Eidgenössische Technische Hochschule Zürich
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Social Data Science: Project Report

Collective Mood-States and Investment Behaviour during a Global Pandemic

A Case Study on the Social Impact of COVID-19.

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Abbreviations

ACF Autocorrelation Function

ADF Augmented-Dickey-Fuller

API Application Programming Interface

DJI Dow Jones Industrial Average

EMH Efficient Market Hypothesis

EU Expected Utility

IID Independent and Identically Distributed

LSTM Long short-term memory

MARE Mean Absolute Rescaled Error

MDA Mean Directional Accuracy

NLP Natural Language Processing

PACF Partial Autocorrelation Function

ROC Receiving Operating Characteristic

SP Standard & Poor's

STF Social Theory of Finance

VAR Vector Autoregression

1 Introduction

Among the countless decisions that humans do in their lives, those involving investments have been especially focused on by scientists. Standard economic theory assumes agents in markets respond rationally (in the standard meaning of the term) to the events in the real world and that the price levels represent the real world accurately. There is, however, a substantial body of empirical evidence that refutes this assumption. According to it, agents do not act rationally, and prices do not represent the real world, at least not entirely. To gain an empirically more adequate understanding of *human* decision-making, one approach has been to investigate the role emotional states play in cognitive processes that guide decisions.

An early approach that describes how equity markets behave, which remains influential, is the Efficient Market Hypothesis (EMH) (Fama, 1965). In its strongest form, it states that changes in market prices perfectly reflect the available information. Therefore, since new information is random, it is impossible to predict the market and prices are thus *fair*, in that they value stocks properly according to the contingent state of the world. How people make decisions involving risk, such as investment decisions, can be modelled by the Expected Utility (EU) framework. It states that people assign subjective probabilities to possible outcomes and integrating this information to an expected utility calculus (Loewenstein et al., 2001), where the way the subjective likelihoods are updated in reaction to new information follows Bayes' rule (De Bondt and Thaler, 1985). This allows people to react "rationally" to any given contingency. Empirical findings, however, refute this, showing that humans instead tend to *overreact* (De Bondt and Thaler, 1985). That is, they overweight the importance of newly available information and underweight prior beliefs (Tversky and Kahneman, 1974), which results in behaviour that is too strong or excessive, given the empirical facts (Arrow, 1982, p.5). Overreacting agents hence render market trends predictable by events of the immediate past (De Bondt and Thaler, 1985).

To explain this "irrational" overreaction, psychologists and economists have started recently to investigate the role emotions play in human decision-making. One approach is put forward by Loewenstein et al. (2001). their model of the decision-making process integrates emotion states. It proposes a symmetric relation between *cognitive evaluations*, as they are understood under EU, and *emotional responses*, reciprocally influencing each other. According to this theory, the decision-maker takes as inputs not only the set of possible choices and their corresponding subjective probabilities but also takes into account other factors, such as the vividness with which risk is pictured, immediacy and as we will see in more detail, the current reigning collective mood.

Generally, collective mood can be understood as a mood or sentiment that is largely correlated across a population (Bar-Tal et al., 2007). Its emergence can occur endogenously within a population or exogenously induced by external events (Frank Schweitzer, 2010). To simplify things, however, we will only consider collective mood resulting from external events. Now, if we allow for emotions to enter investment-decisions, collective mood should too play a role, and more importantly, have significant and observable consequences on markets. In their seminal paper on the relation between collective mood and stock market prices, Bollen et al. (2011) investigate whether and how collective mood can be used to predict stock prices. They take sentiment, as it is revealed in Twitter *tweets*, as an indicator for the current general collective mood in a population and conduct Granger-causality tests correlating Twitter sentiment and stock prices over time.[1] They find that indeed certain emotions have a predictive effect over the stock market. These results, however, do not give us much insight

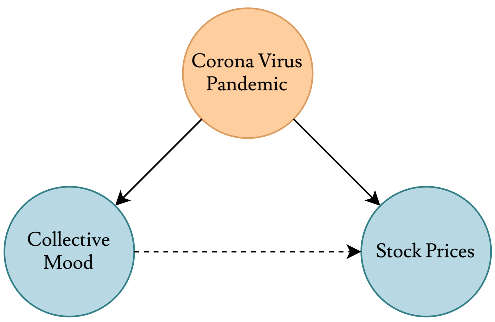
[1]Note that it is not explicitly stated what might be the source for collective mood. However, the authors seem to acknowledge real events as causes for collective mood since they validate their sentiment analysis tool by comparing the analysed sentiment from Twitter with events such as the US presidential elections, to validate their sentiment analysis tool.

and understanding about decision-making in relation with collective mood, since they, as the authors also admit, do not adequately address the causal mechanisms that "may connect online public mood states with [stock prices]" (Bollen et al., 2011, p.7). In the following, we will conjecture, informed by the aforementioned theory, about possible causal mechanisms through which collective mood could influence stock prices.

As has been outlined before, investment behaviour can be modelled as two sorts of reactions to new information, a rational one that follows the EU framework, and an overreaction influenced by emotions, much like Loewenstein et al. lay out. The rational reaction depends only on available information about the world; causally, we interpret it as a direct effect from *real events* to *stock prices*. We take an overreaction to happen when new information about the world triggers a sentiment in many agents, creating a collective mood, which can affect investment behaviour and thus additionally influence stock prices. We interpret this additional influence as a second causal path going first from *real events* to *collective mood* and then from *collective mood* to *stock prices*. As a result, the effect we are interested in, which is the one *collective mood* has on *stock prices*, is confounded by *real event*.[2]

In this paper, we want to investigate whether collective mood, triggered by a real event, has some influence on stock prices considering a causal structure that defines the mechanisms by which collective mood affects stock prices. We take the 2019-2020 coronavirus (SARS-CoV-2) pandemic to be an appropriate example of a real event that influences stock prices directly and causes a change in collective mood. The pandemic affects the world economy and has high media coverage; we assume thus an impact on stock markets. It represents an exogenous variation in the set of beliefs individuals have about the world but also affects their emotional states significantly (which allows us to investigate the role emotional states play in investment behaviour in the first place). Figure 1 represents the causal structure encoding our assumptions about the underlying causal mechanisms. The bolt arrow represents causal effects which we take as given; the dashed arrow stands for a possible but unconfirmed effect. To measure the variation in collective mood states, we develop a tailor-made sentiment analysis tool classifying tweets into positive/negative, active/passive and weak/strong to build a time series reflecting average Twitter sentiment over time. We perform on the resulting sentiment time series a Vector Autoregression (VAR) analysis by regressing the Standard & Poor's (SP) 500 and Dow Jones Industrial Average (DJI) index to our sentiment time series. Subsequently, by conducting Granger causality tests followed by a Johansen co-integration test, we investigate whether our sentiment categories have an effect on stock prices.

Figure 1: Causal Diagram



Intuitively, we would expect *active* and *strong* sentiment to be predictive of changes in prices. Further, we would expect the direction of stock price changes to be predictable by *positive* (*negative*)

[2]The two reactions need not be separate from each other; they can happen simultaneously and in the same mind. However, for the sake of understanding and simplicity we treat them as independent.

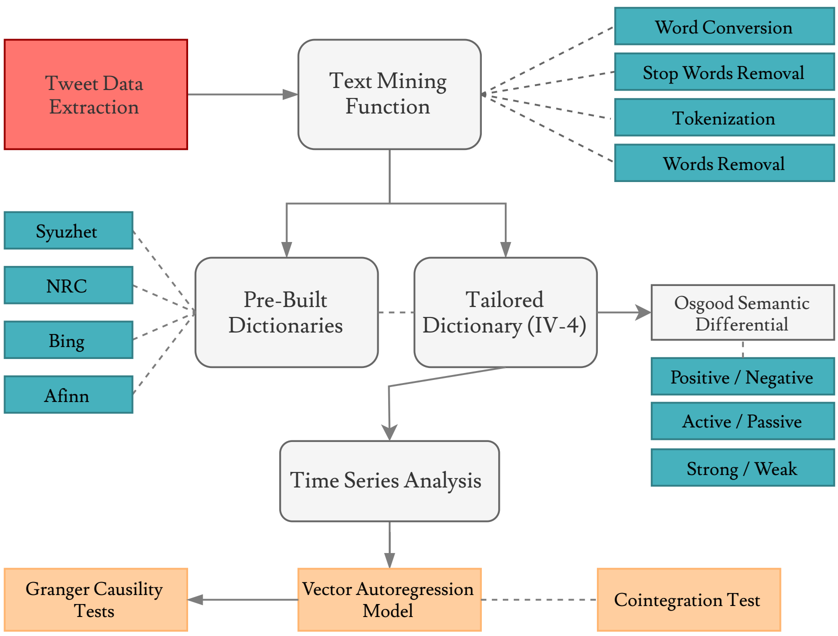
sentiment, reflecting positive (negative) expectations.

Our results show that *active* sentiment with a one-day lag is predictive of stock prices in various model specifications. We are reluctant to identify this as a causal effect, however, since the finding is based on severe shortcomings, namely a lack of sufficient observations and the inability to control for a common cause, in this case, the spread of the coronavirus. Nonetheless, it confirms Bollen et al.'s hypothesis that Twitter sentiment can be predictive for stock prices.

2 Methodology and Results

This section gives an overview of our process. To analyse the sentiment of tweets, we develop a tailor-made dictionary approach following the semantic differential presented by Charles Osgood in Osgood et al. (1957). Hereafter, we validate our tailored dictionary and compare it to standard dictionaries like Syuzhet, NRC, Bing and Afinn. We use our dictionary to construct sentiment time series and analyse them specifying a VAR and conducting Granger causality tests which are then accompanied by Johansen co-integration tests. Our strategy is presented in Figure 2.

Figure 2: Illustration of the Workflow



2.1 Sentiment Analysis

2.1.1 Data

As of April 27th in 2020, more than 3 million cases of coronavirus have been reported in 185 countries, resulting in more than 211,000 fatalities.[3] As a result, the topic has become a subject of intense discussion in social media and in particular on Twitter. For our study we have (as of April 21st) gathered Twitter ID's of over 30 million tweets, of which we analyse a random sample of 500,000 tweets, due to computational constraints.

[3]Information about the spread of COVID-19 has been retrieved from Coronavirus Resource Center of John Hopkins University.

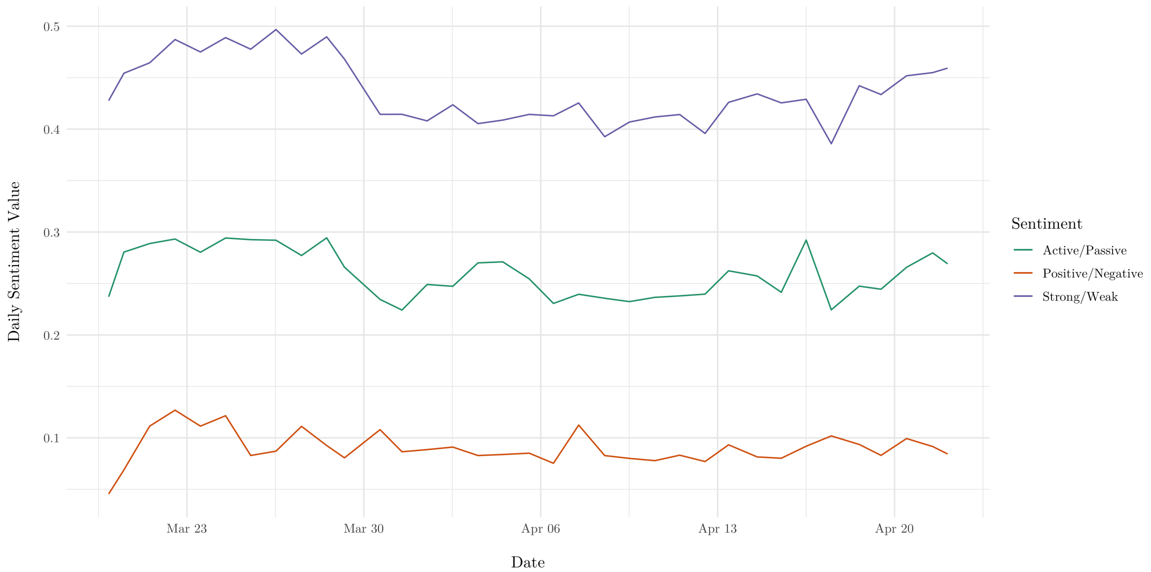
2.1.2 Text Mining: Developing a Tailored Dictionary Approach

We retrieved tweets directly from the Twitter Search Application Programming Interface (API) for a longer time frame than the seven days for free subscribed users. We used a dataset in the IEEE Dataport, which generates a high number of Twitter IDs daily with regards to COVID-19 for a Long short-term memory (LSTM) model using the filters for language *en* and keywords *corona*, *coronavirus*, *covid*, *covid19* and variants of *sarscov2*.

Our tailored dictionary is based on specific categories of the Harvard IV-4 dictionary. The chosen categories, particularly the adjective pairs of positive/negative, active/passive and strong/weak, correspond to the factors of *evaluation*, *potency*, and *activity* which Osgood (1964) found to be the most semantically descriptive in a pan-cultural multivariate analyses.

We develop three sentiment scores, which reflect these three semantic attitudes. To retrieve sentiments of the tweets, they had to undergo a pre-processing, allowing them to be made comparable with our lexicons comprising the six dimensions mentioned. To analyse the sentiment indices in a time series context, we opted to generate daily averages, since intra-day data for the SP 500 and DJI indices were not available.[4] This would have enabled us, for instance, to perform hourly comparisons with the sentiment indices. In Figure 3, we present a comparison of the three sentiment scores of our tailored approach. A comparison with pre-built dictionaries is provided in the appendix in Figure 4.[5]

Figure 3: Daily Sentiments of the Tailor-Made Dictionary



2.1.3 Validating our Text Mining Approach

Testing our tailored approach for its performance, validating and placing it in the context of other pre-built lexicons is crucial for successful sentiment analysis. For that purpose, a validation set of 200 tweets corresponding to the six dimensions of our approach was hand-labelled and then compared with the predictions of our algorithm. Subsequently, we generated ROC curves, which are shown in the Figures 6a and 6b in the Appendix. According to our validation, we find that our tailor-made

[4]Figure 5 illustrates the comparison between the positive/negative sentiment score and the SP 500 index (rescaled on the interval [-1,1]).

[5]Owing to the fact that we computed daily averages of each sentiment score, the indices are smoothed and stand at high levels compared to pre-built lexicons as it is presented in Figure 4.

approach is approximately as well performing as pre-built lexicons, as shown in Figure 6b. Additionally, we present various performance metrics such as accuracy, recall or Mean Directional Accuracy (MDA) and Mean Absolute Rescaled Error (MARE) for each sentiment series.

2.2 Time Series Analysis

2.2.1 A Simple Vector Autoregressive Model (VAR)

The analysis of the SP 500 and DJI indices grounds primarily on a VAR representation. To model the p-dimensional process, we first define an information set as $\{\mathsf{S}_t\} = \{p_t, (\mathsf{pos} - \mathsf{neg})_t, (\mathsf{strong} - \mathsf{weak})_t, (\mathsf{active} - \mathsf{passive})_t\}$. Based on this information set, we specify the following VAR model:

$$p_t = \mathit{\Pi}_1 \mathsf{S}_{t-1} + \mathit{\Pi}_2 \mathsf{S}_{t-2} + \cdots + \mathit{\Pi}_k \mathsf{S}_{t-p} + \epsilon_t, \quad t = 1, \ldots, T \tag{1}$$

Where we assume that ϵ_t follows an Independent and Identically Distributed (IID) Gaussian process with zero mean and covariance matrix $\mathit{\Gamma}$, i.e. $\epsilon_t \sim N(0, \mathit{\Gamma})$ (Stock and Watson, 2015).

Following the analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots and by the implementation of several specifications, we opted for the implementation of two systems: We specify our first VAR with $p = 2$ including $p = 0$. Our second VAR specification features $p = 3$. In addition, based on Augmented-Dickey-Fuller (ADF) tests, we analyzed the behavior of stationarity and decided to differentiate the price indices, $p'_t = p_t - p_{t-1}$. In each VAR specification, we opted for three models in which we first estimated a model without any price lags for the equity indices and once with price lags for the SP 500 and DJI index, respectively. The results of the specified VAR are presented in Table 1 and 2 in the Appendix.[6]

Analysing the VAR models reveals that across different specifications the coefficient for $(\mathsf{active} - \mathsf{passive})_t$ with $p = 1$ yields significant and positive coefficients consistently, whereas $(\mathsf{strong} - \mathsf{weak})_t$ mostly exhibits negative coefficients for $p = 1$. To our surprise, for $(\mathsf{pos} - \mathsf{neg})_t$ we could only determine significant coefficients in the third model, using $p'_{t,DJI}$ as the dependent variable, with $p = 3$.[7]

2.2.2 Testing For Causality and Cointegration

With the VAR specification defined in Equation 1, we a priori assume that all of our time series influence each other, consequently implying that lagged instances of a series determine the progression of a series. Using Granger Causality tests (Granger, 1969), we test the hypothesis that the coefficients of past instances in Equation 1 are zero and thus exert no influence on the progression of the equity indices. We would expect that some lagged instances of the sentiment variables in S_t do Granger-cause p'_t. The results of the Granger Causality tests of all lagged coefficients are presented in the Appendix in Table 4 and 5. Once again, it appears that $(\mathsf{active} - \mathsf{passive})_t$ and $(\mathsf{strong} - \mathsf{weak})_t$ exert significant influence on the progression of equity indices and, hence, constitutes a source of Granger causation.

By using a Johansen co-integration test, presented in Johansen (1991), we aim to investigate the existence of a co-integrating relationship between the time series. Following our defined hypothesis, we would expect that the sentiment variables have a co-integrating relationship with p'_t and thus exhibits a common stochastic trend. We apply the approach of trace statistics and test the null hypothesis that $H_0 : \text{rank}(\mathit{\Pi}) = r$ against $H_1 : \text{rank} \geq r + 1$, i.e. for checking the existence of a co-integrating

[6] To enable a robust estimation process, special attention was paid to extract robust standard errors using a function that performs z and (quasi-)t Wald tests for the estimated coefficients.

[7] Please note that the adjusted R^2 usually is quite low (especially in the first specification). The reason for this is because we have too few observations and thus obtain too few degrees of freedom for the estimation process.

relationship we set $r = 0$. Again, the results of the Johansen Co-Integration test are presented in the Appendix in Table 6. It is apparent that we are unable to detect any co-integration between the sentiment indices and the equity indices. The sentiment indices are merely co-integrating with each other, which we already suspected a priori.

3 Discussion

In this paper, we want to investigate whether the collective mood induced by the coronavirus pandemic has an effect on stock prices. We assume that the spread of the pandemic directly affects both people's mood states and stock prices. By using simple sentiment analysis techniques on tweets about the coronavirus, we determined a sentiment score for each day for a time frame of 38 days, which serves us as an indicator for the collective mood induced by the coronavirus pandemic during that time. We could then analyse how the identified collective mood and stock prices behaved with respect to each other during that time frame. We would expect *active* and *strong* sentiment to be predictive of changes in prices. Further, we would expect the direction of stock price changes to be predictable by *positive* (*negative*) sentiment, reflecting positive (negative) expectations.

The VAR shows a significant positive correlation between stock prices and *active* sentiment lagged by one day, as well as a negative correlation between stock prices and *strong* sentiment lagged by one day. The Granger Causality test shows that *active* and *strong* sentiment are Granger causative of stock prices. However, we are reluctant to call this finding a true causal effect since we assume that the event that caused the collective mood to be also a direct cause for the stock prices, thus acting as a confounding. We would have expected that adding sentiment scores with zero lag in the specification of the VAR model would help us to control for the confounder, but as it shows in the results, there is no such correlation that could account for that. In any case, our results confirm Bollen et al.'s in that they also find certain sentiments revealed in tweets to be predictive of the stock market.

The lagged correlation by one day between stock prices and *active*, respectively *strong* sentiment scores could be explained by collective mood manifesting itself on Twitter more quickly while investment decisions are taking more time. This would intuitively make sense since there are risk and financial costs attached to them. It would also leave the possibility of a causal effect of *collective mood* on *stock prices* open. To be able to decisively establish such a causal relation between, the direct effect real events have on stock prices must be controlled for. That is, the behaviour induced by new information – in our case, the coronavirus pandemic – in a rational agent must be determined.

The absence of sufficient pre-pandemic and post-pandemic observations allowing us to analyse how the spread of the virus has affected the interaction between Twitter and the equity markets is undoubtedly one of the most critical shortcomings of our approach. If these observations were available to us, we could determine the change in collective mood and stock prices induced by the coronavirus pandemic. In the future, further dimensions describing sentiment could be sought to model the progression of stock indices more accurately. Higher computational power would enable us to analyse an even higher bandwidth of tweets. However, this carries the risk that with too many observations per day, the daily sentiment value will be diluted and the variance of the sentiment dimensions, an indispensable criterion in this context, will most likely disappear.

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A Appendix

Figure 4: Daily Sentiments of the Standard Lexicons

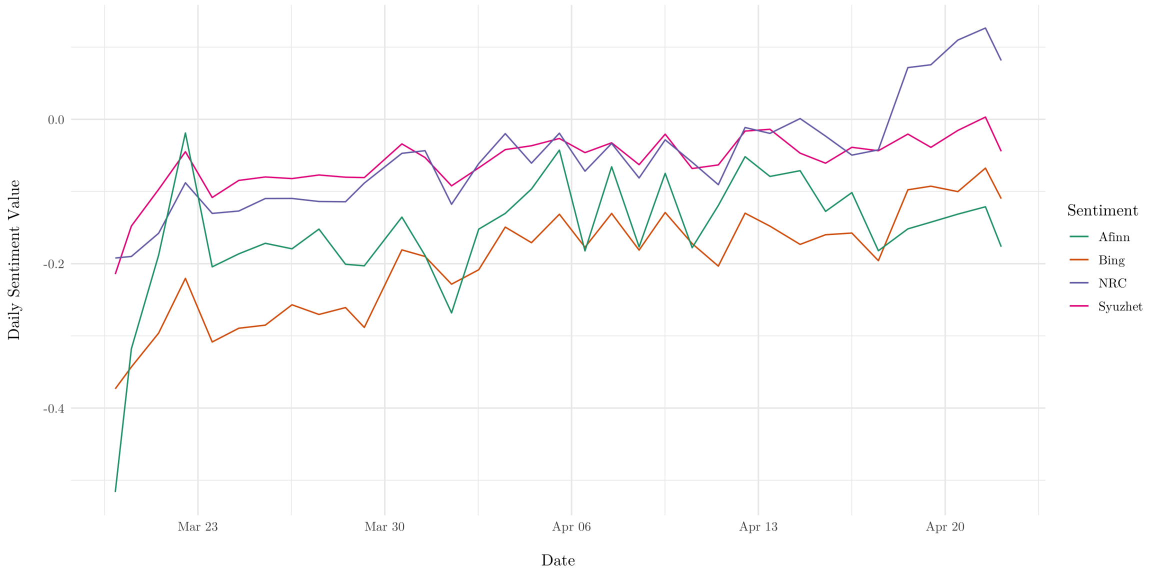


Figure 5: Comparison of Positive/Negative Score with SP 500 Index (scaled)

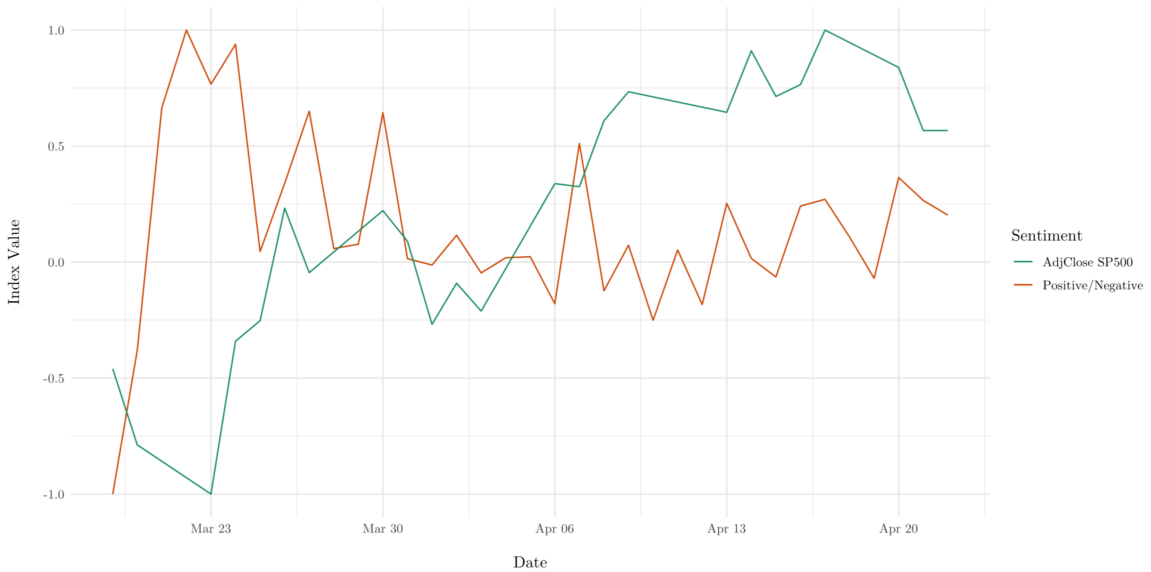
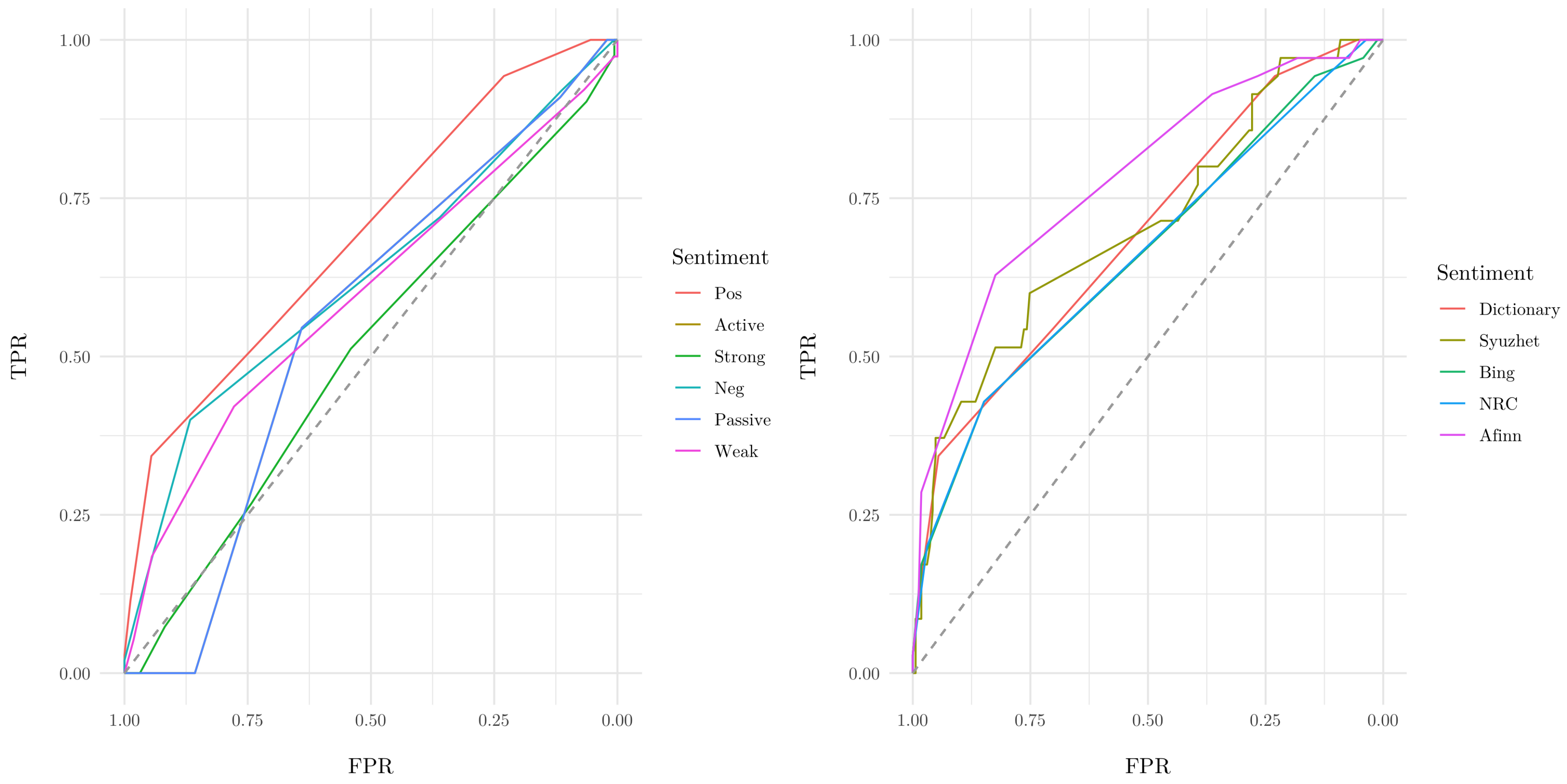


Figure 6: ROC Curves of Validation



(a) ROC Curve of Tailore Dictionary

(b) ROC Curve of Tailore Dictionary

Table 1: 1st VAR Model Specifications with $p = 2$ including $p = 0$

Dependent Variable:	$p'_{t,SP500}$	$p'_{t,SP500}$	$p'_{t,DJI}$
Intercept	-122.96	-80.84	-1080.51
	(176.03)	(192.94)	(1788.14)
$(\mathsf{pos} - \mathsf{neg})_t$	171.50	655.21	6296.31
	(1049.62)	(1246.63)	(11316.23)
$(\mathsf{pos} - \mathsf{neg})_{t-1}$	166.60	894.67	8401.54
	(943.94)	(1150.00)	(10366.41)
$(\mathsf{pos} - \mathsf{neg})_{t-2}$	1444.39	1875.95	17259.44
	(858.40)	(1210.08)	(11197.03)
$(\mathsf{active} - \mathsf{passive})_t$	-2.46	63.57	734.87
	(916.93)	(1019.24)	(9180.77)
$(\mathsf{active} - \mathsf{passive})_{t-1}$	$\underline{2166.63}^{*}$	$\underline{2634.53}^{*}$	$\underline{23316.96}^{*}$
	(906.32)	(994.64)	(8936.70)
$(\mathsf{active} - \mathsf{passive})_{t-2}$	-252.42	255.85	-750.83
	(909.33)	(1250.21)	(11151.50)
$(\mathsf{strong} - \mathsf{weak})_t$	1.21	-508.45	-3532.99
	(863.27)	(1051.62)	(9651.56)
$(\mathsf{strong} - \mathsf{weak})_{t-1}$	-1681.96	-1737.42	-15831.30
	(874.63)	(943.36)	(8545.18)
$(\mathsf{strong} - \mathsf{weak})_{t-2}$	484.52	-22.35	1501.14
	(792.99)	(896.52)	(8138.01)
p'_{t-1}		-0.17	-0.08
		(0.23)	(0.23)
p'_{t-2}		0.36	0.30
		(0.22)	(0.21)
p'_{t-3}		0.10	0.00
		(0.24)	(0.23)
R^2	0.30	0.41	0.42
Adj. R^2	0.02	0.01	0.03
Num. obs.	33	31	31
RMSE	65.44	67.13	613.20

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2: 2nd VAR Model Specifications with $p = 3$

Dependent Variable:	$p'_{t,SP500}$	$p'_{t,SP500}$	$p'_{t,DJI}$
Intercept	-53.14	-51.81	-781.58
	(157.08)	(163.54)	(1481.72)
$(\mathsf{pos} - \mathsf{neg})_{t-1}$	920.74	1377.75	12617.06
	(943.79)	(1078.17)	(9430.62)
$(\mathsf{pos} - \mathsf{neg})_{t-2}$	1291.37	1805.86	17646.19
	(838.05)	(952.17)	(8565.03)
$(\mathsf{pos} - \mathsf{neg})_{t-3}$	1320.56	1987.14	$\underline{18949.05}^{*}$
	(760.68)	(951.46)	(8684.31)
$(\mathsf{active} - \mathsf{passive})_{t-1}$	$\underline{2415.03}^{**}$	$\underline{2568.25}^{**}$	$\underline{23333.05}^{**}$
	(814.99)	(845.09)	(7477.80)
$(\mathsf{active} - \mathsf{passive})_{t-2}$	-318.68	481.86	1675.60
	(811.92)	(1024.74)	(8977.98)
$(\mathsf{active} - \mathsf{passive})_{t-3}$	1271.34	901.97	10057.50
	(807.86)	(976.61)	(8620.24)
$(\mathsf{strong} - \mathsf{weak})_{t-1}$	$\underline{-2061.03}^{*}$	$\underline{-2259.53}^{*}$	$\underline{-20579.42}^{*}$
	(772.64)	(818.72)	(7331.17)
$(\mathsf{strong} - \mathsf{weak})_{t-2}$	1019.29	337.12	4803.01
	(777.48)	(875.45)	(7834.59)
$(\mathsf{strong} - \mathsf{weak})_{t-3}$	$\underline{-1545.68}^{*}$	-1364.33	-13320.21
	(704.07)	(748.09)	(6676.63)
p'_{t-1}		-0.29	-0.23
		(0.21)	(0.20)
p'_{t-2}		0.18	0.12
		(0.21)	(0.20)
p'_{t-3}		0.16	0.06
		(0.20)	(0.19)
R^2	0.47	0.55	0.58
Adj. R^2	0.25	0.25	0.29
Num. obs.	32	31	31
RMSE	57.97	58.50	523.01

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3: Overview of the Results of the Validation (best values in **bold**)

Sentiment	**Accuracy**	**Recall**	**Precision**	**$F1$-Score**	**MDA**	**MARE**
$(\mathsf{pos} - \mathsf{neg})_t$	0.67	**0.38**	0.66	**0.33**	0.485	0.144
$(\mathsf{active} - \mathsf{passive})_t$	**0.69**	0.35	**0.68**	0.27	**0.525**	**0.124**
$(\mathsf{strong} - \mathsf{weak})_t$	0.66	0.35	0.66	0.31	0.485	0.174

Table 4: p-Values of Granger Causality Tests for 1st VAR Model

Lag p	$(\mathsf{pos} - \mathsf{neg})_{t-p}$	$(\mathsf{active} - \mathsf{passive})_{t-p}$	$(\mathsf{strong} - \mathsf{weak})_{t-p}$
0 Days	0.8754	0.9966	0.9985
1 Days	0.8693	<u>0.0016</u>**	<u>0.01368</u>**
2 Days	0.1656	0.6501	0.3108

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: p-Values of Granger Causality Tests for 2nd VAR Model

Lag p	$(\mathsf{pos} - \mathsf{neg})_{t-p}$	$(\mathsf{active} - \mathsf{passive})_{t-p}$	$(\mathsf{strong} - \mathsf{weak})_{t-p}$
1 Day	0.3782	<u>0.0001</u>***	<u>0.0010</u>**
2 Days	0.1319	0.5068	0.0767
3 Days	<u>0.0394</u>*	<u>0.0079</u>**	<u>0.0155</u>*

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Co-integration Rank based on Johansen Procedure

H_0	**Test statistic**	**Critical values**		
	$n = 4$	10 %	5 %	1 %
$r = 0$	<u>33.447</u>	24.78	27.14	32.14
$r \leq 1$	18.216	18.9	21.07	25.75
$r \leq 2$	4.435	12.91	14.9	19.19
$r \leq 3$	2.485	6.5	8.18	11.65