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COVID-19 LED TO PRICE SLUMPS IN THE GERMAN STOCK MARKET. IS SENTIMENT APPLICABLE AS AN EXPLANATORY FACTOR?

Explaining and forecasting returns and other statistical moments of returns in the stock market have always been critical challenges. Recent studies postulate a relation between investor sentiment and future stock market returns. Supported by evidence from other countries, this study explores the statistical moments of stock returns in Germany and analyses to what extent an explanation can be found through investor sentiment.

The recent COVID-19 induced market distortions provide an opportunity to investigate the suitability of predictive sentiment-based analyses. These are presented in this study and appear to be meaningful. The main concept behind the sentiment-based return explanation is built on the assumption that stock returns are linked to investor psychology. This theory often serves as an explanation for market movements that cannot be explained by fundamental data which are directly linked to stocks. However, the extraction of various sentiment proxies for further analysis in statistical models remains challenging. Problems occur because sentiment proxies do not have a constant influence and depend greatly on what currently drives the market. Furthermore, the correlation between sentiment indicators varies over time, especially in times of market distress.

In this study, 73 sentiment indicators were examined in the aggregate with regard to the explainability of future stock market return distribution moments such as mean, variance, skewness, and kurtosis. This study examines 169 one-month periods from 2006 to 2020 and shows a potential solution to these challenges by applying a neural network based on long short-term memory (LSTM) neurons. The authors were able to identify a good model fit and reasonable forecasting power, which seem to work particularly well in trend forecasting. The results can be valuable in the area of portfolio risk management.

Keywords: behavioural finance, investor sentiment, stock market returns, risk management, Germany

JEL Classification: G17, G41, C45, C53
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1. INTRODUCTION

COVID-19 induced global market shifts have brought new momentum to sentiment-based capital market research (Jiang et al. 2021; Singh and Yadav 2021; Mensi et al. 2020) even though, academic literature and empirical economic models have long been based on the axiom of efficient markets. The widespread efficient--market hypothesis (EMH) was significantly influenced by Fama (1970) and is increasingly challenged by empirical studies, especially on the US market (Baker and Wurgler 2007, 2006; Malandri et al. 2018). The studies are examining empirical findings like arbitrage limits and other market shortcomings, but also people as rational investors are increasingly being questioned (Lakonishok et al. 1994; Kahneman and Tversky 1979). According to EMH, only new information shifts prices in the direction and with the magnitude that the new information implies. That what calls existing paradigms into question through new findings, also provides opportunities for new explanatory approaches. While precise and reliable trend forecasts were not considered possible under the assumption of efficient markets, rationally acting investors, and the random walk theory (Fama 1995), recent studies with empirical evidence on the predictability of returns in the stock market are increasing (Gao and Liu 2020; Trichilli et al. 2020; Zaremba et al. 2020; Al-Nasseri et al. 2021; Szczygielski et al. 2021). COVID-19 induced market movements have been visible around the world. This study focused on the German stock market as an illustrative example.

Germany is by far the strongest exporting economy in the European Union and its economy is particularly affected global developments (such as COVID-19). In fact, the German stock market is highly relevant as a subject of research in this context, since the German economy with its focus on exports and regularly high trade surpluses is extraordinarily exposed to future economic expectations reflected in investor sentiment. In 2018, evidence was presented for the fundamental suitability of sentiment factors to explain return differences in multi-factor models on the German stock market (Hövel 2018; Shen et al. 2018). Important insights as to the suitability of neural networks to explain statistical moments based on mood followed (Malandri et al., 2018). Innovative methodological approaches such as artificial neural networks produced encouraging results.

In particular, the use of long short-term memory (LSTM) neurons is considered promising in this context as they have the potential to address the suspected changing influences of sentiment on stock market returns (Li et al. 2020). This study presents the first results of this research on the German stock market using LSTM neurons during the COVID-19-induced market turbulences. Since the influence of sentiment on stock returns on international markets as well as on the German stock market (Hövel 2018) has been observed by various studies, this study aimed to show that an LSTM-based neural network can be used to explain the developments induced by COVID-19 on the German stock market.

What is remarkably unique about the COVID-19-induced sharp decline is the fact that it was not of a sustained nature, but rather there was a spontaneous strong recovery based on widespread speculation and investor enthusiasm. In addition to the pandemic-induced price slumps expressed in returns, the authors also attempted to explain other important portfolio management risk metrics such as variance and skewness and to show that the approach is promising. In the context of portfolio allocation, higher statistical moments, in addition to variance, find their application in financial risk assessment (Kim et al. 2018; Khan et al. 2020; Ebrahimi and Pirrong 2018). The conjectures regarding the explainability of these moments by sentiment are largely confirmed in this study; only the kurtosis of the return distribution could not be explained satisfactorily.

2. LITERATURE REVIEW REGARDING SENTIMENT AND MARKET EFFICIENCY

Investor sentiment analysis interprets moods in their significance for the development of markets or individual financial products, as it helps to develop well-founded assumptions about future market developments and an explanation for current market movements. The assumptions can then serve as the basis for short-term trading or long-term investment decisions. Baker and Wurgler (2007) defined sentiment as expectations about future cash flows and investment risks that cannot be explained by fundamental data. For instance, weather phenomena, plane crashes (Kaplanski and Levy 2010), and even football matches that were lost (Edmans et al. 2007) could influence sentiment among market participants influencing the stock market.

Current capital market theoretical research on the further development of financial models gives rise to the assumption that further potential for interpretation and improvement can be assumed in (as yet) unknown risk factors. It is, therefore, necessary to investigate whether, in addition to the known influencing factors of widely adapted multi-factor models, factors that are difficult to quantify, such as sentiment, can also influence the valuation of shares. In the past, Lakonishok et al. (1994) observed that irrational investor behaviour can be used to achieve higher returns at the same level of risk and corresponds to market inefficiency. Russell and Thaler (1985) showed that market participants sometimes behave irrationally or rather, as they refer to it, quasi rationally, which means a non-rational but nevertheless regular behaviour. Kahneman and Tversky's prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1973), which states that decisions are made based on the expected subjective benefit, provided an understanding of this irrational decision making. Expectations of losses or gains are based on heuristics.

These heuristics are used to make decisions more effectively under uncertainty, even though they lead to cognitive distortions and predictable errors. Research shows that individual investors suffer from faults like the availability bias, where they are biased towards investing in assets that have attention-attracting qualities (Barber and Odean 2008). Investors also suffer from disposition effects, by selling winning assets too soon in order to realize a gain, and keeping 'losers' too long in order to avoid realizing a loss (Odean 1998). They are also overconfident in their ability to predict the market (Heuer et al. 2017). The overconfidence bias that probably plays a major role in the context of this research was taken up and empirically confirmed in (Daniel et al. 1998). In addition to the well-recognized loss aversion of the average investor, herd behaviour (social proof) also seems to play a decisive role in the emergence of general market sentiment. De Bondt (1998) observed that investors follow simple patterns in price movements and do not always act optimally. An overview of biases and dispositions can be found in Barber and Odean (2013). Bradshaw (2004) noted that besides private investors, experienced equity analysts also rely on heuristics in their decision-making. Since these are not exact, there is reasonable cause to suspect that shares could be temporarily mispriced, whereby the market price of the share does not always reflect its true value. If the use of heuristics leads to foreseeable errors, there is a rational cause to believe that these patterns should be incorporated into the valuation of equities.

Other important contributions were made by Long et al. (1990), on the influence of irrational market participants (noise traders) who formalized investor sentiment in the finance literature, and Barberis et al. (1998) on the psychological foundations of investor sentiment. Since individual market participants are regarded as price takers and it would be difficult to capture and measure individual investor behaviour, research tends to focus on models where assumptions about investor behaviour are made at an aggregated level. Jackson (2003) assumed the plausibility of this approach and showed that aggregated trading decisions follow systematic patterns. Based on aggregated investor behaviour, Baker and Wurgler (2007) demonstrated empirically that sentiment makes a significant explanatory contribution to stock market returns, however prediction remains difficult because the foundations and variation in investor sentiment over time is not yet explainable. The findings of previous work do not contradict the considerations of Fama and French, who stated that risk factors of the three-factor model represent aggregated proxies (mimicking returns) for various risks and anomalies in stock valuation, which are not directly explained by the three-factor model (Fama and French 1993). Since sentiment reflects individual investor mood on an aggregate level, it will be considered a general market sentiment at an aggregated level in the further course of this paper. Sentiment should be furthermore divided into short, medium, and long-term segments.

Only monthly sentiment indicators are analysed in this study, which is part of medium-term sentiment. What all sentiment indicators have in common, however, is that they attempt to reflect a dichotomous mood of the market, namely optimism and pessimism. So far various studies on the relations between sentiment and stock market returns have been based on Pearson's correlation coefficient, linear regression, and nonlinear causality tests. The three-factor model of Fama and French is often chosen as the control model, sometimes extended by the Carhart momentum factor (Carhart 1997). It is notable that most studies have been conducted in the US market (Broadstock and Zhang 2019; Albulescu 2021; Gutierrez Pineda and Perez Liston 2021).

For the German stock market there is a significant lack of reliable studies. To name just a few relevant studies, Finter et al. (2012) showed that based on survey and market implicit sentiment sources, certain stock groups react more sensitively to sentiment than others without being able to determine a significant explanatory content for future stock returns. Krinitz et al. (2017) used the Granger causality test to show that news sentiment has an impact on German stock market returns. Recent studies are particularly concerned with sentiment feature classification in deep learning models (Seungho 2021) as well as traditional classification algorithms (Steyn et al. 2020) and deal with COVID-19 as the latest recent extreme event with implications for stock market returns (Zhang et al. 2020). In the following sections, the various sources of sentiment are presented from which indicators can basically be derived.

2.1. Survey-based sentiment

Survey-based sentiment has been used for decades in research on stock returns. The elementary challenge of sentiment analysis is the quantification of unstructured data. An established and easy-to-use method is the direct determination of sentiment using surveys. However, by critically reviewing various studies, the requirements of inference statistics such as the temporal, spatial, and objective ex-ante definition of the population or the randomization of the survey participants are often not met in the survey and sample selection, yet this does not mean that surveys that suffer from these ex-ante flaws do not provide meaningful and usable information. Pioneers in the field of survey-based sentiment, such as Shiller et al. (1996), tried to capture sentiment by interviewing institutional investors every six months by letter about their assessment of the US and Japanese markets. Qiu and Welch (2004) investigated relations between consumer satisfaction and market sentiment. Hengelbrock et al. (2013) examined time horizons for effect on market prices of survey-based sentiment. Hilliard et al. (2016) showed that a sentiment factor based on weekly surveys provides significant explanations for stock market returns; even after verification by the control variables of Carhart's four-factor model, the sentiment factor provides significant explanatory contributions to stock market returns. Tiwari et al. (2018) investigated, based on weekly surveys by the German market research institute, Sentix GmbH, whether sentiment influences different markets, and observed that nonlinear causality tests provide better explanations than linear models. It is also assumed that sentiment differs significantly from institutional and private actors. These differences should be taken into account when quantifying sentiment.

2.2. Market-implicit sentiment

In addition to survey-based sentiment indicators, sentiment analysis also focuses on market-implicit sentiment, which is indirectly derived from future-oriented market data. Implicit volatility and put-call ratios often reflect the future expectations of market participants and are repeatedly applied as indirect indicators of market sentiment. Initial findings in this area were made decades ago. In the early 1990s, Lee et al. (1991) put forward hypotheses on influencing stock returns through sentiment. Relatively simple approaches to market implicit sentiment can be located in measurable cash flows. Goetzmann et al. (2000) found evidence of a negative correlation between cash flows to equity funds and fund returns. Grinblatt and Keloharju (2001) showed that inflows of liquid funds from foreign investors influence share prices. Brown et al. (2003) also indicated a correlation between inflows to equity funds and fund returns. Baker and Wurgler (2006) revealed, based on market-implicit sentiment, that this provides a significant explanation for stock market returns. Kumar and Lee (2006) observed almost at the same time that investments by private investors follow cognitive biased patterns in their investment decisions. Recent studies on survey-based sentiment also examined a majority of significant market implicit sentiment factors. Félix et al. (2020) found evidence that implied volatilities explain equity returns, while Zha (2018) showed that market-implicit data such as turnover rates and new emissions have an impact on Chinese equity market returns.

2.3. Social sentiment

A relatively new aspect is a news-based or social sentiment, which comprises online media reports in the broad sense, where the quantity of news is also crucial. In the narrower sense, however, this means social networks. Social sentiment is developing into a much-discussed area in behavioural finance, especially when short periods of time are concerned. As this study was conducted on a monthly basis this had no impact, but it is worth adding for the sake of full disclosure. It is important to distinguish between sentiment based solely on the quantity of certain information (frequency of news and search queries), and sentiment which also takes into account the qualitative component by means of text mining (e.g. the evaluation of the sentiment of tweets). The advantage of social sentiment is the fast availability, which can also take place in real-time, depending on the method, and can therefore also be relevant for day traders, unlike survey-based sentiment. Regarding maturity, Checkley et al. (2017) showed that sentiment of social networks can lead to causal effects on stock markets within minutes. Since social sentiment is not part of the investigation in this study, it will not be discussed in a more detailed manner.

3. TIME-VARYING RISK PREMIA

Before delving deeper into the study design, it is important to illustrate the assumption made here regarding the relationship between return and risk. Return is not directly (but rather indirectly) derived from fundamental data like corporate profits and expected cash flows and is a reward for risk-bearing capacity. Thus, return and risk are linked in such a way that risk is a compelling condition for return. In addition to the more objective concepts such as variance, standard deviation, and shortfall risks, subjective risk perception is added depending on time, situation and investor. Furthermore, risk tolerance varies over time (time-varying risk premiums) (Kommer 2018; Chaieb et al. 2018). This applies not only to the individual investor, but also to the aggregate, i.e. the entire market. Risk premiums are quantifiable, objective characteristics of securities that statistically have a particularly strong explanatory power for historical and future returns and risks of asset classes. Regression analysis can be applied to measure the intensity of the ex-ante defined causal drivers of the observed market or portfolio returns and to calculate a statistical probability that this cause-and-effect relationship is not the product of a random event. In diversified portfolios, this can explain up to 95% of the return differences between the portfolio under review and the benchmark (market). The best-known risk factors which have been empirically tested most intensively, are the size effect, i.e. the return premium that small stocks, measured in terms of market capitalization, have over large stocks.

Additionally, there is empirical evidence for a value effect, which is a return premium that value stocks with a high book-to-market ratio have over growth stocks with a low book-to-market ratio (Cakici and Topyan 2014). Furthermore, there is a momentum effect, which represents the tendency of stocks to continue their positive or negative performance relative to the overall market for some time. Besides these, there are other effects such as quality and liquidity.

Recent publications demonstrate that sentiment is a suitable risk factor that can also be applied in multi-factor models. For the German stock market, sentiment is shown to provide stronger explanatory contribution than the momentum factor (Hövel 2018). Since risk factors are country-specific, partly unknown, and not time-stable (see Figure 1; Merville and Xu 2002), a neural network was used in this study to explain future moments of return distributions based on investor sentiment for the present. By utilizing the respective weightings of the neural network, the factors prevailing at the time of observation can be identified.

Figure 1 shows various sentiment indicators which temporarily form dependencies in the sense of correlations. This dependence can also occur with a time lag.

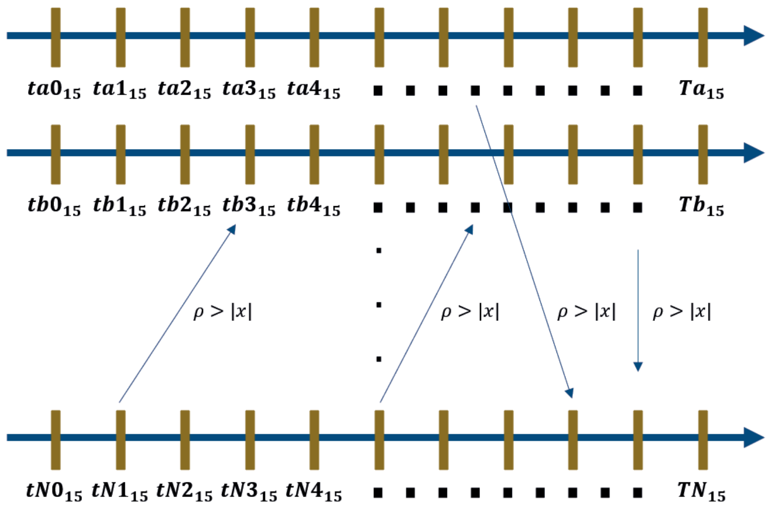

Fig. 1. Intertemporal dependencies among sentiment indicators

Source: own study.

4. EMPIRICAL ANALYSIS

4.1. Database

The subject of the study are the monthly returns of an equal-weighted German CDAX equities portfolio. The composition of the CDAX was reviewed on a monthly basis so that, unlike in other studies, no survivorship bias is present. All share-specific data originate from the data provider, Refinitiv, and refer to the Frankfurt Stock Exchange. Sentiment indicators were in part based on those proposed by Finter et al. (2012). Specific data were obtained from the public time series database of the Deutsche Bundesbank, and extended with Refinitiv lead indicators for the German economy. Returns and related statistical moments were determined from mid-month to mid-month. The CDAX is a stock market index calculated by Deutsche Börse. CDAX is a composite index of all stocks traded on the Frankfurt Stock Exchange that are listed in the General Standard or Prime Standard market segments. The CDAX covers almost the entire German market capitalisation, with the exception of a very small number of shares listed on regional stock exchanges.

Equal weighted CDAX values were analysed in order to also represent smaller, according to the findings of Baker and Wurgler (2007), more mood-sensitive values. Kumar and Lee (2006); Barber and Odean (2008) also suggested that small stocks are less liquid and thus react more sensitively to changes in investor sentiment. In this analysis, the period from March 2006 to March 2020 (T = 169 months) was covered. On average, 537 individual shares were considered in each period. A set of 73 monthly sentiment indicators served as independent variables. The sentiment indicators applied in this study largely correspond to those proposed by Finter et al. (2012), which were complemented by further lead indicators from the Refinitiv database (formerly Thomson Reuters Datastream) which can be followed in more detail in Appendix.

4.2. Descriptive statistics

In order to ensure the uniform comprehensibility of the values considered, the use of percentage notation has been dispensed with for all subsequent values, including yields. The equally weighted CDAX portfolio showed a decline in log return of –0.3115 in the period 15 February 2020 to 15 March 2020. At the same time, the variance of the portfolio increased by 0.0677 to 0.1204 compared to the previous period. The skewness of the return distribution in the portfolio increased by 3.4943 from 0.6601 to 4.1543 compared to the previous period and the kurtosis also increased by 23.5140 from 54.1343 to 77.6483. The calculations for the respective moments of the portfolio are shown in Appendix.

The respective statistical moments of the CDAX return distribution were determined monthly. In the following overview, all statistical moments of the entire period are presented using histograms and box plots. Referring to the distribution of the first moment (see Figures 2 and 3), which represents the distribution of the monthly returns, one can observe a distribution with a mean of –0.0092, a variance of 0.0025, a skewness of –1.7889, and kurtosis of 7.1536.

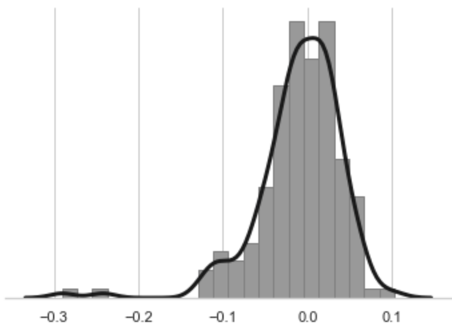

Fig. 2. Distribution of first moment

Source: own study.

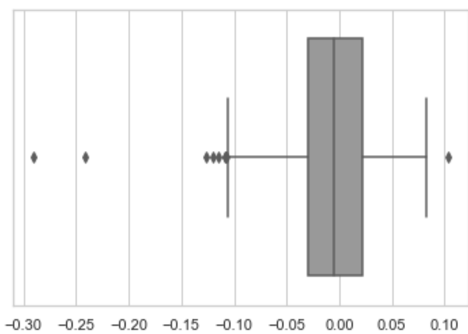

Fig. 3. Box plot of first moment

Source: own study.

Conversely, the second moment (see Figures 4 and 5) shows the following values: mean 0.0328, variance 0.0003, skewness 2.4898, kurtosis: 9.5424. One should bear in mind, however, that there is no negative variance. Particularly high variances are very rare, which is typical for stock market returns. Additionally, a relatively high kurtosis can be observed, which makes the distribution leptokurtic.

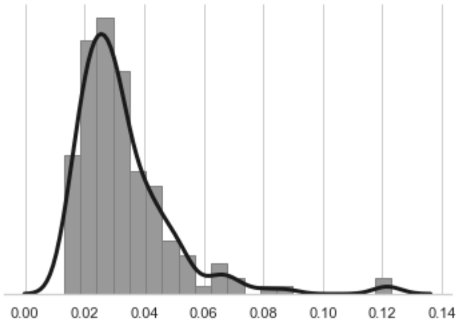

Fig. 4. Distribution of second moment

Source: own study.

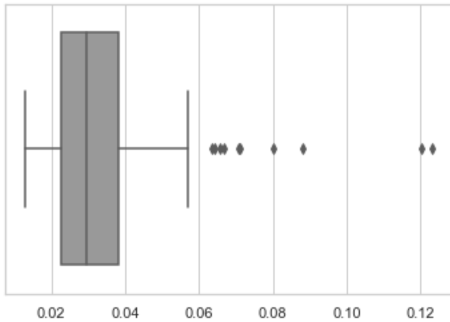

Fig. 5. Boxplot of second moment

Source: own study.

The third moment represents a distribution of the monthly portfolio-skewness during the observation (see Figures 6 and7). The cross-sectional four moments of this third moment are mean –0.9190, variance 8.1194, skewness –0.7261, and kurtosis 2.0271.

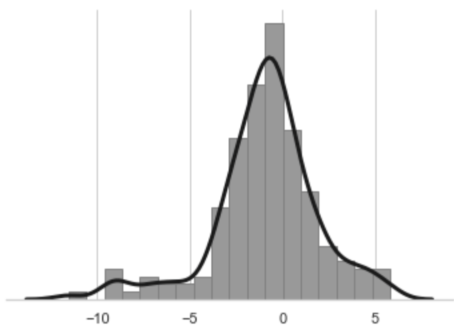

Fig. 6. Distribution of third moment

Source: own study.

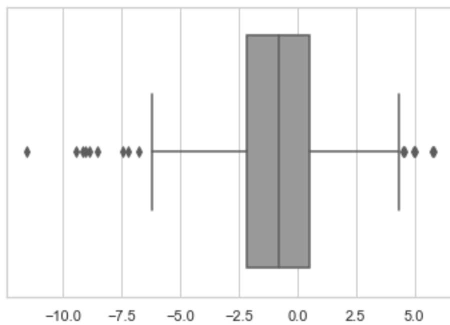

Fig. 7. Boxplot of third moment

Source: own study.

The kurtosis (see Figures 8 and 9) has the following values: mean 30.2095, variance 966.8614, skewness 2.9025, kurtosis 10.7539. Here one can see best that the scales on which the moments move are very different.

The correlation matrix (see Figure 10) shows that the moments are relatively weakly correlated in the cross-section, with the exception of the moments variance and kurtosis, which are significantly positively correlated with a Pearson correlation coefficient of .5042. The negative correlation between variance and return should also be highlighted. This confirms the assumption already made that there is

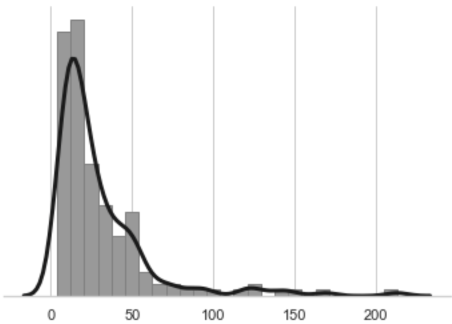

Fig. 8. Distribution of fourth moment

Source: own study.

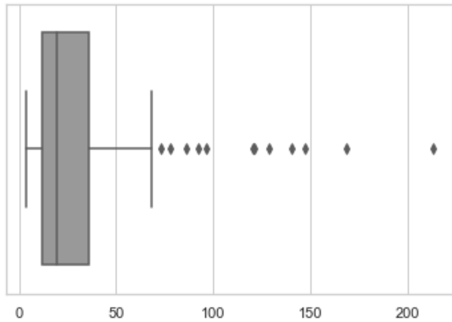

Fig. 9. Box plot of fourth moment

Source: own study.

a negative relation between risk and return. A slightly positive correlation between return and skewness can also be observed in the cross-section. Furthermore, a negative correlation between skewness and kurtosis is shown by the Pearson correlation coefficient of –.4650.

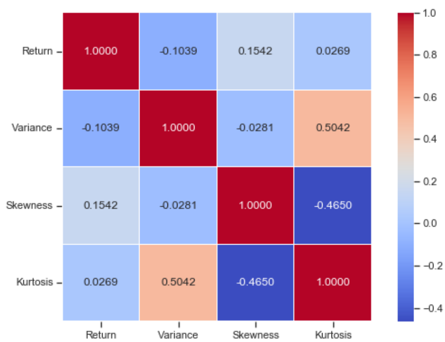

Fig. 10. Cross-sectional correlations

Source: own study.

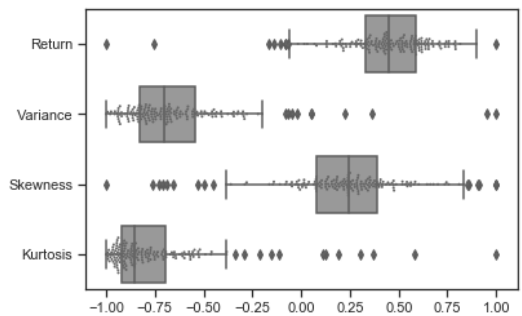

Fig. 11. Box plot of scaled moments

Source: own study.

It was also checked whether the sentiment indicators correlated in cross section; this was true in some cases and it does not necessarily mean that the correlation was present throughout the analysis. However, no large correlation clusters could be identified. A dimensional reduction by a PCA was intentionally not carried out in order to provide the neural network with the greatest possible depth of information. In a further study, however, the feasibility of dimensional reduction by using autoencoders could be investigated. Since the data show that all moments are on different scales, they cannot be compared directly in the cross-section. In order to achieve comparability between the different distribution moments, they were re-scaled to a consistent numerical space. The range from –1 to +1 was appropriate for scaling, since the model output was also scaled to this very same range due to the hyperbolic tangent activation within the LSTM cell (see Figure 13). An overview of the actual scaled moments is shown in Figure 11. The scaled box plots show that the median of return and skewness are generally positive and that of variance and kurtosis are negative.

4.3. Methodology and model selection

Figure 12 illustrates the setup of the study. The hypothesis was that the delta in sentiment of the preceding period contributed to the development of the statistical moments of the following month.

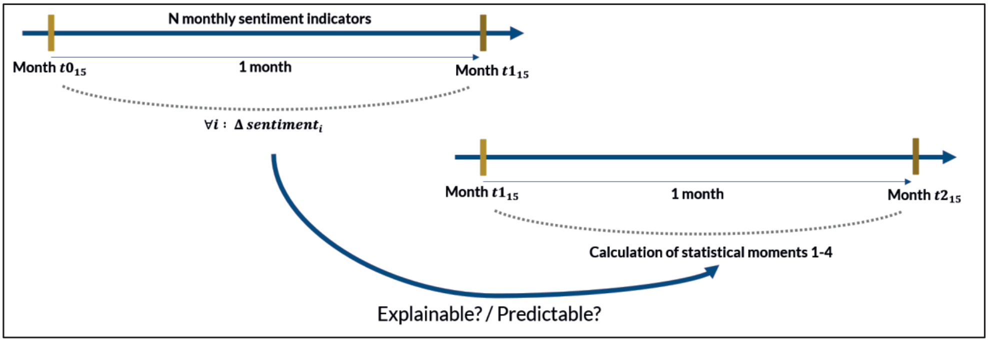

Fig. 12. Hypothesis in this analysis

Source: own study.

Since the sentiment is not time-stable (Kozak et al. 2018) and highly complex, and a non-linear relationship to the statistical moments of return distributions is assumed, a neural network based on LSTM neurons can be used to account for these properties of sentiment. For this reason, cross-sectional methods for analysing the influence of sentiment on stock returns often lead to insignificant results. The study implemented a neural network with LSTM cells that can process data sequentially and keep its hidden state through time to explain future moments of the monthly return distribution of an equally weighted CDAX portfolio.

The authors assumed that LSTM-based models provide a high degree of applicability and outperform other models when it comes to learning from long-term dependencies among single sentiment indicators. LSTM's ability to forget, remember, and update the information pushes it one step ahead of *standard* Recurrent Neural Networks. Figure 13 provides an overview of how an LSTM cell functions in a neural network.

Originally introduced by Hochreiter and Schmidhuber (1997), LSTM cells have been since improved continually. An example of an LSTM cell is shown in Figure 13

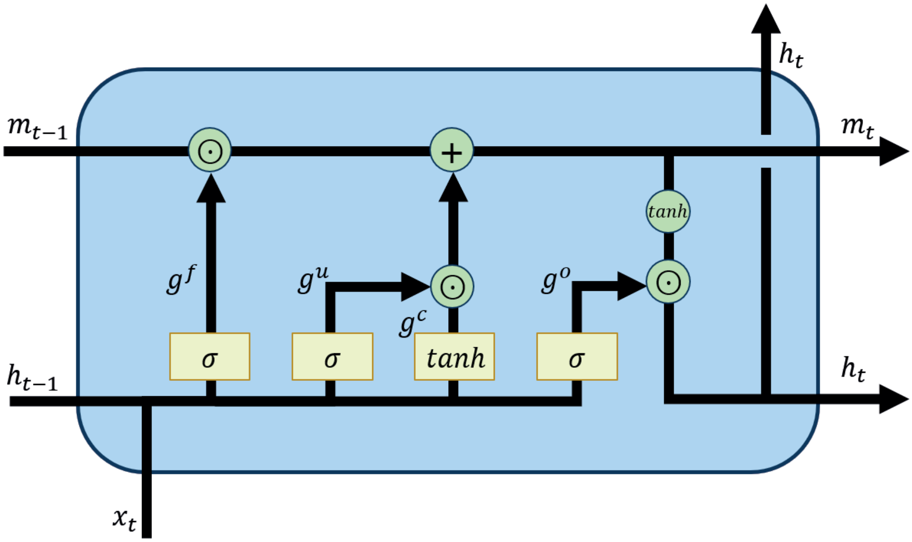

Fig. 13. LSTM cell

Source: representation based on Graves (2012).

where the yellow boxes represent neural network layers, while the green circles – pointwise operations. The arrows represent the vector transfer. Usually, two activation functions apply in an LSTM cell, namely a logistic sigmoid activation (Figure 14) represented by σ and the hyperbolic tangent (tanh) activation (Equations 1 and 2 and Figure 15).

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$tanh(x) = \frac{e^{2x}-1}{e^{2x}+1} \tag{2}$$

In the bottom left corner of Figure 13, it is determined which information from the memory vector m_{t-1} should be forgotten. The logistic sigmoid layer that decides this is also called the *forget-gate layer*. This is of relevance if a certain sentiment indicator no longer provides an explanatory contribution for the return distribution moment at a certain point in time. The hidden vector h_{t-1} and input values x_t are considered and a value between 0 and 1 is output for each number in the memory vector. Subsequently, it is determined which new information is to be stored in the cell state. The *input-gate layer*, which contains a sigmoid activation, decides which values are to be updated (g^u). A hyperbolic tangent activation layer generates a vector with new candidate values (g^c). Both are combined in a pointwise operation and update the cell status. The LSTM cell output is based on the updated cell status m_t.

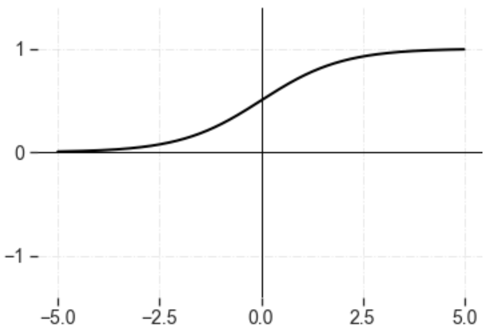

Fig. 14. Logistic sigmoid activation

Source: own study.

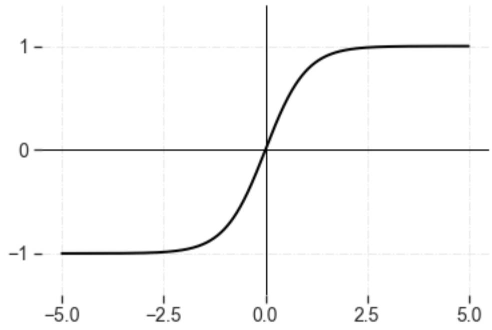

Fig. 15. Hyperbolic tangent activation

Source: own study.

A sigmoid layer (g^o) determines which parts of the cell status should be output. The cell state passes through a hyperbolic tangent layer to normalize the values to a range from –1 to 1 (see Figure 15). The pointwise multiplication outputs a normalized and filtered part of the cell stat (h_t). Graves (2012) and Karim et al. (2018) described the process at time step t as follows:

$$g^u = \sigma\left(\boldsymbol{W}^{\boldsymbol{u}} h_{t-1} + \boldsymbol{I}^{\boldsymbol{u}} x_t\right), \tag{3}$$

$$g^f = \sigma\left(\boldsymbol{W}^{\boldsymbol{f}} h_{t-1} + \boldsymbol{I}^{\boldsymbol{f}} x_t\right), \tag{4}$$

$$g^o = \sigma\left(\boldsymbol{W}^{\boldsymbol{o}} h_{t-1} + \boldsymbol{I}^{\boldsymbol{o}} x_t\right), \tag{5}$$

$$g^c = \tanh\left(\boldsymbol{W}^{\boldsymbol{c}} h_{t-1} + \boldsymbol{I}^{\boldsymbol{c}} x_t\right), \tag{6}$$

$$m_t = g^f \odot m_{t-1} + g^u \odot g^c, \tag{7}$$

$$h_t = \tanh\left(g^o \odot m_t\right), \tag{8}$$

with $\odot$ for pointwise multiplication, $\boldsymbol{I}^{\boldsymbol{u}}$; $\boldsymbol{I}^{\boldsymbol{f}}$; $\boldsymbol{I}^{\boldsymbol{o}}$; $\boldsymbol{I}^{\boldsymbol{c}}$ for projection matrices, and $\boldsymbol{W}^{\boldsymbol{u}}$; $\boldsymbol{W}^{\boldsymbol{f}}$; $\boldsymbol{W}^{\boldsymbol{o}}$; $\boldsymbol{W}^{\boldsymbol{c}}$ for recurrent weight matrices. In the authors' assessment, this process, which is presented here in a slightly simplified form, is well suited for the application of sentiment-based explanations of return distribution through the ability to learn temporal dependencies in sequences. For further information see Graves (2012); Karim et al. (2018).

In the first preliminary step, it was generally examined whether the neural network can adapt sufficiently well to the characteristics of sentiment. The authors applied RMSprop as a gradient descent optimization algorithm in the sequential model since it is suitable for optimizing a non-convex objective (Soydaner 2020). This first investigation included all observations and showed that a very flexible two-layered LSTM neural network with a 20-period rolling look-back window can adapt very well over 10000 epochs, which is reflected in the high predictive power of the labelled training data based on sentiment.

5. IMPLEMENTATION AND RESULTS

5.1. Pre-training and initial plausibility checks

The main finding during preliminary training was that it is possible to create a model with a very good fit for the explanation of each statistical moment based on sentiment. This is an important initial finding since it is known that any mathematical function can be approximated with a neural network designed according to the respective application. To do this, however, a function to which the model can adapt must also exist in the background. The relation between sentiment and the moments of future distributions of returns must therefore not be completely random. The following results were achieved: in a labelled training scenario over all the moments with 10000 epochs, all the moments (mean – Figure 16, variance – Figure 17, skewness – Figure 18, and kurtosis – Figure 19) are likely to be explained well by the selected 73 sentiment indicators, using a neural network with two LSTM layers. Since the present problem is not a classification or categorisation problem, no accuracy metric can be defined here. However, the accuracy of the fit is described by R^2 as the square of Pearson's correlation coefficient, a two-sided t-test, and the MSE. For the first moment (see Figure 16), the R^2 is .9993, the p value of a two-sided t-test is .9920 (here: retaining the null hypothesis that the mean value of the forecast sample fitted based on labelled training data does not differ from the mean value of the actual sample). The MSE is $4.6446 \cdot 10^{-5}$. The metrics and the graph reflect a very good model fit for returns. Similar results were obtained in training for scaled

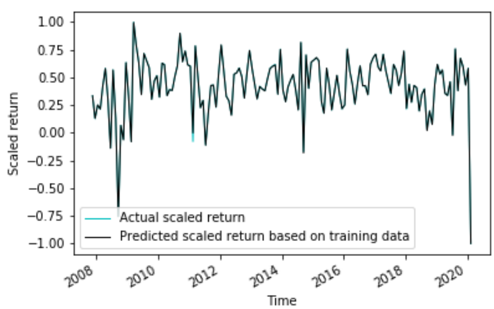

Fig. 16. Training first moment

Source: own study.

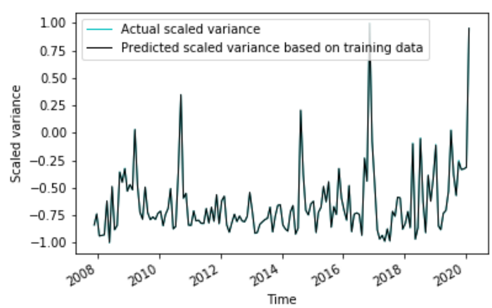

Fig. 17. Training second moment

Source: own study.

variance. For the second moment the R^2 is 1.0000, the p value .9894. The MSE is $5.0222 \cdot 10^{-6}$.

Although the fit to skewness and kurtosis in training is marginally worse than for the first two moments, one can still consider it a good model fit. For the third moment, R^2 is 1.0000, the p value is .9688. The MSE is $5.8810 \cdot 10^{-6}$.

The fourth moment, kurtosis, shows the least good results. For the fourth moment, R^2 is .9897, the p value .9229. The MSE is $9.3728 \cdot 10^{-4}$. A poorer fit is also visible in the graph in the case of kurtosis (Figure 19). Between 2012 and 2014 an amplitude cannot be explained by the sentiment model.

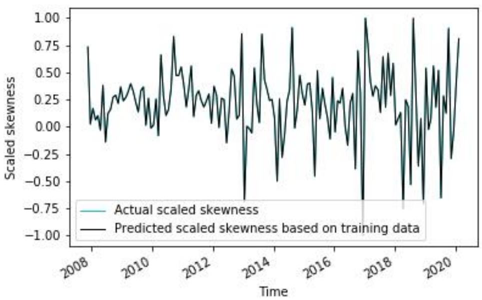

Fig. 18. Training third moment

Source: own study.

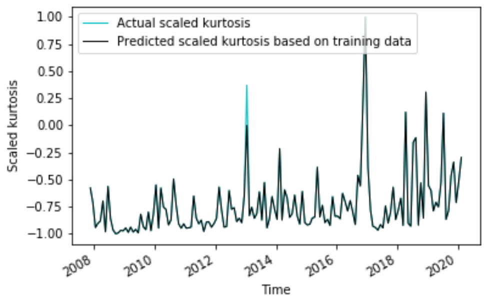

Fig. 19. Training fourth moment

Source: own study.

The MSE (loss) for the models that are based completely on training data all asymptotically approach 0 after 2000 epochs. The loss shows the deviation between the sentiment-based prediction of the model and the actual value. Since little spikes can be observed in the loss plots for all moments, it can be assumed that none of the loss functions is actually convex. The loss is minimized by a gradient descent procedure over each epoch.

5.2. Training of a prediction model and prediction based on test data

Since the actual loss function is not known, the authors decided to train again the models for prediction based on test data only to the first sustainable minimum, knowing that these may be local minima of the loss functions. Sustainable minimum means here that it is a minimum of the loss which was not caused by an outlier value (negative spike), but is consistent with the development of the loss values in the previous and subsequent epochs. To train a predictive model, the authors also added a hidden dropout layer between the two LSTM layers that randomly selects 10% of neurons to be ignored during training. Although the models tend to be underfitting the training data as a result, this makes them fundamentally more suitable for trend forecasting in different market situations. The dataset was split so that all but the last two data points (COVID-19 time window) were labelled as training data. Predicting two data points has the advantage that in addition to assessing the precision of the prediction of moments, it is also possible to check whether the models can fully predict a trend. The loss plots of the individual models with training and test data are shown in Figures 20 to 23.

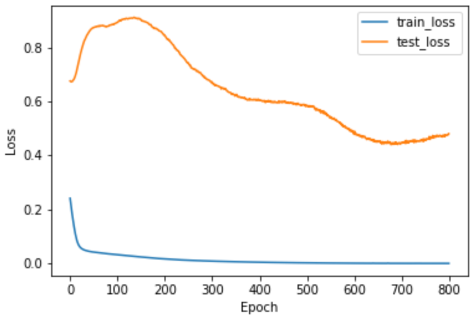

Fig. 20. Training/test history first moment

Source: own study.

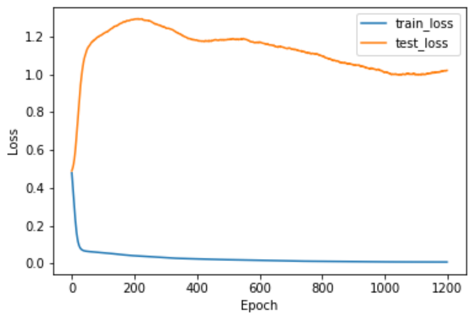

Fig. 21. Training/test history second moment

Source: own study.

For the first moment about 800 epochs were necessary to identify the first sustaining minimum that could be identified at epoch 678. For the second moment 1200 epochs were chosen. The first sustaining minimum was identified at epoch 1054. It is noticeable that the training loss again asymptotically approached 0.

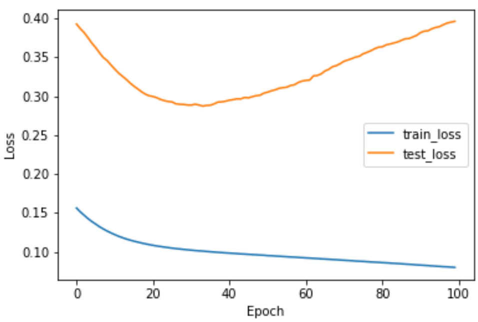

Fig. 22. Training/test history third moment

Source: own study.

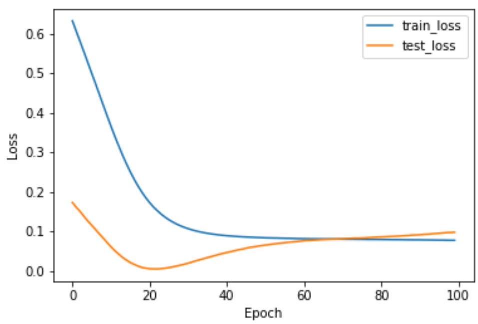

Fig. 23. Training/test history fourth moment

Source: own study.

For the moments of skewness and kurtosis only 100 epochs each were needed to identify the first sustainable minima, which could be identified for skewness at epoch 34 and for kurtosis at epoch 23. However, it must be assumed that these are local minima. In addition, the training loss does not asymptotically approach 0, which corresponds to a relatively strong underfitting to the training data. When the predictive models were fitted based on the training data, that the first loss minimum of the test data has been identified, the predictive power and the model qualities of the prediction models could be then analysed. For the first moment, R^2 is .9135, the p value is .9486. The MSE is $6.1326 \cdot 10^{-3}$. During the COVID-19 window, the actual drop in scaled return was –1.5851, while the model, which was not trained on the test data, predicted a drop in scaled return of –0.6876 (see Figure 25). While the model was not able to predict the amplitude of the drop in scaled return correctly, it was able to predict the trend.

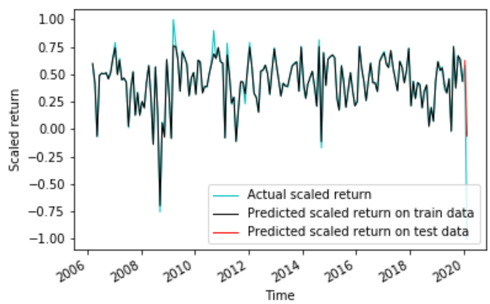

Fig. 24. Prediction first moment

Source: own study.

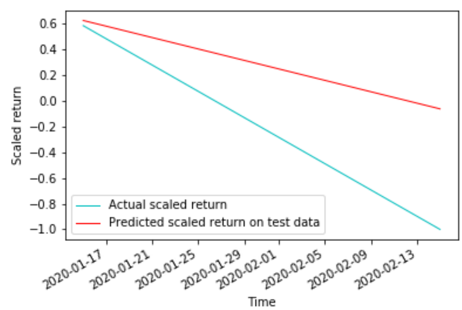

Fig. 25. COVID-19 time window

Source: own study.

For the second moment, R^2 is .7899, the p value is .5791. The MSE is 0.0204. During the COVID-19 window, the actual rise in scaled variance was 1.2308, while the model which was not trained on the test data, predicted a rise in scaled variance of 0.1405 (see Figure 27). Again, the model was not able to predict the amplitude of the rise in scaled return correctly, but it was able to predict the trend. Unlike for the first moment, it became clear that the amplitudes in the high and especially in the low scaled variance range were not explained.

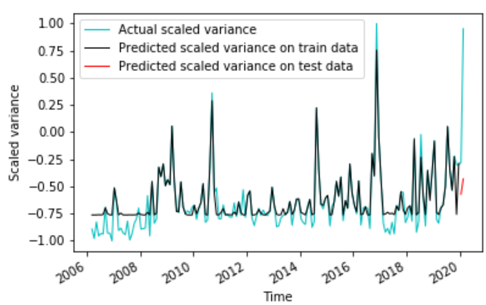

Fig. 26. Prediction second moment

Source: own study.

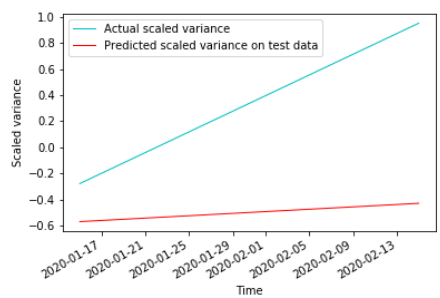

Fig. 27. COVID-19 time window

Source: own study.

For the third moment, R^2 is .0615, the p value is .3197. The MSE is 0.1026. During the COVID-19 window, the actual rise in scaled skewness was 0.4028, while the model which was not trained on the test data, predicted a rise in scaled skewness of 0.1829 (see Figure 29). Just like for the first and the second moment, the model was not able to predict the amplitude of the rise in scaled skewness correctly, but it was able to predict the trend.

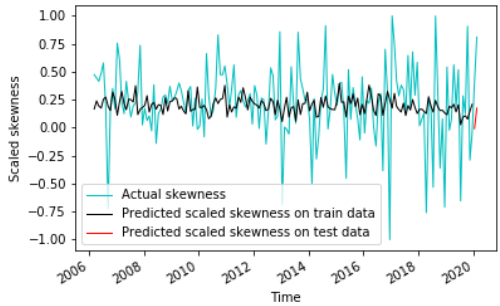

Fig. 28. Prediction third moment

Source: own study.

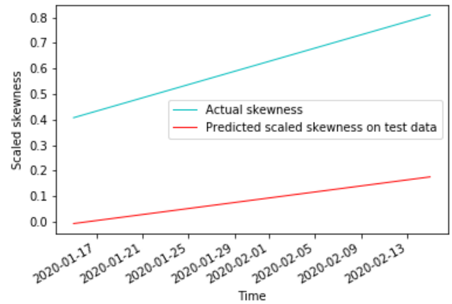

Fig. 29. COVID-19 time window

Source: own study.

For the fourth moment, R^2 is .0422, the p value is $8.5121 \cdot 10^{-102}$ (here: rejecting the null hypothesis that the mean value of the forecast sample fitted based on training data does not differ from the mean value of the actual sample). The MSE is 0.1457. During the COVID-19 window, the actual rise in scaled kurtosis was .2250, while the model which was not trained on the test data, predicted a rise in scaled kurtosis of 0.0780 (see Figure 31). As previously, the model was not able to predict the amplitude of the rise in scaled kurtosis correctly, but it was able to predict the trend.

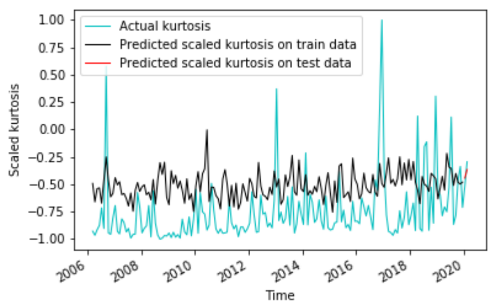

Fig. 30. Prediction third moment

Source: own study.

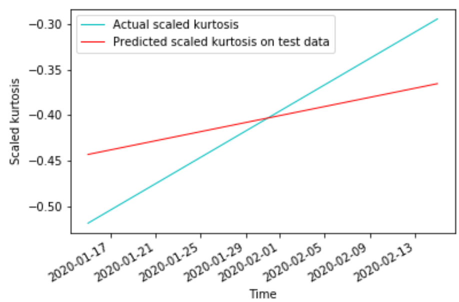

Fig. 31. COVID-19 time window

Source: own study.

The first sustaining loss minimum at both the third and fourth moments for the test data could be determined after relatively few epochs compared to the first two moments, so both moments are relatively less adapted to the training data. This underfitting is reflected both in the forecast graphs and in the model metrics. When comparing the model metrics, however, it became clear that the model quality for the fourth moment was worse than in the other models. This is evident from the fact that the lowest R^2 value was obtained for this model. It is also the only model that rejects the null hypothesis (no differences in means) based on the two-sided *t*-test. Further research is needed here to check whether the trend prediction also works in the long term or whether the observed fit is merely coincidental.

CONCLUSION AND OUTLOOK

This study postulates that sentiment from different sources in a neural network based on LSTM cells can explain, on a monthly basis, all moments of future return distributions of an equally weighted portfolio covering the majority of the market capitalization relevant stocks in Germany. Furthermore, the authors were able to observe that sentiment for the first three moments can satisfactorily forecast the trend of future developments on the German stock market on a monthly basis during the COVID-19 window. For the fourth moment (kurtosis), the results obtained to date are not clear enough to support a decision. However, this study adds important value for predicting stock trends.

This work also makes a valuable contribution to explaining stock market returns and stock market volatilities in times of turmoil. In addition to various insights for the US-market (Albulescu 2021; Zhang et al. 2020), the Chinese market (Jiang et al. 2021), the Indian market (Sreelakshmi et al. 2021), and the Saudi-Arabia market (Hadi and Shabbir 2021), this study adds contemporary insights to the puzzle of sentiment-based return explanation during the crisis, and shows that an innovative neural network based approach is suitable for further research in this matter. However, for the other moments there are not enough predictive observations on test data to support the first impression with further metrics. The authors considered the market distortions in the German stock market caused by the global COVID-19 pandemic as an event to be investigated and were able to partially support their hypotheses. The research results show that sentiment is an appropriate measure to explain the moments of return distribution in the following period.

As far as prediction is concerned, the results are less accurate and require further investigation. For return and variance, however, a good sentiment-based trend prediction could be achieved based on first preliminary perceptions. From the academic perspective, the results can be valuable for portfolio risk management. As part of further research, it would be interesting to extend the analysis to different time horizons such as a weekly and daily index covering all sentiment categories.

Furthermore, a portfolio simulation over a longer period of time would be worthwhile in order to evaluate the performance of sentiment-based trading decisions against a benchmark. Using neural network-based technology to solve this kind of problems related to the long-term dependencies of certain factors to an independent variable is not novel, but the possibility to publicly access the needed computational power, e.g. via cloud services, makes rigorous research into such problems far more feasible. Finally, further research will show whether the exemplary results obtained in this study on the German stock market can be applied to other countries.

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APPENDIX 1

List of sentiment-indicators considered

Indicator	Source/TRDS Mnemonic	Reference
1	2	3
BD CONSUMER CONFIDENCE INDICATOR – GERMANY SADJ (GFK)	BDCNFCONQ	Finter et al., 2012
BD G – MIND: GERMAN MARKET INDICATOR–STOCKS(RANGE –10 TO +10) NADJ (G–Mind)	BDGMSTCKR	Finter et al., 2012
SENTIX NEUTRAL 1 M –DAX INDEX – ECONOMIC SERIES	DAXINU1	Finter et al., 2012
DAX (XETRA) TURNOVER – TURNOVER BY VALUE	FFOVDAX	Finter et al., 2012
Delta of in- and outflows of German open end equity mutual funds	Deutsche Bundesbank, own calculations	Finter et al., 2012
Equity issuance to aggregated debt issuance, E/D ratio	Deutsche Bundesbank, own calculations	Finter et al., 2012
EUREX BOND OPTIONS PUT/CALL RATIO – PRICE INDEX	EUXBFPC	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
EUREX INDEX OPTIONS PUT/CALL RATIO – PRICE INDEX	EUXDIPC	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
EUREX STOCK OPTIONS PUT/CALL RATIO – PRICE INDEX	EUXCAPT	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
EUREX TOTAL OPTIONS PUT/CALL RATIO – PRICE INDEX	EUXTOTL	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IFO BUSINESS CLIMATE GERMANY: BUS CLIMATE, INDEX VOLA	BDCNFBUSQ	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD CPI: TOTAL NADJ	BDCONPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD NEW PASSENGER CAR REGISTRATIONS VOLN	BDCAR...P	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD UNEMPLOYMENT: \% CIVILIAN LABOUR(\% DEPENDENT LABOUR TO DEC 196	BDUN\%TOTR	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

Appendix 1, cont.

1	2	3
BD CONSUMER CONFIDENCE INDICATOR – GERMANY SADJ	BDCNFCONQ	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IFO BUSINESS CLIMATE GERMANY EXPECT IN 6MO, INDEX VOLA	BDCYLEADQ	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD INDL PROD: MANUFACTURING (CAL ADJ) VOLA	BDIPMAN.G	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD DAX SHARE PRICE INDEX, EP NADJ	BDSHRPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD INDL PROD: INDUSTRY INCL CNSTR (CAL ADJ) VOLA	BDIPTOT.G	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD CPI (\%YOY) NADJ	BDCONPR\%F	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD MANUFACTURING ORDERS (CAL ADJ). VOLA	BDNEWORDG	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD CURRENT ACCOUNT BALANCE CURN	BDCURBALA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EMPLOYED PERSONS (RESIDENCE CONCEPT, ILO) VOLA	BDEMPTOTO	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EXPORTS OF GOODS (FOB) CURA	BDEXPGDSB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD HICP: TOTAL NADJ	BDCPHARMF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD NEW ORDERS RECD: CNSTR – RESL CNSTR VOLA	BDHOUSE.G	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD RETAIL SALES EXCL CARS (CAL ADJ) X-12 – ARIMA VOLA	BDRETTOTG	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD RETAIL SALES EXCLUDING CARS INDEX VOLN	BDRETTOTH	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

1	2	3
BD BOP CAPITAL \ FINANCIAL ACCOUNT BALANCE (PAN BD M0790) CURN	BDCAFBALA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD BOP: VISIBLE TRADE BALANCE CURA	BDVISBOPB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EMPLOYED PERSONS (RESIDENCE CONCEPT) (\%YOY) VOLA	BDEMPTO\%O	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EUROPACE HEDONIC HOUSE PRICE COMPOSITE INDEX NADJ	BDHOUPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EXPORTS FOB (PAN BD M0790) (\%YOY) CURA	BDEXPBO\%B	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD FIBOR – 3 MONTH (MTH.AVG.) NADJ	BDINTER3	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD GERMAN MARKS TO US\$ (MTH. AVG.) NADJ	BDXRUSD.	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IMPORTS OF GOODS (CIF) CURA	BDIMPGDSB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD INSOLVENCIES – BUSINESS ENTERPRISES VOLN	BDBNKRPTP	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD INTERNATIONAL RESERVES CURN	BDRESERVA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD LENDING TO ENTERPRISES \ INDIVIDUALS CURN	BDBANKLPA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD MNY.SUPL–M3(CONTRIB TO EUR BASIS FM.M0195), FM M06 2010 EXC	BDM3....B	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD MONEY SUPPLY – GERMAN CONTRIBUTION TO EURO M1(PAN BD M0790)	BDM1....A	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD MONEY SUPPLY – M2 (CONTRIBUTION TO EURO BASIS FROM M0195) CURA	BDM2....B	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

Appendix 1, cont.

1	2	3
BD PPI: INDL. PRODUCTS, TOTAL, SOLD IN THE DOMESTIC MARKET NADJ	BDPROPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD PRODUCTIVITY: OUTPUT PER MAN-HOUR WORKED, M\Q\MFG SCT(B+C)	BDPRODVTQ	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD RETAIL SALES EXCL CARS (CAL ADJ) X–12–ARIMA SADJ	BDRETTOTE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD TERMS OF TRADE (PAN BD FROM 1991) NADJ	BDTOTPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD TOTAL EXPORTS OF GOODS CURN	BDEXPBOPA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD TOTAL IMPORTS OF GOODS CURN	BDIMPBOPA	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD UNEMPLOYMENT LEVEL (PAN BD FROM SEPT 1990) VOLN	BDUNPTOTP	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD VACANCIES (PAN BD FROM M0790) VOLN	BDVACTOTP	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD VISIBLE TRADE BALANCE CURA	BDVISGDSB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD WAGE \ SALARY,OVERALL ECONOMY–ON A MTHLY BASIS (PAN BD M0191)	BDWAGES.F	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
SALARY: ON HRLY. BASIS – PRDG. SECTOR (BDHRWAGEF) NADJ	BDWAGMANF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EXPORT PRICE INDEX NADJ	BDEXPPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IMPORT PRICE INDEX NADJ	BDIMPPRCF	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IMPORTS CIF (PAN BD M0790) (\%YOY) CURA	BDIMPBO\%B	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

1	2	3
BD MONEY SUPPLY M0 CURN	BDM0...A	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD WAGE\SALARY, OVERALL ECONOMY – ON A MTHLY BASIS (\%YOY) NADJ	BDWAGES\%F	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD WAGE\SALARY, HRLY.BASIS – PRDG. SECTOR (BDHRWAGEF) (\%YOY) NADJ	BDWAGMA\%F	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD INFLATION NADJ	BDCPANNL	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD UNEMPLOYMENT REGISTERED (PAN BD FROM JAN 1992) (CAL ADJ) VOLA	BDUNPTOTO	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD CPI (CAL ADJ) SADJ	BDCONPRCE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD MANUFACTURING ORDERS SADJ	BDNEWORDE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD BOP: EXPORTS FOB CURA	BDEXPBOPB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD BOP: IMPORTS CIF CURA	BDIMPBOPB	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD BUSINESS EXPECTATIONS (PAN GERMANY) (\%YOY) SADJ	BDCYLE\%D	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD COMPOSITE LEADING INDICATOR – TREND RESTORED SADJ	BDCYLEADT	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD EXPORT PRICE INDEX (CAL ADJ) SADJ	BDEXPPRCE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD IMPORT PRICE INDEX (CAL ADJ) SADJ	BDIMPPRCE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD TERMS OF TRADE (ON THE BASIS OF PRICE INDICES) (CAL ADJ) SADJ	BDTOTPRCE	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

Appendix 1, cont.

1	2	3
BD US \$ TO 1 EURO (DEUTSCHEMARK DERIVED HISTORY PRIOR 1999) NADJ	BDXRUSE.	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD VACANCIES (DEC 1999 ONWARDS NEW DEFINITION) VOLA	BDVACTOTO	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY
BD WAGES\SALARIES: PER UNIT OF OUTPUT, M\Q\MFG SCT (B+C) VOLA	BDLCOST0G	TRDS Key Indicator List for Germany Mnemonic: M\#BDKEY

APPENDIX 2

Equations used for determination of return–distribution moments

$$Variance = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2$$

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \overline{x}}{\sigma}\right)^3$$

$$Kurtosis = \frac{N(N+1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{x_i - \overline{x}}{\sigma}\right)^4 - \frac{3(N-1)^2}{(N-2)(N-3)}$$