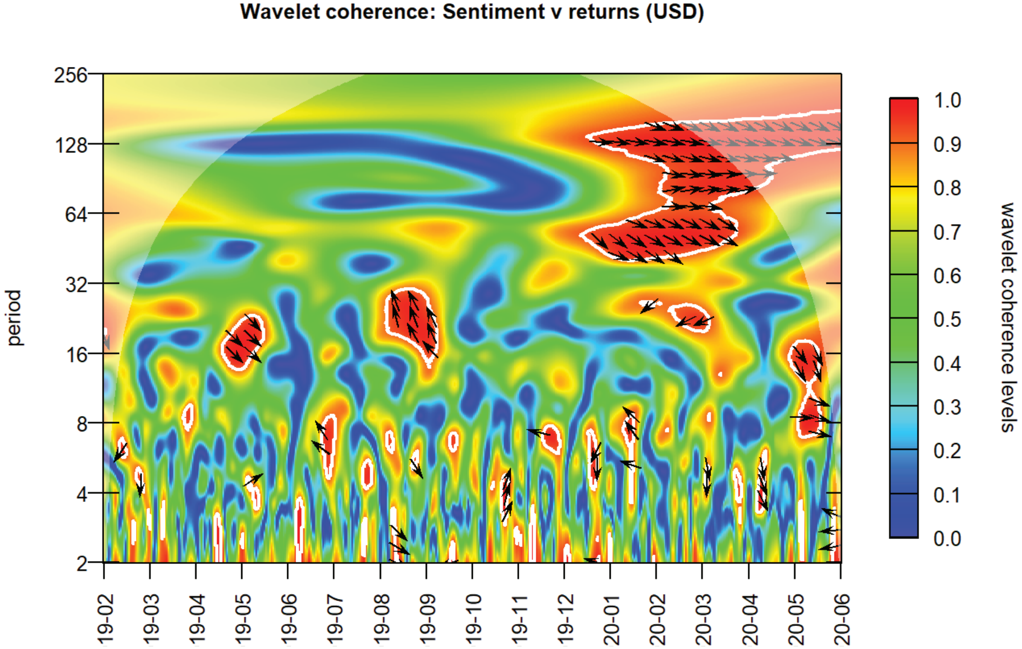
In terms of the wavelet coherence of the Twitter sentiment and the OMLZ USD-denominated return, Figure 8 shows that there is significant coherence between the series in the middle of 2019 as well as the beginning of 2020. In the middle of 2019, the significant coherence is in the 16-32-day frequency while in the latter period the significant coherence occurs at lower frequencies of 32-128 days. In terms of the lead-lag relationship, USD-denominated returns lead sentiment anti-phase in August and September of 2020 which is a reflection of fear in the market, likely from the bouts of inflationary pressure experienced in the country during that period. This demonstrates that even in USD terms, the period was characterised by fear. The January 2020 to May 2020 period is marked by USD returns leading sentiment in-phase which reflects that the market was characterised by greed. This shows that increased USD returns of the OMLZ stock led to increased bullishness in the market.

Figure 7: Morlet Wavelet Transform Coherence Spectra of Sentiments and USD Return



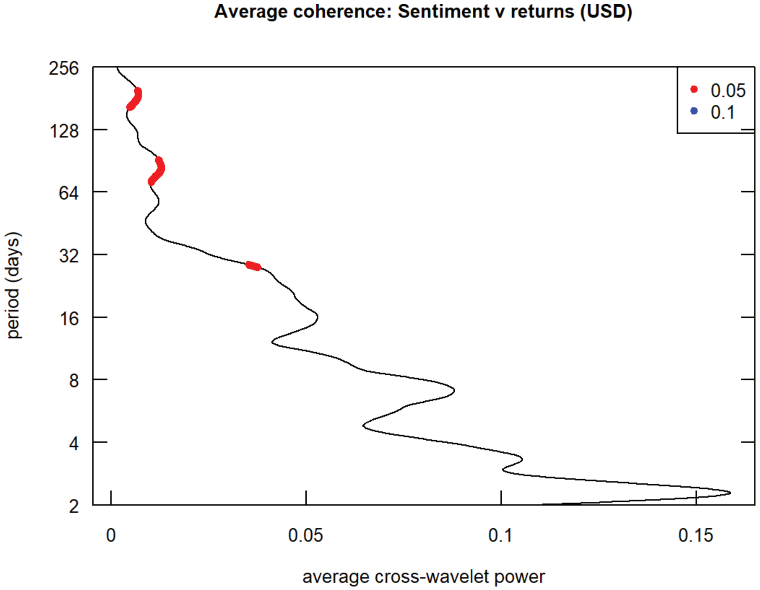
Source: Authors' estimates.

FIGURE 8: MORLET WAVELET TRANSFORM COHERENCE SPECTRA OF SENTIMENTS AND USD RETURN



Source: Authors' estimates.

FIGURE 9: AVERAGE COHERENCE BETWEEN SENTIMENT AND USD RETURNS



Notes: Areas marked in red show significant average cross wavelet power at the 5% level of significance.

The average cross wavelet power also shows that the average power is significant at lower frequencies while at higher frequency intervals the power is insignificant.

6. Conclusion

This study has examined the relationships between the Average Twitter Sentiment and the stock market returns for Old Mutual Zimbabwe Limited. Existing literature shows contradicting findings on the relationship between textual sentiment extracted from social media and stock returns. It is expected that in a fragile market like Zimbabwe, market participants are most likely to be influenced by psychology and sentiments compared to the developed financial markets. A time-frequency view of the relationships between Twitter sentiment and OMLZ over sixteen months suggests that the linkage is not always significant, particularly at higher frequencies. The findings from the study indicate that the relationship between Twitter sentiment and stock returns has both frequency and time-varying features. The findings show that the coherence between average sentiment and the OMLZ stock return increased during inflationary periods as well as after the onslaught of the COVID-19 pandemic. During inflationary periods, returns lead sentiment anti-phase which is a signal of fear in the market. In the COVID-19 period, returns lead sentiment in-phase, which signals greed in the market. The results show the importance of sentiment from social media in the stock market and corroborate the results found in Ghana (Nti *et al*., 2020) and South Africa (Johnston & Maree, 2015) where sentiment from *tweets* was found to significantly predict stock returns though these studies used static models. So, it appears that the experiences from frontier and fragile markets are analogous.

There are several policy implications from the findings of this study. Firstly, the Government of Zimbabwe should come up with a market-related and robust exchange rate regime that can be trusted by all stakeholders. Failure to do so leads to economic agents resorting to the nearest proxy for the exchange rate for rent-seeking purposes, and this proxy might be sensitive to other non-fundamental factors like sentiment. Resorting to the OMIR by investors was a result of the absence of a robust exchange rate. The Government of Zimbabwe, therefore, made the right call by relisting the OMLZ on a USD-denominated stock exchange and at the same time launching an auction-based exchange rate, which has managed to reduce the inflation rate significantly thus far. Secondly, the authorities should prioritise macroeconomic stability as instability leads to increased coherence between sentiment and returns which may lead to bubbles and busts. Thirdly, in terms of strategic asset allocation, sentiment-based strategies may not be the best strategy in fragile markets because there is evidence that sentiment plays an insignificant role in stable environments. Future studies can explore the effect of Twitter sentiment on stock returns using a multivariate framework that includes other forms of sentiment like news media sentiment. Theoretically, the results confirm the significance of behavioural finance as the investor overreaction on the announcement of the COVID-19 pandemic can only be explained by psychology rather than from fundamental information.

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Conflicts of interest

The authors declare no conflict of interest.

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