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Volatility and Sentiment

– The Explanatory Power of Social Media Sentiment on Volatility for the U.S. Equity Market

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ABSTRACT

In this paper, we analyse to what extent sentiment explains and predicts volatility. We perform simple linear regressions with sentiment as the independent variable for a sample of different dependent variables. These dependent variables belong to the VIX, the VVIX, five business-to-business companies, five business-to-consumer companies and the S&P 500. In order to approximate the volatility of the individual companies and the S&P 500, conditional volatility is estimated through GARCH(1,1) models. Sentiment is derived from Twitter data based on the search term "S&P 500" as well as the individual company names. We find that sentiment and the implied volatility carry a inverse contemporaneous relationship at the 1% significance level while no predictive power is found. The conditional and historical volatility of other instruments, and portfolios, show no significant explanatory nor predictive relationship with sentiment. The relationship between sentiment and volatility is not found but sentiment is proven to be related to either the perception of future volatility or the demand for structured products which have volatility as their underlying instrument.

Keywords: Sentiment analysis, Volatility, VIX, U.S Equity Market, Twitter

⋆**Acknowledgements**: We wish to take this moment to sincerely thank our supervisor, Michael Halling, for his support and precious advice throughout the process.

Contents

1 Introduction

In this section, we first outline the methods and corresponding results of our research and then give a short background to our study.

1.1 Methods and Results of Our Research

This paper studies to what extent sentiment explains and predicts volatility. First we run simple linear regressions on the changes of the VIX with changes of sentiment, characterized by processed data from Twitter for the search-term "S&P 500" as the independent variable for the time period 2015-01-01 to 2017-12-31. The coefficient for intra-day changes in sentiment on changes in the VIX is -3.49 and significant at the 1% significance level while no predictive power is found. The same methodology is applied to the VVIX as the dependent variable and similar results are found.

Second we run a set of simple linear regressions on the changes of the conditional volatility of a set of individual companies, i.e., business-to-business and business-to-consumer companies separately, as well as aggregated portfolios, and the "S&P 500" as the dependent variables and their respective sentiment values as the independent variables. No explanatory, nor predictive, power is found for these tests.

Interestingly, different findings between the regressions with the implied volatility as the dependent variable and the regressions with the conditional volatility as the dependent variable are found in the two sections. Therefore, future research should focus on the question of whether the relationship is truly between sentiment and volatility or between sentiment and the demand for products based on volatility.

1.2 Background of Our Research

Sentiment analysis has become more popular in recent years, partly because the increased volume of large pools of data through social media became continuously easier to download and analyse. Some companies are interested in the sentiment among their customers in order to identify shifts in consumer trends and demand (*Pradeep Govindasamy, 2017*) while more and more investors are starting to use sentiment analysis to identify the overall sentiment of the market in order to observe aggregate demand for different asset classes (*Kumesh Aroomoogan, 2015*).

A multitude of empirical studies have employed sentiment as a proxy for noise trader risk which refers to the phenomenon that the unpredictable sentiments of noise traders, or investors that are not fully rational, create a risk in the asset price which diverge prices from fundamental values even in the absence of fundamental risks (*Shleifer and Summers, 1990*). This study aims to further delve into this notion of noise trader risk and more specifically if, and to what degree, sentiment predicts future volatility and explains present volatility in the stock market.

Furthermore, there may justifiably be large differences in how sentiment drives volatility depending on the type of company. According to *Score(2016)*, business-to-business clientele are motivated, to a large extent, by logic and facts. Sentiment, or emotions, is mostly seen as a fear of making a poor decision. Business-to-customer purchasers are however primarily motivated by sentiment, or emotion. Our hypothesis is therefore that the volatility of business-to-customer companies carry a stronger relationship with sentiment than the volatility of business-to-business companies do. This is in line with the hypothesis that sentiment can act as a way to gauge shifts in demand from consumers and hence impact the company's share price. This impact on the share price will then influence the volatility of the company.

This study focuses on the volatility of the stock market rather than the returns due to the fact that sentiment has been empirically found to account for a part of the noise trader risk and that more companies are starting to view the sentiment from social media and other sources as a way to minimize downside risks (*Rachael King, 2011*). Furthermore, several studies have already analysed the possible effect that sentiment has on returns for different markets and individual equities (*Bing, Chan, Ou, (2014)*), while few have focused on the volatility and risk aspect.

From the multitude of available sources to gather data that can be used as a proxy for the sentiment of the market, Twitter is one that has been used empirically due to the large number of data points available and the short-concise nature of the data. We use Twitter-data in this study to proxy for sentiment while the S&P 500 index; and some individual companies, are used to proxy for the market, business-to-business and business-to-consumers segment. The S&P 500 is one of the most well-known stock indices and due to the fact that it contains both business-to-business and business-to-consumer companies, although all larger in terms of market capitalization, as well as being located in the United States which has the most active Twitter-base (*Statista, 2018*) it felt like the obvious choice.

By understanding the possible relationship between sentiment and the three different types of volatility, we believe that a greater understanding of how the stock market operates can be achieved. The results presented in this paper strengthens the efficient market hypothesis in terms of no significant predictable power over volatility. The contemporaneous relationship between sentiment and implied volatility means that we do not know which variable affects which, or if there is another independent variable which has a causal effect on the two.

2 Literature Review

2.1 Noise Trader

The efficient markets hypothesis(EMH) developed by Paul A. Samuelson and Eugene F. Fama in the 1960s maintains that asset prices fully reflect all information. The belief in EMH lost ground soon after the publication of *Shiller's (1981)* and *Leroy and Porter's (1981)* volatility tests, both of which found that stock market volatility is greater than could be justified by changes in dividends. However, the critics of the tests, *Kleidon (1986)* and *Marsh and Merton (1986)* challenged the statistical validity of volatility tests.

One alternative approach to efficient market hypothesis is called the noise trader approach. There are two types of investors in the market; One is "arbitrageurs", also called "smart money" and "rational speculators" who are fully rational investors while another is "noise traders" who are not fully rational. Arbitrageurs trade until the prices of portfolio and its substitutes are equalized. In contrast, noise traders' demand for risky assets is affected by their beliefs or sentiments that are not fully justified by fundamental facts (*Andrei Shleifer and Lawrence H. Summers, 1990*).

According to *De Long, Shleifer, Summers, and Waldmann (1990)*, unpredictable sentiments of noise traders create a risk in the asset price, which diverges prices from fundamental values even in the situation with no fundamental risks. In other word, trading of uninformed noise traders can temporarily create mispricing and increased volatility. (e.g. *Black, 1986; De Long et al., 1990*).

Hereafter, many researchers have studied noise traders based on the theory. *Kelly (1997)* studied the relationship between the likelihood an individual is a noise trader and income levels. Similarly, in the agent-based models of stock market volatility (e.g. *Lux and Marchesi, 1999; Alfarano and Lux, 2007*) noise traders are seen as a source of additional volatility in the stock market. The risk noise traders cause is volatility (*Volatility, Sentiment, and Noise Traders, Brown, 1999).* Furthermore, *Kumari and Mahakud (2015)* found that negative investor sentiment influences volatility and supports the statement that what affects the market's volatility is the pessimism of noise traders. Similarly, *Lee, Jiang and Indro (2002)* found that positive changes in sentiment put downward revisions in volatility while negative changes in sentiment lead to upwards revisions in volatility.

Wayne Y Lee a, Christine X Jiang b, 1, Daniel C Indro c (2002) adopted the Investors' Intelligence sentiment index and employed a generalized autoregressive conditional heteroscedasticity-in-mean specification to test the impact of noise trader risk on both the formation of conditional volatility and expected return. The empirical results show that sentiment is a systematic risk that is already incorporated in prices. Excess returns are contemporaneously positively correlated with shifts in sentiment. Moreover, the magnitude of bullish (bearish) changes in sentiment leads to downward (upward) revisions in volatility and higher (lower) future excess returns.

In our study, we believe that noise trader sentiment is one investor sentiment is one risk factor in stock prices of both business-to-business and business-to-consumer companies.

2.2 Mood and Finance, Behavioral Finance

The Behavioral Finance field acknowledges the possibility of noise-traders, or investors who are not fully rational, and one aspect within the field refers to the relationship between mood and the stock market. *Isen (1999) and Schwarz (1990)* found that negative mood within test-subjects resulted in a narrowing of the focus of attention and made them more vigilant in information processing. Positive mood on the other hand was found to induce more tolerance to risk, consideration to alternatives as well as a lower loss-aversion (*Isen, Nygren & Ashby 1988*).

A study by *Hirschleifer and Shum way (2003)* found a minor, but significant, predictable power for weather effects on the stock market. This was linked to the impact on the over-all mood for which the difference in weather had.

A multitude of studies seem to show that in order for mood variables to have an effect on stock prices, and hence volatility, there must be something which drives mood in an substantial and unambiguous way as well as have an impact on a large proportion of the population and the effects must be correlated across the majority of individuals within a country.

There is however some evidence regarding the opposite relationship holding true, namely that the performance of stocks drives the mood. *Engelberg & Parsons (2016)* found correlation between stock returns and medical admission records in which especially black swan events such as severe market crashes lead was strongly correlated to increased medical admissions.

2.3 The Relationship Between Sentiment, Returns, and Volatility

Bodurtha et al. (1995) report that changes in country fund discounts reflect a previously unidentified risk factor, which they conclude, is related to the sentiment of US investors. *Brown and Cliff (1999)* find weak evidence of short-run predictability but a strong correlation between sentiment and long-horizon (2–3 years) returns. Additionally, they observe not only the existence of individual sentiment but also of institutional sentiment, and reject the generally accepted theory that sentiment of individual investor should only affect small stocks. *Zhang & Skiena (2010)* found that yields sentiment/based market/neutral trading strategies which gives consistently favorable returns with low volatility over a long period. *Ranco, Aleksovski, Caldarelli, Grcar & Mozetic (2015)* found low Pearson correlation and Granger causality between the corresponding time series over the entire period. *Wang, Keswani, Taylor (2006)* found that most of the sentiment measures were caused by returns and volatility rather than the opposite. Lagged returns were found to cause volatility. All sentiment variables had very limited forecasting power once returns were included as a forecasting variable. *Kumari, Mahakud (2015)* found that significant effects of investor sentiment on the stock market volatility. Negative investor sentiment influences volatility and supports the proposition that the noise traders' pessimism increases the market volatility.

According to *Lee, Jiang, Indro (2002)*, sentiment is a systematic risk that is already priced and excess returns are contemporaneously positively correlated with shifts in sentiment.

Brown & Cliff (2004) does however not support conventional wisdom that sentiment primarily affects individual investors and small stocks. Tests show that sentiment has little predictive power for near term future stock returns.

2.4 Sentiment Measurements

Zhang & Skiena (2010) used a neuro linguistic programming system (Lydia) to perform a study on how company related news and variables anticipates and reflects companies stock trading volumes and returns.

Kissan, Babajide & Zhang (2010) used a sample of S&P 500 firms over the period 2005-2008 and found over a weekly horizon that online search intensity reliably predicts abnormal stock returns and trading volumes. Also noted that the sensitivity of returns to search intensity is positively related to the difficulty of a stock being arbitraged.

Bollen, Mao & Zeng (2010) Analysed text content of daily twitter feeds by two mood tracking tools, OpinionFinder that measures positive vs. negative mood and GPOMS that measures mood in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy)

Da, Engelberg & Gao (2015) used Harvard IV-4 Dictionary and the Lasswell Value Dictionary in order to categories words into “Positive”, “Negative”, “Weak”, “Strong” etc. By filtering to Economic words with positive or negative sentiment they received 149 words. They then put this through Google Trends in order to find other commonly searched for words which gave 1.490 related terms (1.245 after removing duplicates). Then removed other words which contained to few data points and did not yield economic meaning.

The usage of rule-based sentiment methodologies through the usage of dictionaries has hence been used in past empirical studies. The benefit of such an approach, in relation to the machine-learning approach, is that the rule-based approach empirically has a very good performance within a narrow field and is a lot faster and simpler to create *(Medhat, Hassan, Korashy, 2014)*.

Since closed-end fund shares are primarily held by individual investors, *Lee, Shleifer and Thaler (1991)* infer that fluctuations in closed-end fund discounts proxy for changes in investor sentiment. They find that changes in closed-end fund discounts are highly correlated with the returns on small capitalization stocks that are predominantly held by individual investors. *Neal and Wheatley (1998)* also find that (larger) closed-end fund discounts predict (higher) small firm returns, and that net redemption captures the investor sentiment in closed-end fund discounts. Surprisingly, another popular measure of investor sentiment, the odd-lot sales to purchases, appears to have no ability to predict small or large firm returns.

2.5 Sentiment Analysis to Predict Returns

Baker, Wurgler (2006) found evidence that sentiment can have significant effects on the cross-section of stock returns. The study found that companies which were smaller, unprofitable, non-dividend paying or with extreme growth potential are more likely to be affected by changes of investor sentiment. Furthermore a number of proxies used in other empirical studies for investor sentiment include the dividend premium, NYSE share turnover, the equity share in new issues, the number and average first-day returns on initial public offerings and the closed-end fund discount.

Ho, Hung (2012) analysed the predictive power of investor sentiment on the return and volatility at the aggregate market level in the U.S., four largest European countries and three Asia-Pacific countries. They found that in the U.S., France and Italy periods of positive investor sentiments are followed by low market returns. In Japan both the level and the change in consumer confidence boost the market return in the next month. Further, shifts in sentiment significantly affect conditional volatility in most of the countries, and in Italy such impacts lead to an increase in returns by 4.7% in the next month.*Oh & Sheng (2011)* used 72,221 micro blog postings for 1909 stock tickers and 3874 distinct authors and revealed that stock micro blog sentiments had predictive ability for simple and market-adjusted returns.

Unlike previous approaches where the overall moods or sentiments are considered, *Nguyen, Shirai, Velcin, (2015)* built a stock prediction model using the sentiments of the specific topics of the company and found the similar result that the sentiment analysis in the stock prediction task via a large scale experiment.*Bing, Chan, Ou, (2014)* downloaded 15 million records of tweets and tried to predict price of a selection of 30 companies listed in NASDAQ and New York stock exchange. Extracted ambiguous textual tweet data through neuro linguistic programming techniques to define public sentiment then used data mining technique to discover patterns between public sentiment and real stock price movements based on individual companies (rather than entire stock market). It was possible for the stock closing price of some companies to be predicted with an average accuracy as high as 76.12%.

Ray Chen, Marius Lazer (2013) started using crude analysis through implementing basic sentiment framework which yielded close to zero correlation. Then used more comprehensive and accurate dictionary for positive and negative sentiments (SentiWordNet), which provided better results. They used linear regression due to speed, required a regressor to quantify movement, accuracy. Found best fit when Twitter data predated the market by 3 days (3 days lag). Showed 60% accuracy over no information model which had 50% accuracy. After applying nearly all available data to train, classification accuracy as high as 70% (out of sample).

Used two models (Classification and Regression). Classification look only at sign of anticipated change in price while Regression tried to gauge how large the move would be. Both models showed to outperform Default Model.

2.6 Sentiment Analysis to Predict Volatility

Yang, Wu, (2010) studied the relationship between investor sentiment and price volatility in the Taiwanese stock market. A sequential relationship is identified between investor sentiment and price volatility. Empirical results show that short sales volumes may be an individual leading indicator useful in observing the effects of sentiment on price volatility, followed by open interest put/call ratios and trading volumes, and buy/sell orders. Institutional investors are related, to a lesser extent, to price volatility and sentiment. Qualified foreign institutional investors, or more rational investors, are the least influenced by price volatility, followed by securities investment trust companies and dealers. TAIEX options exert the strongest influence on sentiment during the study period, making them a valuable reference for gauging price volatility.

Arias, Arratia, Xuriguera (2013) have seen that nonlinear models do take advantage of Twitter data when forecasting trends in volatility indices, while linear ones fail systematically when forecasting any kind of financial time series. The Twitter data hence seem to have an effect on volatility that is not linear but rather depending on the magnitude of the change in Sentiment it is estimated to affect volatility differently.

The correlation between volatility and sentiment was further found by *Brown (1999)* in which an Empirical study found that unusual levels of investor sentiment on an individual basis were associated with greater volatility of closed-end funds. These effects stayed after the study controlled for market wide volatility and changes in the discounts of the funds as well.

As previously mentioned, *Kumari and Mahakud (2015)* found that lagged sentiment data taken through different aggregate market related sentiment proxies in India were significant on the stock market volatility of the country. This was attributable to the noise trader risk and shows that Sentiment might have predictive power over volatility for at least certain markets.

2.7 Other Methods to Predict Volatility

There are two main volatility-forecasting approaches: historical volatility models and volatility implied from options. Academics have been studied both models and found many interesting results. Thomas Dimpfl, *Stephan Jank (2016)* found a strong co-movement between the Dow Jones' realized volatility and the volume of search queries for its name. Furthermore, a heightened number of searches today is followed by an increase in volatility tomorrow. Including search queries in autoregressive models of realized volatility improves volatility forecasts in-sample, out-of-sample, for different forecasting horizons, and in particular in high-volatility phases. *Siem, Borus, Eugenie (2005)* found that realized volatility models have far more accurate predictive ability for volatility than models based on daily returns.

Bevan J Blair, Ser-Huang Poon, Stephen J Taylor (2001) found that the in-sample estimates show that nearly all relevant information is provided by the VIX index, and for out-of-sample forecasting, the VIX index provides the most accurate forecasts for all forecast horizons and performance measures considered. But no incremental forecasting information in intraday returns was found.

2.8 Methodology – Volatility Forecasting Models

(Generalized) Autoregressive Conditional Heteroskedasticity, or GARCH, family of models proposed by *Engle (1982)* and *Bollerslev (1986)*, stochastic volatility (SV) models (see, for example, *Taylor(1986)*), or exponentially weighted moving averages (EWMA), as advocated by the Riskmetrics methodology (*Morgan (1996)*) (see *McAleer, 2005* for a recent exposition of a wide range of univariate and multivariate, conditional and stochastic, models of volatility, and *Asai et al. (2006)* for a review of the growing literature on multivariate stochastic volatility models). *Thomas Dimpfl, Stephan Jank (2016)* study the dynamics between realised volatility, search queries and trading volume by estimating three vector autoregressive (VAR) models. *Hao and Zhang (2013)* finds that GARCH implied VIX is consistently and significantly lower than the CBOE VIX. They conclude that the GARCH option pricing under the locally risk-neutral valuation relationship fails to incorporate the price of volatility or variance risk premium.

In the study of *Robert F. Engle, Takatoshi Ito, Wen-Ling Lin(1988)*, ARCH models are employed to model heteroskedasticity across intra-daily market segments. Statistical tests lead to the rejection of the heat wave and therefore the market dexterity hypothesis. Using a volatility type of vector autoregression we examine the impact of news in one market on the time path of volatility in other markets.

Harry and Ronald (2001) studied the forecast performance of different volatility models for different specific asset classes and found out for stock indices the best volatility predictions are generated by the stochastic volatility model and for currencies on the other hand, the best forecasts come from the GARCH (1,1) model.

Many studies find that the simple GARCH (1,1) model provides a good first approximation to the observed temporal dependencies in daily data (*Baukkue and Bollerslev (1989), Bollerslev (1987), Engle and Bollerslev (1986), and Hsieh (1989)*). We find that, across asset classes and volatility regimes, the simplest asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) specification, the threshold GARCH model of Glosten et al (1993), is most often the best forecaster. Meanwhile, it is a well-established fact, dating back to *Mandelbrot (1963)* and *Fama (1965)*,that financial returns display pronounced volatility clustering.

While the vast majority of the earlier studies relied on the Autoregressive Conditional Heteroskedastic (ARCH) framework pioneered by *Engle (1982)*, there is now a large and diverse time-series literature on volatility modeling. Almost universally, reported results point towards a very high degree of intertemporal volatility persistence; see, e.g., *Bollerslev, Chou and Kroner (1992), Bollerslev, Engle and Nelson (1994), Ghysels, Harvey and Renault (1996) and Shephard (1996)* for surveys.

Yet, in spite of highly significant in-sample parameter estimates, numerous studies find that standard volatility models explain little of the variability in ex-post squared returns; see, e.g., Cumby, Figlewski and Hasbrouck (1993), Figlewski (1997), and Jorion (1995, 1996).

Torben G. Andersen (1998) showed that well-specified volatility models provide strikingly accurate volatility forecasts, typically accounting for about fifty percent of the ex post variability in the latent volatility factor.

The majority of the volatility forecast evaluations reported in the literature rely on some MSE criteria involving the ex-post squared or absolute returns over the relevant forecast horizon. Although the MSE may be a natural choice when evaluating traditional model forecasts for the conditional mean, it is less obvious in a heteroskedastic environment; see, e.g., Bollerslev, Engle and Nelson (1994), Engle et al. (1993), Diebold and Mariano (1995), Lopez (1995), and West, Edison and Cho (1993). However, for simplicity we do not pursue any of these more complex non-linear forecast evaluation criteria here.

3 Data and Methodology

3.1 Proxy for Market

This study uses the S&P 500 as a proxy for the U.S market and furthermore utilizes the VIX in order to gauge the volatility of the S&P 500. The VIX, or the CBOE Volatility Index, is a measure of market expectations of near-term volatility and is since 2003 based on the market prices of options on the S&P 500 and also includes out-of-the-money options. VIX squared was shown by Carr and Wu (2006) to approximate the conditional risk-neutral expectation of annualized variance of the S&P 500 over the coming 30 days. Since the VIX was first announced in 1990 it has shown a strong mean-reversion characteristic, strong negative correlated to S&P 500, and a mean level of approximately 19. This relationship can be partly explained by time-varying risk premia (Campbell and Hentschel, 1992) and the leverage effect (Black, 1976).

Since VIX is derived from the price from options, it may carry a risk premium as well as the implied volatility. This means that VIX may change given investor's increased sensitivity to volatility while the actual volatility remains the same. The volatility of the VIX, or the VVIX, is also used in order to see whether sentiment can explain and/or predict future volatility of the volatility.

Daily Adj. Closing prices for the VIX and the VVIX is downloaded from Yahoo Finance from 2015-01-01 to 2017-12-31. Data for 2015-01-01 to 2016-12-31 is used to fit the different models while 2017-01-01 to 2017-12-31 is left for out-of-sample testing and robustness checks.

Table 1: Descriptive statistics, in-sample VIX and VVIX

Table 1 shows summary descriptive statistics for the two different time-series, VIX and VVIX. Column two and three shows statistics regarding the level of the data while column four and five shows statistics regarding the change of the data. As can be seen the level and change of the VVIX is substantially larger than the level and change of the VIX in absolute terms

	Level		Change	
	VIX	VVIX	VIX	VVIX
Observations	755	755	755	755
Mean	14.53	92.55	-0.01	-0.016
Std	4.26	11.65	1.39	5.62
Min	9.14	73.18	-5.7	-26.83
25%	11.54	84.51	-0.59	2.76
50%	13.48	89.78	-0.05	-0.19
75%	15.98	97.69	0.49	2.49
Max	40.74	168.75	12.71	34.72

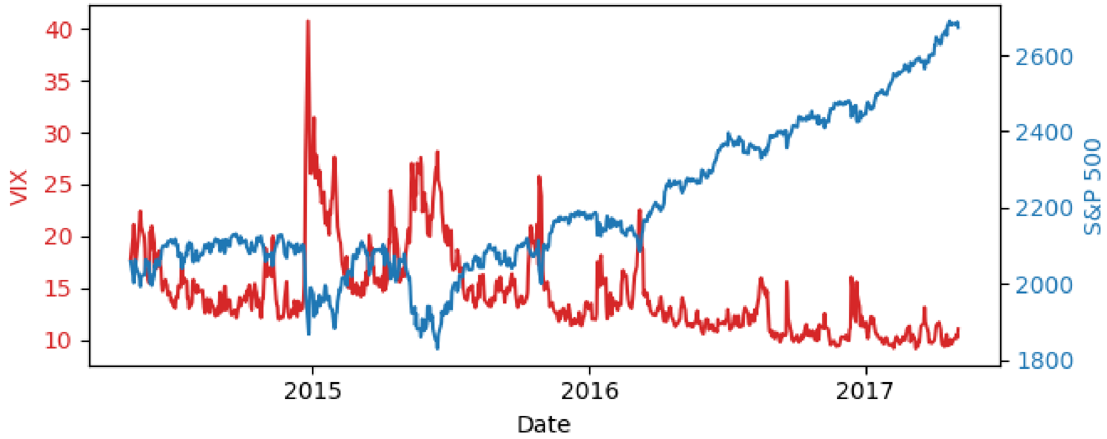

Figure 1: Time Series of VIX and S&P500

The figure shows the Daily Adjusted Closing prices of the VIX and the S&P 500 for the period 2015-01-01 to 2017-12-31, downloaded from Yahoo Finance. A clear Inverse Relationship between the two is observed with the largest spikes of volatility happening during severe negative market shocks.

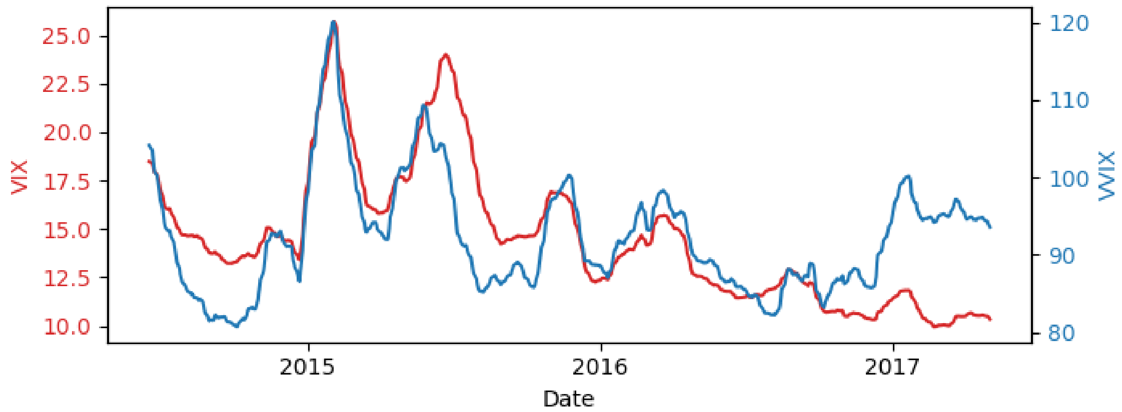

Figure 2: Time Series of smoothed VIX and VVIX

The underlying data is the Daily Adjusted Closing Prices of the VIX and the VVIX. Post collection a 20-day moving average is calculated and then plotted above. The smoothed time series of the VIX and the VVIX seem to share a high degree of correlation and the main difference seem to be in the level of the two and hence the magnitude of the change.

3.2 Proxy for Business-to-Business and Business-to-Consumer Companies

In order to analyse the potential difference between how different types of companies are affected by Sentiment, Price data for five of the largest business-to-business companies and five of the largest business-to-consumer companies from the S&P 500 is downloaded from 2017-01-01 to 2017-12-31. A complete list of the individual companies and key information regarding the companies are shown in Table 2. The companies are selected due to their large market capitalization, weight in the S&P 500 index as well as notability. All of the different companies are large, international organizations for which we expect to find sufficient amount of data for in order to draw interesting inferences. As can clearly be seen the business-to-business companies contains a lower part of tweets per day on average than the business-to-consumer companies, in line with the notion that those who post their views on social media are often consumers who react positively or negatively to different experiences with the individual companies. Amazon and Facebook are the two clear outliers in regards to market capitalization and liquidity.

Table 2: Key Data, individual Business-to-Business and Business- to-Consumer companies.

Market capitalization is in millions of USD as of 2016-12-31 downloaded from Bloomberg. Liquidity is calculated as the average daily volume between 2016-06-30 and 2016-12-30 and shown in millions of USD. Weight in S&P 500 is shown as percentage points and taken from Bloomberg as of 2016-12-30. The average tweets per day are based on the simple average for the whole period. As previously mentioned due to the substantial parts of tweets for most of the business-to-consumer companies we only downloaded a maximum of 1 000 data points per day for those companies.

	Market Cap.	Liquidity	Weight in S&P 500	Avg. Tweets/day
Caterpillar	54 259	384	0.28	46
Cisco	151 697	641	0.79	1 516
General Electric	279 546	945	1.45	194
Gilead Sciences	94 343	745	0.49	46
Pfizer	197 100	723	1.02	177
Amazon	356 313	2.719	1.53	1 000
Walmart	212 419	579	0.54	982
McDonalds	101 082	509	0.52	1 000
Facebook	332 402	2.518	1.39	1 000
Coca-Cola	178 815	508	0.83	589

Given how the volatility of these portfolios is equal to the actual volatility and not implied volatility derived through options, part of potential differences between results for VIX and these portfolios might be due to changes in investors' sensitivity to volatility. The portfolios in turn are constructed as equal-weighted portfolios of the different constituents in each category.

Daily Adj. Closing prices for the individual companies are downloaded from Yahoo Finance from 2017-01-01 to 2017-12-31 and then aggregated into the business-to-business or business-to-consumer portfolios. Descriptive statistics for the daily return of these two portfolios are shown in Table 3.

Table 3: Descriptive statistics, in-sample Business-to-Business and Business-to-Consumer portfolios

The table shows summary statistics for the two equal-weighted portfolios comprised of the different individual holdings previously mentioned. The statistics are based on the daily simple-returns including dividends.

	Daily Simple-Returns (%)	
	Business-to-consumer	**Business-to-business**
Observations	355	355
Mean	0.19	0.06
Std	1.4	1
Min	-6.49	-5.86
25%	-0.30	-0.30
50%	0.22	0.06
75%	0.77	0.45
Max	5.63	3.19

3.3 Sentiment Construction

The raw data for the sentiment analysis on the market is acquired from Twitter through a web parser that collects each post for a set date interval. For this study, data from 2015-01-01 to 2017-12-31 is downloaded and besides the actual string of characters, the tweet, we also download number of retweets and followers that the user who posted the tweet had. These are used to create different variables in which individual observations of sentiment are filtered out before aggregated into the daily sentiment value.

The web parser requires a specific "Search-term" on which to collect data from and since the study aims to analyse how Sentiment has a relation to the U.S. stock market and used S&P 500 as a proxy the search-term used is simply "S&P 500". Given more time, or a more open API, other Search-terms could have been included in order to 1) analyse differences between search-terms and 2) increase the number of tweets in order to make sure that the actual sentiment for the U.S. market is captured.

The dictionary which is used in order to turn the string into sentiment values only allows for English words hence the web parser is adjusted to only search for posts in English. The above-mentioned data-gathering methodology leads to an average of 500 tweets per day to be downloaded throughout the three years. This study did not use the built-in Twitter API for Python due to the fact that the API only yields historical data for a couple of weeks.

The same methodology is applied to download company specific tweets yet due to time constraint and the difficulty of downloading data from twitter we only collect the tweets from 2017-01-01 to 2017-12-31. There is also too many tweets for certain companies, Amazon and Facebook to name a few, for which we chose to only download a maximum of 1.000 tweets per day. The Tweets chosen for these companies are taken randomly in order to avoid a measurement bias.

From the multitude of options available in order to gauge Sentiment from text, this study choose to use the lexicon and rule-based sentiment analysis tool VADER Sentiment Analysis from the NLTK package for Python. This particular tool is specifically focused on sentiments expressed through social media, such as posts on Twitter (Hutto, C.J. & Gilbert, E.E. (2014)). The tool has also been empirically validated by multiple independent judges and used in past research regarding sentiment analysis.

The tool takes the text as an input and yields four parameters, three of which measure the sentiment on the negative, neutral and positive spectrum and one which compiles all information and yields a compound, i.e. an aggregated score, that runs from -1.0 to 1.0. It is this score that has mostly been used to gauge the sentiment and we have later used the mean sentiment of each day to stand for the daily Sentiment. This study tests to use the compound score as a raw score as well as to classify it into the typical thresholds used in previous literature and recommended by the creators of the NLTK package:

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Positive Sentiment: Compound SCORE >= 0.5
Neutral Sentiment: (Compound SCORE > -0.5) and (Compound SCORE < 0.5)
Negative Sentiment: Compound SCORE <= -0.5
```

However, these classifications do not yield significant results for the dependent variable VIX nor VVIX given how the mean of the aggregated sentiments collected results in very small amounts of strong positive and/or negative sentiment.

The compound score is a normalized score based on the sum of Valence computed based on the sentiment lexicon and rule-based sentiment analysis tool. The normalization is done by dividing the sum of the Valence scores by its square, plus an alpha parameter that increases the denominator of the normalization function.

To incorporate that certain tweets might have a stronger predictive power over future volatility than others three different sentiment metrics are calculated. The base sentiment variable takes all of the tweets into account and then simply takes the mean sentiment of the day as the daily sentiment. The two other variables, Sentiment_Fav and Sentiment_Ret, uses only the tweets that had been favoured or retweeted at least 10 times respectively. By comparing these different proxies for the market sentiment, we believe that additional interesting inferences might be drawn. However, the number of tweets are severely diminished once the tweets that contained less than desired numbers of retweets and/or favourites with less than a third were removed. As can be seen in Table 4 as well as Table 5 where the Sentiment_Fav and Sentiment_Ret acts very similar to one another and contains more extreme values when compared to the regular sentiment variable. This is especially noted in row 4 (Min) and row 8 (Max) and holds true for both level and change.

Table 4: Descriptive statistics, in-sample S&P 500 sentiment

The table shows summary statistics for the three different sentiment metrics calculated based on the twitter data for S&P 500 during the interval 2015-01-01 and 2017-12-31. The sentiment incorporates all of the tweets during the each day and then takes the mean in order to yield a time-series of sentiment values. The Sentiment_Fav metric is derived through the same methodology yet only incorporates the tweets that have been favoured more than 10 times by other users. The Sentiment_Ret metric is also derived through the same methodology yet only incorporates the tweets that have been retweeted more than 10 times by other users.

	Level			Change		
	Sentiment	Sentiment_Fav	Sentiment_Ret	Sentiment	Sentiment_Fav	Sentiment_Ret
Observations	755	755	755	755	755	755
Mean	0.12	0.11	0.10	0.01	0.01	0.01
Std	0.11	0.24	0.25	0.12	0.32	0.32
Min	-0.33	-0.71	-0.71	-0.43	-1.20	-1.02
25%	0.05	-0.03	-0.07	-0.08	-0.20	-0.21
50%	0.14	0.11	0.11	0.01	-0.01	-0.01
75%	0.20	0.27	0.28	0.08	0.20	0.21
Max	0.42	0.82	0.91	0.42	1.13	1.13

Table 5: Descriptive statistics, in-sample business-to-business and business-to-consumer sentiment

The table shows summary statistics for the independent variables we use when we analyse the potential relationship between sentiment and volatility for the business-to-business and business-to-consumer portfolios. The data is derived from twitter for the period 2017-01-01 to 2017-12-31. The sentiment for each portfolio is equal to the mean of the sentiment of the individual holdings that constitutes the portfolio. There is no weight applied to the individual sentiment values since the constructed portfolios are equal-weighted.

	Level		Change	
	B2C	B2B	B2C	B2B
Observations	250	250	249	249
Mean	0	0.14	0	0
Std	0.14	0.02	0.24	0.02
Min	-0.69	0.07	-0.69	-0.07
25%	-0.1	0.13	-0.15	-0.01
50%	0	0.14	0	0
75%	0.1	0.15	0.15	0.01
Max	0.44	0.2	1.13	0.06

Dispersion between the different metrics in terms of Level is further illustrated in Figure 3. This graph noticeably shows how the clear sentiment variable, which incorporates all of the downloaded tweets for S&P 500, indicates a lot less volatility than the other two metrics that are based on favourites or retweets. One reason for this might be that the tweets which are likely to be retweeted or favoured might be written in a way as to spur emotion in the recipients and hence contains more charged words which in turn translates into larger swings in the aggregated sentiment score.

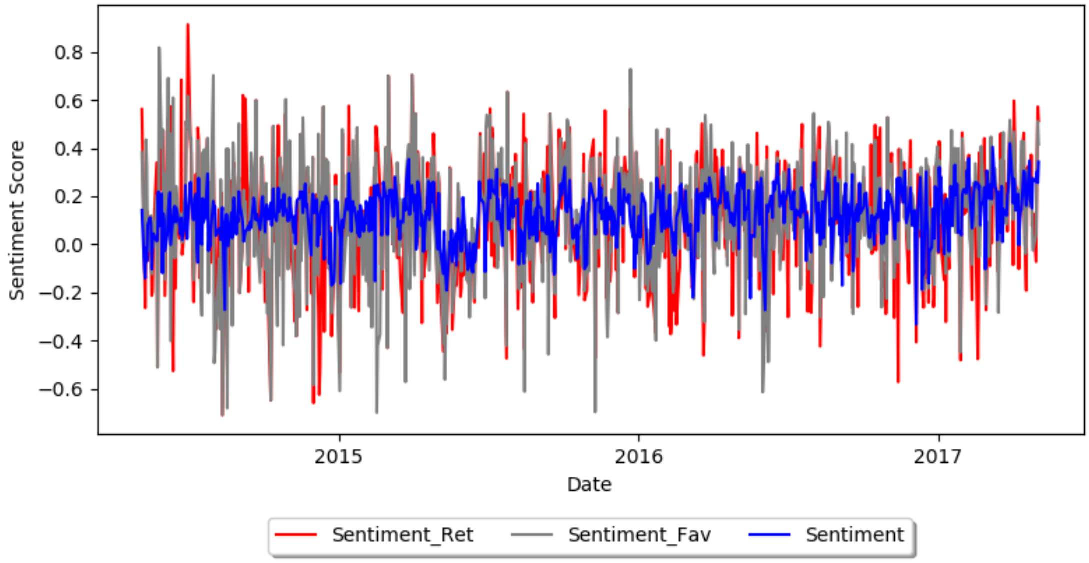

Figure 3: Time Series of sentiment metrics for S&P 500

The underlying data is daily-sentiment metrics shown in Table 3. Data is downloaded between 2015-01-01 to 2017-12-31. The y axis shows the level of the different metrics values. The sentiment favorites and sentiment retweets contain a fraction of the tweets that the sentiment variable employs and yields a lot more volatility.

Figure 4 shows the 20-day moving average of the level of VIX and level of sentiment gathered on the S&P 500. This graph shows an interesting inverse relationship between the two time-series and that they are at least correlated to some degree. Figure 4 also illustrates the continuous decrease of the VIX since the middle of 2016. Interesting to note is that the 20-day moving average of sentiment are almost always positive for the entire period, although quite substantial negative changes occurred during the period. This is in-line with the idea that positive sentiment can be linked to decreased volatility.

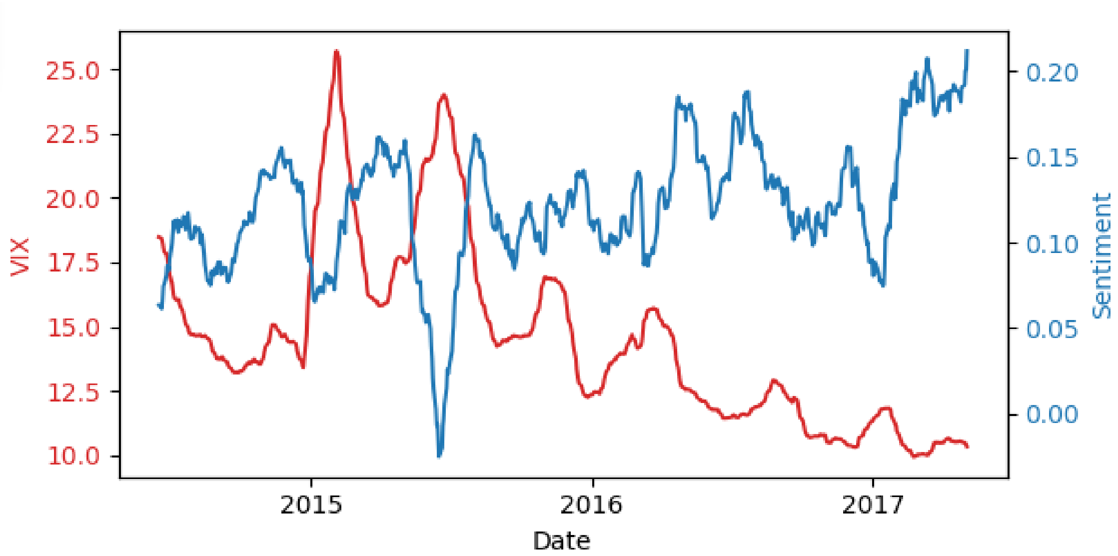

Figure 4: Time Series of smoothed VIX and sentiment

The underlying data is the Daily Adjusted Closing Prices of the VIX and aforementioned sentiment variable, downloaded for the period 2015-01-01 to 2017-12-31. Post collection and transformation, a 20-day moving average is calculated and illustrated above. The smoothed time series of the VIX and the sentiment seem to share an inverse relationship for most periods.

3.4 Volatility Measurements

This study employs three different metrics of volatility. One of which is found indirectly, the implied volatility, by taking the adjusted closing prices of the VIX which is partly based on the implied volatility of the S&P 500 index. The implied volatility refers to the expected fluctuations of an underlying instrument, or set of instruments, over a specific time-frame. This in turn is based on imbalances between supply and demand which can be affected by a multitude of factors that must not necessarily have any basis on actual movements in the returns of the underlying instruments (Jeff Krohnfeldt, 2016).

The two other volatility metrics used are the conditional volatility and the historical volatility. The historical volatility is also referred to as statistical volatility and shows the fluctuations of underlying instruments by measuring the difference in returns over a set period of time (Jeff Krohnfeldt, 2016). For this study, a 20-business day moving average is used which is consistent with the 30 day measurement observed in the VIX.

The conditional volatility is the volatility of a random variable given additional information, such as past values of itself. This is used since volatility always changes and is therefore seen as a non-directly observable variable. The conditional volatility is hence the underlying volatility in at a point in time and modelled by various models, such as the GARCH (Jondeau, Rockinger 2003).

In order to observe the volatility measurement used as the dependent variable in the company specific portfolios a GARCH(1,1) is therefor used. The GARCH(1,1) yields a vector of conditional volatilities which acts as an estimation of the underlying volatility of respective portfolio. For this to hold, we assume that the expected daily return is equal to zero for both of the two portfolios.

The GARCH(1,1) is chosen due to its rigid empirical background. GARCH is the most appropriate model to use when one has evaluates the volatility of the returns of groups of stocks with large amounts (thousands) of observations according to Marius MATEI (2009).

Equation:

$$\sigma_n^2 = \gamma \times V_L + \alpha \times \mu_{n-1}^2 + \beta \times \sigma_{n-1}^2$$

where $\alpha > 0, \beta > 0, \alpha + \beta < 1$, so that the next period forecast of variance is a blend of the last period forecast and also last period's squared return.

V_L is the long-run variance rate and γ is the weight assigned to V_L

μ_{n-1}^2 is last period's squared return and α is the weight assigned to μ_{n-1}^2

σ_{n-1}^2 is the variance of the returns of a portfolio or asset of last period and β is the weight assigned to σ_n^2

σ_n^2 is the variance of the returns of a portfolio or asset of the next period.

3.5 Regression

For VIX, different regressions are fitted to the data, which is split between a training set of two thirds and a testing set of the last third. The data set is split in order to avoid over-fitting and in order to increase the robustness of the model.

Firstly, a simple linear-regression in which the sentiment measurement is supposed to explain the current daily change of the price of the VIX. Secondly, a simple linear-regression in which the sentiment measurement is supposed to explain the next day changes of the price of the VIX. The VVIX is treated in the same fashion as the VIX.

For the business-to-business and business-to-consumer portfolios we calculate the conditional volatility measurement mentioned in the previous chapter, as well as the historical volatility and daily sentiment. We calculate the historical volatility by taking volatility of the previous 20 days and then rolling it forward. This means that for the regression in which the historical volatility is used, we lose the first 20 trading days' worth of observations. The same regression methodology as for the VIX is then used for these portfolios.

Different time-horizons, as well as sentiment measurements, is used as robustness tests for the model.

The Linear-regression is chosen due to its empirical rigidness as well as the fact that the previous figures show what seems to be a linear relationship between the sentiment and the different dependent variables.

Main Equations:

$$\mathrm{VIX}_t = \beta \times \Delta\mathrm{Sentiment}_t$$

$$\mathrm{VIX}_t = \beta \times \Delta\mathrm{Sentiment}_{t-1}$$

Secondary equations include different measurements of sentiment as well as different dependent variables. The different dependent variables tested are, VIX, VVIX, conditional volatility of S&P 500, conditional volatility of a portfolio of business-to-business companies, conditional volatility of a portfolio of business-to-consumer companies and the conditional volatility of the individual companies. Furthermore, the 20-day historical volatility is used instead of the conditional volatility for robustness checks.

4 Results and Analysis

4.1 Linear-Regression: VIX and Sentiment

The first step in order to measure the relationship between sentiment and volatility is to understand the relationship between the sentiment and the VIX. This relationship is estimated by performing a linear regression on the change of the Sentiment on the change of the VIX. The results for this regression, with VIX as the dependent variable, are shown in Table 6. The results show a significant relationship at 1% with a coefficient of -3.49 and a R-Squared of 9.2%.

The negative coefficient is in-line with previous research (Lee, Jiang and Indro, 2002) and theory, that it is the highly negative sentiment that increases volatility and hence the VIX. The relatively low R-Square proves that there are a lot of other factors that explains the change in the VIX yet 9.2% is still seen to be a significant part.

A secondary model contains solely the lagged sentiment in order to see if sentiment has any predictive power over the VIX. This model shows that the lagged sentiment variable is not significant at a 1% level and clearly shows that the changes in sentiment does not seem to have any predictable power over the changes in VIX. The coefficient is however negative which is once again in-line with previous research.

Table 6: Linear-Regression results testing the sentiment for VIX

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the different variables as input in order to capture the relationship between the sentiment and the VIX. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column.

Dep. Var.	**VIX**	
	Coef. (Std. Err)	R^2
Sentiment	-3.49*** (0.48)	9.2%
Sentiment$_{t-1}$	-0.56 (0.52)	-0.2%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

In order to validate the methodology and avoid over-fitting, Figure 5 illustrates the estimated trend line in regards to a set of scatter Figures of the change of VIX and the change of the sentiment for S&P 500. The left plot in Figure 5 shows the in-sample dataset of 2015-01-01 to 2016-12-31 while the right plot shows the out-of-sample dataset of 2017-01-01 to 2017-12-31. Except one strong outlier which yields a change in VIX of 12.5 while sentiment had close to no change, the two graphs look very similar.

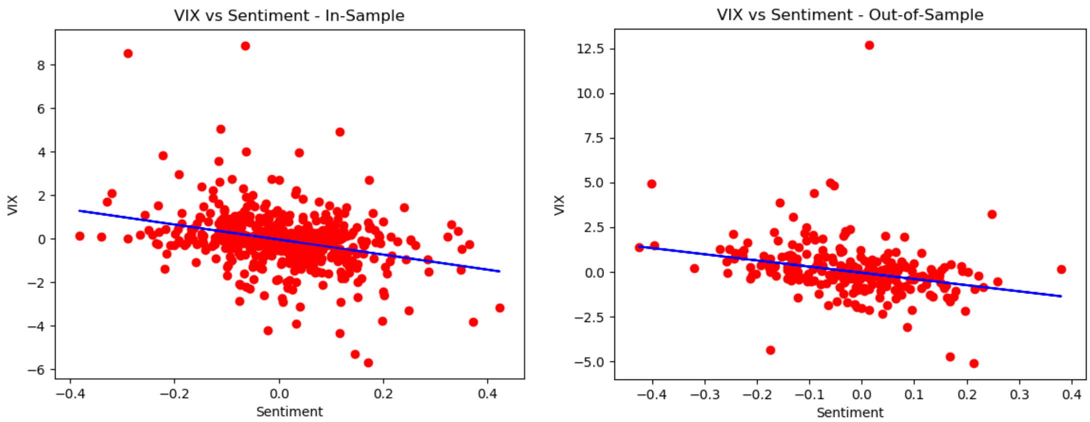

Figure 5: In-sample and out-of-sample change of sentiment on change of VIX

The left chart is the fitted regression discussed previously for the time period 2015-01-01 to 2016-12-31 while the right chart is the trend line plotted against the out-of-sample data for the time period 2017-01-01 to 2017-12-31.

By dividing the three years of data into a training-set and a test-set we make sure that over-fitting of the model is minimized, and the results are further strengthened since the model seems to perform decent for both of the different samples, increasing the robustness of the model. However, one reason for this might be due to the nature of the periods selected. The three different years for which data is downloaded are all characterized by overall low volatility and small changes. Given how the out-of-sample period characteristic is very close to the in-sample period, it is not surprising that the model performs well out-of-sample as well.

This section has aided in the quantification of the relationship between the changes in the sentiment and the changes of VIX. The next step is to see whether this relationship holds for the volatility of the VIX traded product VVIX as well. If the VVIX shows to also have a relationship with sentiment it then becomes interesting to try to identify if the relationship is between the actual volatility and sentiment or investors demand for volatility and sentiment.

4.2 Linear Regression: VVIX and Sentiment

The VVIX, which is a security derived from the option price on the volatility of the VIX, is another instrument that is structured quite similarly to the VIX and hence by finding if there is a relationship between Sentiment and the VVIX as well, it strengthens our model and the claim that sentiment and volatility share a simultaneous relationship with one another.

Given the established relationship between the changes of sentiment and the changes of VIX, the same model is applied with the VVIX as the dependent variable. The results for this model, as well as the one in which the lagged sentiment is used as the independent variable are shown in Table 7. Sentiment is once again shown to have a significant relationship with a volatility-based product and the coefficient is negative which is once again in-line with previous research. The coefficient is higher for VVIX than for VIX which is likely due to the overall higher level of the VVIX than the VIX. The R-Squared is 0.1% smaller for the VVIX than for the VIX but otherwise it seems from these results that the relationship between sentiment and VVIX is the same, or at least very similar, to the relationship between sentiment and VIX.

A secondary model constituted of the change of lagged sentiment is once again used in order to show whether it has any significant explanatory power for the VVIX. However, the results for this model is very similar to those found in Chapter 4.1, namely that sentiment does not seem to have any predictable power over volatility, nor the volatility of the volatility.

Table 7: Linear-Regression results testing the sentiment for VVIX

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the different variables as input in order to capture the relationship between the sentiment and the VVIX. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column.

Dep. Var.	**VVIX**	
	Coef. (Std. Err)	R^2
Sentiment	-13.8*** (1.95)	9.1%
Sentiment$_{t-1}$	-2.19 (2.12)	-0.2%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

Figure 6 show scatter plots of each days change in VVIX and sentiment in the in-sample dataset of 2015-01-01 to 2016-12-31 and the out-of-sample dataset of 2017-01-01 to 2017-12-31 respectively. This illustrates how well the model works out-of-sample and illustrates potential outliers. Most of the outliers seen are observed where there are large positive changes in the VVIS although close to zero change in the sentiment. This is especially interesting given how the previous in-sample vs. out-of-sample analysis for Chapter 4.1 show that the different periods included in each respective sample are characterized by overall low volatility and very similar.

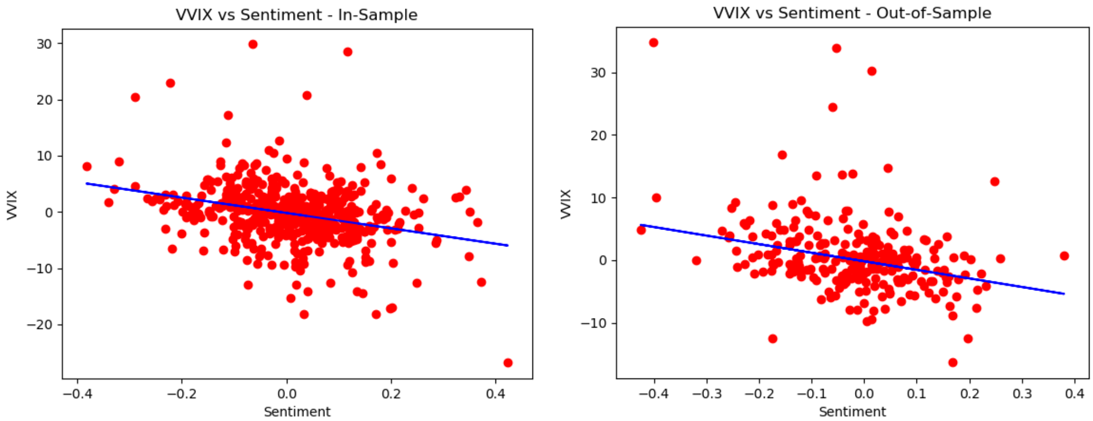

Figure 6: In-sample and out-of-sample change of sentiment on change of VVIX

Both of the charts contains changes in daily adjusted closing prices of the VVIX as well as for the Sentiment derived from the downloaded twitter data for the search-term "S&P 500". The left chart is the fitted regression discussed previously for the time period 2015-01-01 to 2016-12-31 while the right chart is the trend line plotted against the out-of-sample data for the time period 2017-01-01 to 2017-12-31.

The findings from Chapter 4.1 and 4.2 both indicate that there is a significant contemptuous relationship between sentiment and options which has volatility as their underlying product. In order to investigate deeper into whether this relationship is between the sentiment and the underlying volatility or between the sentiment and investors demand for volatility, hence affecting the prices of the VIX and the VVIX, the next step is to look at variables which only contains the volatility by using individual companies and if there exist any relationship between Sentiment and those measurements. This is important because it also allows us to estimate potential relationships between sentiment and different types of volatility, namely conditional volatility and historical volatility instead of solely focusing on implied volatility.

4.3 Linear Regression: Business-to-Business and Business-to-Consumer and sentiment

To begin looking at the potential relationship between volatility and sentiment for individual companies we simulate two portfolios, one for business-to-business and one for business-to-consumers, including five constituents each equal weighted and rebalanced monthly. By dividing the portfolios into these two segments, further inferences can be drawn as to which types of companies might have more of its volatility explained by sentiment. The usage of conditional volatility, rather than implied volatility, also opens up for a better discussion regarding the relationship between sentiment and volatility.

The main results for these portfolios are seen in Table 8 in which the conditional volatility, estimated by GARCH (1,1) with non-robust standard errors and assuming that daily expected returns are equal to zero, is the dependent variable and the sentiment change is based on the mean sentiment for the different companies in each portfolio. By testing portfolios based on individual companies and estimating their conditional volatility instead of using implied volatility through options, which also carries a cost through demand, we are able to isolate the relationship between the sentiment and the volatility.

Both the change in the same day sentiment and change in the lagged sentiment are insignificant at the 1% level and yields close to zero in R-Square for the business-to-business portfolio. These results are not in-line with the previous found results found in Chapter 4.1 and Chapter 4.2.

Table 8: Linear-Regression results testing the Sentiment for VIX

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the different variables as input in order to capture the relationship between the sentiment and the two different portfolios created. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column. Each Independent Variable is fitted against the conditional volatility of the portfolio that they adhere to.

Dep. Var.	**Conditional Volatility**	
	Coef. (Std. Err)	R^2
Sentiment_B2B	0.07 (0.2)	0.1%
Sentiment_B2C	-0.01 (0.038)	0%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

The second row of Table 8 shows the results for the business-to-consumer group and these are also highly insignificant with a R-Square of zero. These findings solidify the notion that sentiment does not explain volatility for business-to-business nor business-to-consumer companies. Important to note is that the business-to-consumer companies carry a much larger number of tweets, and hence sentiment values, than the business-to-business companies and hence these results show that it is not the lack of data that generates insignificant results.

These results strengthen the notion that the relationship might not be between sentiment and all types of volatility but rather sentiment and the demand for volatility. This hypothesis is found in, for example, Isen, Nygren & Ashby (1988) in which a positive mood leads to slightly decreased risk-aversion while negative mood leads to an increased risk-aversion. The findings in Chapter 4.1, 4.2 and 4.3 strengthens this claim yet it could also be that sentiment has a relationship to implied volatility but not to conditional volatility. Furthermore the relationship could be between sentiment and the ex-ante volatility, implied volatility, rather than the ex-post metric we calculate when we use the conditional volatility.

In order to further validate the conclusion that conditional volatility for business-to-business and business-to-consumer companies do not share a relationship with sentiment, the next step is to observe how the model works on the individual companies within each portfolio. The reason for this is to make sure that the way of which the sentiment values are aggregated, and the portfolio is weighted, does not skew the results.

4.4 Linear Regression: Business-to-Business and Business-to-Consumers Individual Companies and sentiment

Given how Chapter 4.3 shows that the volatility of the aggregated holdings that constituted the business-to-business and business-to-consumer portfolios does not have a significant relationship with sentiment we look at each individual company separately to see if the problem is due to the way each portfolios sentiment value is estimated or something deeper.

Table 9 shows the results for the linear-regression where the change in conditional volatility is regressed on the change in sentiment. It is clear from the results that the change in sentiment has no significant relationship with the majority of the companies within the business-to-business category that are tested. The only company for which significant results are found is Caterpillar and in which the change in sentiment is found to have a positive coefficient of 0.0053 and a R-square of 4.1%. This positive coefficient is interesting given how it is a contradiction to previous empirical research as well as findings in earlier chapters of this paper. However, when we look deeper into the data these different companies do not seem to have a lot of negative sentiment but instead quite neutral with very miniscule changes. It is hence likely that given how no, or very few, large negative sentiment changes occured during the period for these companies that the positive sentiment is the main, although often insignificant, driver in terms of sentiment.

Table 9: Linear-Regression results testing the Sentiment for Business-to-Business Companies

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the individual companies Sentiment as input in order to capture the relationship between the sentiment and conditional volatility of each individual company. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column.

Dep. Var.	**Conditional Volatility**	
	Coef. (Std. Err)	R^2
Caterpillar$_{\textbf{Sentiment}}$	0.005*** (0.002)	4.1%
Cisco$_{\textbf{Sentiment}}$	0.04 (0.11)	0
General Electric$_{\textbf{Sentiment}}$	0.02 (0.03)	0.2%
Gilead Sciences$_{\textbf{Sentiment}}$	0.02 (0.03)	0.2%
Pfizer$_{\textbf{Sentiment}}$	0 (0)	0.5%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

The fact that the change in sentiment is found to have no significant relationship with the change in volatility for the individual business-to-business companies, nor the business-to-business portfolio could either imply that the investors of this type of companies do not express their views, nor are they influenced by the views, on Twitter. Another reason could be that the change in sentiment did not explain the relationship between mood and underlying volatility but rather the demand for volatility of investors in Chapter 4.1 and 4.2.

Another reason could be that there simply were not enough large events during the year leading to a large span of sentiment changes for these individual companies and hence no significant relationship could be found. A final interpretation is that the implied volatility and the conditional volatility act substantially different form one another and that sentiment simply has a contemporaneous relationship with the conditional volatility but not the implied volatility.

The findings in Table 10 show that changes in sentiment also fails to explain the changes in conditional volatility for the selected business to consumer companies. These companies had a lot more tweets to process given the nature of the companies and hence this is a strong suggestion that the changes in sentiment do not explain ex-post volatility for individual companies nor small equal-weighted portfolios.

Table 10: Linear-Regression results testing the Sentiment for Business-to-Consumer companies

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the individual companies sentiment as input in order to capture the relationship between the sentiment and conditional volatility of each individual company. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column.

Dep. Var.	**Conditional Volatility**	
	Coef. (Std. Err)	R^2
$\textbf{Amazon}_{\textbf{Sentiment}}$	0.0006 (0.04)	0%
$\textbf{Walmart}_{\textbf{Sentiment}}$	0.003 (0.03)	0.07%
$\textbf{McDonalds}_{\textbf{Sentiment}}$	-0.53 (0.78)	0.3%
$\textbf{Facebook}_{\textbf{Sentiment}}$	-0.0003 (0.001)	0.1%
$\textbf{Coca - Cola}_{\textbf{Sentiment}}$	0.07 (0.07)	0.7%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

Given these findings the following and last step is to see whether the changes in sentiment can explain part of the conditional volatility for the S&P 500. If this is the case, then the hypothesis that sentiment has a relationship with conditional volatility can still hold for large diversified portfolios.

4.5 Linear Regression: S&P 500, Conditional Volatility and Sentiment

Given the results in previous sections we believe that it is important to analyse if the relationship that is found in previous chapters is between sentiment and volatility or sentiment and demand for volatility. In order to accomplish this daily closing prices for the S&P 500 Index is downloaded and turned into a time-series of daily returns. This series is then fitted to a GARCH (1,1) in order to yield a time-series of conditional volatilities. The conditional volatility variable is then used as the dependent variable on the regular sentiment variable used in Chapter 4.1 and Chapter 4.2. The S&P 500 index is a large diversified portfolio and which yields a contemporaneous relationship between sentiment and volatility hence this last test is required in order to understand what relationship sentiment and volatility has.

The result of the regression is shown in Table 11 and confirms that there is no significant relationship between the two variables at 1% significance level. This finding strongly suggests that the relationship is between sentiment and demand for volatility rather than volatility itself or that the methodology of estimating a time-series of volatility for S&P500 through a GARCH (1,1) is erroneous. The strong empirical prevalence and success of the GARCH (1,1) for modelling and forecasting volatility, for example Srinivasan (2011), argues for the former. The previous research in behavioral finance however argues the later due to the fact that a negative coefficient is found in Chapter 4.1 and Chapter 4.2. If the relationship is truly between the sentiment and the demand of volatility, negative sentiment ought to suggest loss-aversion or some other trait associated with negative, or fearful, emotions that have been found to lead investors to take on less risk, volatility, and not more. A third hypothesis is that investors of VIX and VVIX are the ones who try to profit from market turbulence and pessimism and hence as the market has negative changes in sentiment their demand for the traded options studied increase due to expectations of increased volatility. If this is the case, the findings of this study are strictly generalizable to options which trade instruments which play on market pessimism.

Table 11: Linear-Regression results testing the Sentiment for S&P 500

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the different variables as input in order to capture the relationship between the sentiment and the conditional volatility of the S&P 500. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column. Each independent variable is fitted against the conditional volatility of the portfolio that they adhere to.

Dep. Var.	**Conditional Volatility**	
	Coef. (Std. Err)	R^2
Sentiment	-0.02 (0.04)	0.1%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

4.6 Robustness - VIX

Different robustness tests are performed in order to validate the results found in Chapter 4.1.

Firstly, two additional models are created using the two-other metrics for sentiment; Sentiment_Favorites and Sentiment_Retweets for the in-sample period 2015-01-01 to 2016-12-31. These replaced the regular Sentiment metric for the two previously mentioned models and show very similar results, although lower adjusted R-Squared. The model that incorporated the Sentiment_Favorites metric yields significant results at a 1% significance level with a coefficient of -0.69 and an Adjusted R-Squared of 2.4%. The significant results and same sign on the coefficient increases the validity of our methodology and previously mentioned results. This is further strengthened by the fact that the model that use the Sentiment_Retweets metric also showed significant results at a 1% significance level with a coefficient of -0.97 and an adjusted R-Squared of 5.3%. The difference in magnitude of the coefficient is likely due to the nature of the changes in the different metrics. As shown in Figure 3, the two subsets of the original Sentiment metric are characterized by much larger swings and hence the coefficients are likely to be lower. The difference in adjusted R-Square is likely attributed to some valuable information being removed when we ignore those tweets that does not meet the previously mentioned criteria's in order to be classified as either Sentiment_Favourite or Sentiment_Retweet.

Secondly, each of the two years used for the in-sample dataset are fitted individually to the different models discussed. The regression based on the full-year 2015 data yields a significant coefficient of -4.9 and a R-Square of 10.5%, while the full-year 2016 data results in a significant coefficient of -4.3 and a R-Square of 10.9%. Given how the individual years leads to significant results and very similar coefficients to the original model this further establishes the robustness of the model and methodology.

4.7 Robustness - VVIX

The same robustness tests that are performed to validate the results found in Chapter 4.1 are performed to validate the results found in Chapter 4.2 as well.

Firstly, the two additional models that are created using the two-other metrics for sentiment for the in-sample period 2015-01-01 to 2016-12-31 show that the same day changes in both the Sentiment_Favorites and Sentiment_Retweets are significant at a 1% significance level with coefficients of -2.62 and –3.46 respectively. The adjusted R-Square is slightly lower than it is for the model that uses the VIX as the dependent variable, namely 2.1% and 4% respectively for the two models. The lagged variables, both for the changes in Sentiment score and changes in VIX, show no significant results. The fact that these results are in-line with both the previously mentioned model in Chapter 4.1 as well as those found in Chapter 4.2, further strengthens the methodology and the theory that sentiment does not necessarily predict volatility, but that it can explain part of it. The difference between the coefficients in the models that incorporated the three-different metrics are once again attributable to the nature of the changes in the metrics, shown in Figure 3. The difference in R-Square is also attributed to the same reason as it is for the robustness test in Chapter 4.6, namely that some explanatory information is lost when different data points are ignored in the aggregation of the sentiment score.

Secondly, once again the model is fitted to the individual full-years of 2015 and 2016. The results are significant coefficients of -17.76 and -11.70 as well as R-Squares of 10% and 6.6% respectively. These results are in-line with those noticed for the individual full-years seen in Chapter 4.6 as well as those seen in the original model on the change in VVIX in Chapter 4.2. All of these models therefor give supporting evidence that the same day changes in sentiment and the changes in the VIX, or VVIX, has a relationship.

4.8 Robustness - Business-to-Business, Business-to-Consumer and S&P 500

A secondary volatility measurement, Historical Volatility, is calculated in order to test the robustness of the results found in Chapter 4.3 as well as Chapter 4.4. The same model as for 4.4 is then applied to this new dependent variable for both business-to-business and business-to-consumer and finds no main difference between the results. The findings, which can be found in Table 11 row one and two, are still highly insignificant with a miniscule R-Square. This further strengthens the notions that the previous results are not found to be insignificant due to measurement error in the GARCH (1,1) but rather due to the underlying non-existent relationship between changes in sentiment and changes in volatility for portfolios based on either business-to-business or business-to-consumer companies.

The robustness test for Chapter 4.4 also shows highly insignificant results with a very low R-Square. The findings for this model are shown in the last row in Table 11 and further illustrates that the previous fitted GARCH (1,1) model gave accurate results in regard to not proving a relationship between the changes in sentiment and changes in volatility for the S&P 500.

Table 12: Linear-Regression results testing the Sentiment for Historical Volatility

We run a simple-linear regression based on the independent variables for the in-sample period of 2015-01-01 to 2016-12-31. The regression uses the change of the aggregated individual companies sentiment as input in order to capture the relationship between the sentiment and conditional volatility of each individual portfolio. The standard error is shown in the parenthesis below the coefficient and the R-Square for each individual model is shown in the second column.

Dep. Var.	**Historical Volatility**	
	Coef. (Std. Err)	R^2
$\textbf{Sentiment}_{\textbf{B2B}}$	0.13 (0.17)	0.4%
$\textbf{Sentiment}_{\textbf{B2C}}$	0.09 (0.17)	0.2%
$\textbf{Sentiment}_{\textbf{S\& P 500}}$	-0.02 (0.04)	0.1%

*, **, and *** indicate 10%, 5% and 1% statistical significance respectively that the coefficient is different from zero.

5 Discussion, Conclusions and Future Research

5.1 Discussion

This study finds, what initially seems to be a contradictory result in Chapter 4, that the results for the VIX and the VVIX are in-line with previous research, both in terms of negative coefficient and a R-Square of approximately 10%, while the results for the business-to-business, business-to-consumer and the regression for changes in conditional volatility on changes in sentiment for S&P500, are found to be insignificant.

One interpretation of these results is that the inverse relationship exists between the sentiment and the demand for structured products which derive their value from volatility, rather than volatility itself. This could be associated to the findings in previous behavioral finance research regarding negative and positive mood. A negative change in sentiment should imply loss-aversion or some other signification associated with a pessimistic emotion that empirically has been found to lead investors to take on less risk or volatility. The negative coefficient between sentiment and implied volatility observed in Chapter 4.1 and Chapter 4.2, however, is in a way a contradiction to these findings. The negative coefficient observed would imply that as people become pessimistic the demand for volatility based products increases. This explanation acts as a direct contradiction to previous findings in behavioral finance studies that negative changes in sentiment leads to increased loss-aversion.

To remedy this, an alternative interpretation is that the investors of the VIX and VVIX are not the usual investors who share the market sentiment but rather try to exploit it by buying VIX and VVIX products. Therefore as the sentiment grows more pessimistic, the investors of the studied products expect increased volatility and the demand for the products grows larger, possibly affecting the price. This interpretation could explain the seemingly contradictory results for why sentiment is found to have a contemporaneous relationship with VIX, and the VVIX, but not with the conditional volatility, nor with the historical volatility of the S&P 500.

The dissimilarity of the different volatility measurements can also be the cause of the distinctive results. The significant results for simple regression on the implied volatility, found in Chapter 4.1, and the non-significant results for simple regression on the conditional volatility, could imply changes in sentiment has a contemporaneous relationship with investors belief of future volatility, ex-ante, and not with the realized volatility, ex-post. The implied volatility is derived through the five inputs: market price of the option, underlying stock price, strike price, time to expiration and risk-free rate. If we assume that sentiment has no relationship to neither the risk-free rate, time to expiration nor the strike price, then the only inputs left are the underlying stock price and the market price of the option. Given how the conditional volatility uses the underlying stock price and that the tests performed on the conditional volatility as dependent variables yields non-significant results, the contemporaneous relationship found for the VIX and the VVIX is most likely related to the market price of the option rather than the stock price. This conclusion is in-line with the findings of Hao and Zhang (2013), namely that deriving implied VIX formulas under locally risk-neutral valuation relationship through a GARCH fails to incorporate the price of volatility or variance risk premium.

A final interpretation is that the way the independent variable, the time-series of conditional volatility, estimated through the GARCH (1.1) yields faulty values in this case. Given the strong empirical prevalence and success of the GARCH (1,1) for modeling and forecasting volatility makes this interpretation rather weak. Furthermore, the usage of a 20-day historical volatility measurement also fails to yield significant results, further strengthening the notion that the failure to capture a relationship between the change of sentiment and the change of volatility is not due to errors in measurement.

5.2 Conclusion

We find a contemporaneous relationship between the two instruments that are based on the implied volatility of options, the VIX and the VVIX, and the derived sentiment index. No predictive relationship is found between the change of the sentiment and the change of the VIX, nor the VVIX. These findings are further strengthened by rigorous robustness tests in which the relationship is found to hold for different estimations of sentiment and over different time-periods.

Further analysis based on the conditional volatility, as estimated by GARCH (1,1), on two portfolios, business-to-business and business-to-consumer, as well as on the actual S&P 500 index is performed and show no significant relationship between volatility and sentiment. The same conclusion is drawn for tests with a 20-day moving average historical volatility metric as the dependent variable instead of the conditional volatility.

Larger numbers of tweets for business-to-consumer companies than business-to-business companies do not yield better results, contrary to our hypothesis that sentiment has a larger impact on business-to-consumer companies than business-to-business companies. The measurement method of volatility in this study could limit the validity of this conclusion.

Since the price of the VIX and the VVIX reflects not only the implied volatility but also the demand for the products, there could be a contemporaneous relationship between the demand for products that derive their value from volatility. A secondary interpretation is that decreased sentiment leads to changes in investors beliefs regarding future volatility yet yield no significant effect on actualized volatility. This is the distinction between variance risk premium and ex-ante or ex-post beliefs.

5.3 Implications for Future Research

The first recommendation for future research regarding the relationship between sentiment and volatility is how it might affect the demand for products such as the VIX and the VVIX. Researchers can analyse whether sentiment has a relationship with the volume of contracts traded in either of the two instruments. By establishing a significant relationship between the sentiment and the volume traded the hypothesis that pessimistic markets correlate with investors who wish to increase their exposure towards volatility in order to capture future gains from strong stock movements.

The second recommendation is to analyse the relationship between sentiment and daily expectations of conditional volatilites, which would then be a time-series of ex-ante observations. These tests could yield great insights regarding if there is a significant discrepancy between ex-post and ex-ante or between conditional volatility and implied volatility. If a difference between the conditional volatility and the implied volatility exists, the hypothesis that the variance risk premium is correlated with sentiment is further strengthened.

Thirdly, we recommend researchers to construct implied volatility metrics for some of the larger companies for which there exist a large number of actively traded options and analyse if those metrics have a relationship with sentiment. This is another way to take the variance risk premium of individual companies into account.

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Appendix A

Table A1: 2015-01-01 to 2016-12-31, In-Sample

VIX	**Coef**	**Std Err**	**[0.025**	**0.975]**	R^2	**Adj** R^2
Sentiment_Fav	-0.69	0.18	-1.047	-0.333	0.028	0.024
Lagged VVIX	-0.003	0.05	-0.091	0.085		
Lagged Sentiment_Fav	0.03	0.18	-0.329	0.380	0	-0.004
Lagged VVIX	-0.01	0.05	-0.1	0.08		

Table A2: 2015-01-01 to 2016-12-31, In-Sample

VIX	**Coef**	**Std Err**	**[0.025**	**0.975]**	R^2	**Adj** R^2
Sentiment_Ret	-0.97	0.18	-1.319	-0.626	0.057	0.053
Lagged VIX	0.001	0.04	-0.086	0.088		
Lagged Sentiment_Ret	0.02	0.19	-0.351	0.386	0	-0.004
Lagged VIX	-0.01	0.05	-0.102	0.081		

Table A3: 2015-01-01 to 2016-01-01, In-Sample

VVIX	**Coef**	**Std Err**	**[0.025**	**0.975]**	R^2	**Adj** R^2
Sentiment_Fav	-2.62	0.74	-4.076	-1.169	0.025	0.021
Lagged VVIX	0.01	0.04	-0.068	0.095		
Lagged Sentiment_Fav	-0.43	0.73	-1.871	1.015	0.001	-0.003
Lagged VVIX	0.01	0.04	-0.077	0.089		

Table A4: 2015-01-01 to 2016-01-01, In-Sample

VVIX	**Coef**	**Std Err**	**[0.025**	**0.975]**	R^2	**Adj** R^2
Sentiment_Ret	-3.46	0.72	-4.877	-2.042	0.044	0.04
Lagged VVIX	0.02	0.04	-0.066	0.095		
Lagged Sentiment_Ret	-0.3	0.76	-1.791	1.199	0	-0.004
Lagged VVIX	0.01	0.04	-0.077	0.090		

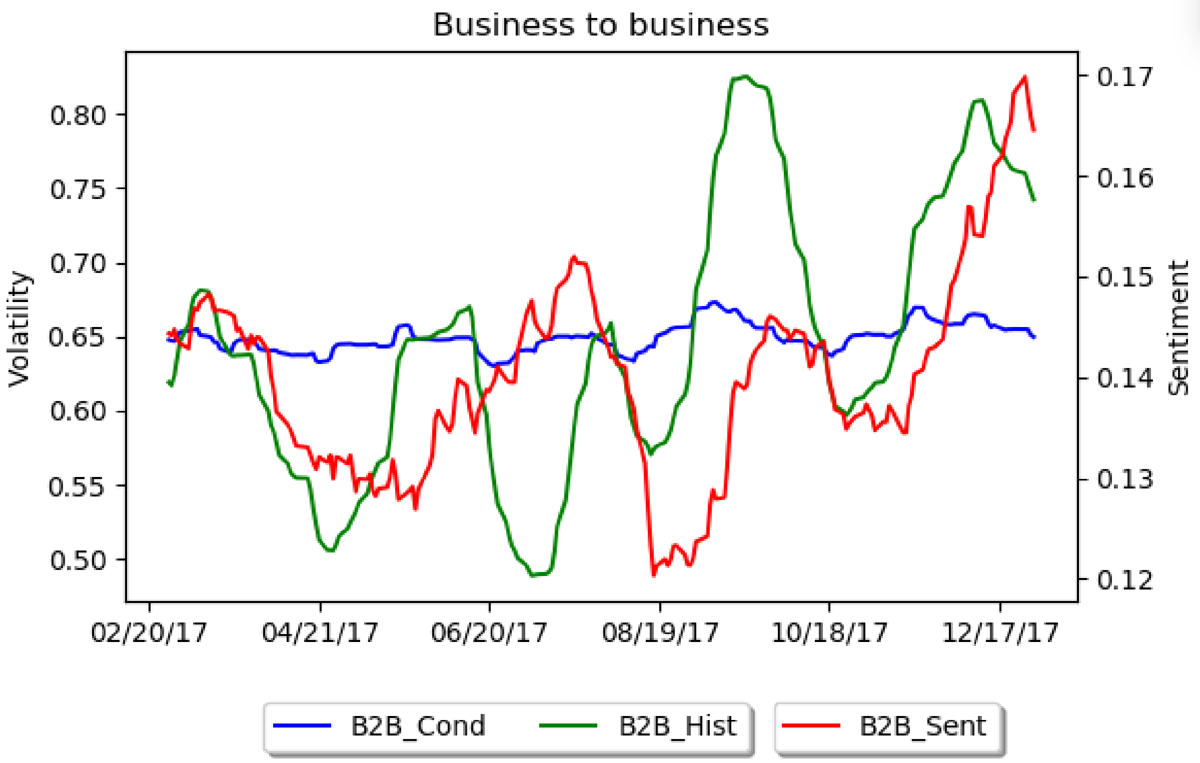

Figure A1: 20-day Moving Average - B2B

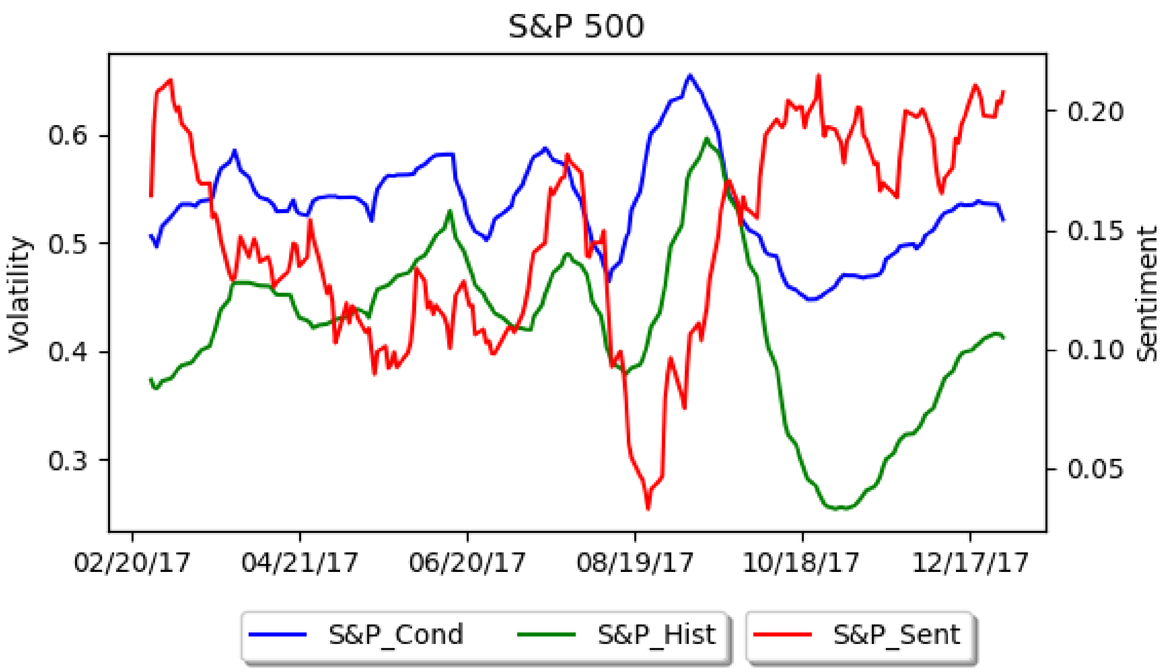

Figure A2: 20-day Moving Average - S&P 500

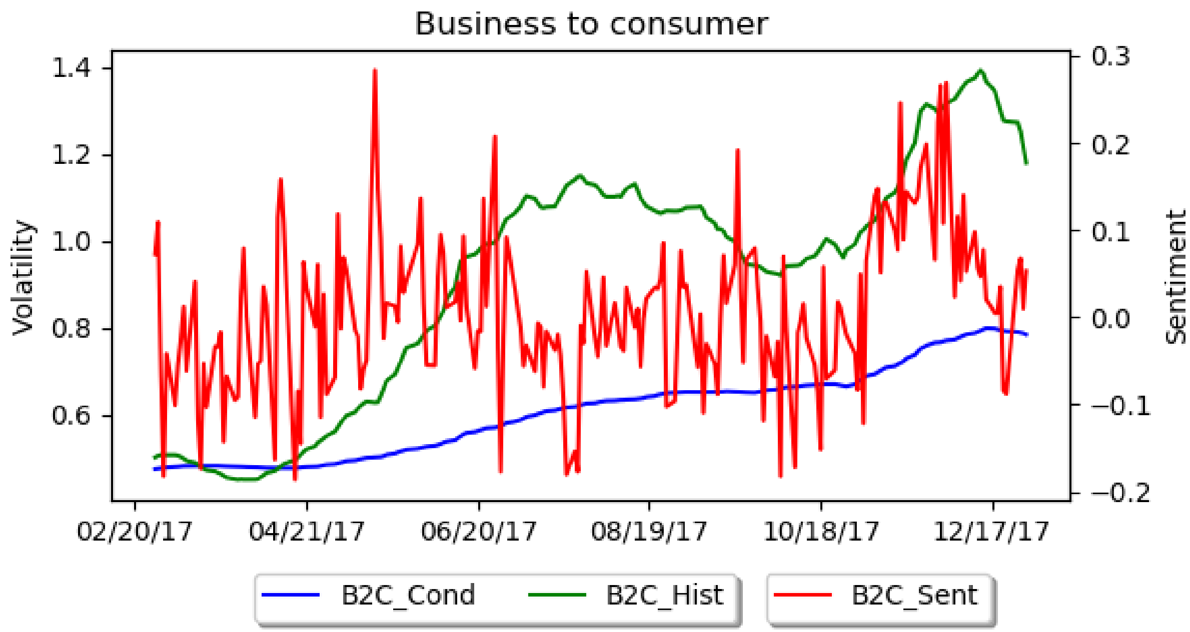

Figure A3: 20-day Moving Average - B2C