

Janda, Karel; Rozsahegyi, Marketa; Quang Van Tran; Zhang, Binyi

**Working Paper**

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*Suggested Citation:* Janda, Karel; Rozsahegyi, Marketa; Quang Van Tran; Zhang, Binyi (2025) : The Impact of Machine Learning Derived Green Bonds Sentiment on Performance of Green Bond Portfolio, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/335550>

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# The Impact of Machine Learning Derived Green Bonds Sentiment on Performance of Green Bond Portfolio

Karel Janda, Marketa Rozsahegyi, Quang Van Tran, Binyi Zhang<sup>1</sup>

## Abstract

This paper investigates the role of investor sentiment in the pricing and volatility dynamics of green bond exchange-traded funds (ETFs). For a construction of green sentiment one original and two already existing natural language processing models are used and evaluated. The VAR model found no significant impact of green sentiment on ETF returns. The GARCH (1,1) estimation strongly supported the presence of volatility clustering and time-varying volatility in green bond ETF returns, validating the use of conditional heteroskedasticity models. Regressing the conditional volatility on sentiment scores revealed a significant negative relationship – higher sentiment is associated with lower volatility. This finding implies that positive green sentiment contributes to market stability and may reduce perceived risk, reinforcing the importance of investor psychology in green financial markets.

Keywords: Machine learning, NLP model, ESG, Exchange Traded Funds

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<sup>1</sup> Karel Janda Prague University of Economics and Business and Charles University, Email: < Karel-Janda@seznam.cz >; Marketa Rozsahegyi University of Economics and Business, Email: <kosm17@vse.cz>; Quang Van Tran University of Economics and Business and Czech Technical University, Email; <tran@vse.cz>; Binyi Zhang Charles University, Email: <[Binyizhang@outlook.com](mailto:Binyizhang@outlook.com)>. This paper is part of a project that has received funding from the European Union's Horizon 2020 research and innovation programme GEOCEP under the Marie Skłodowska-Curie grant agreement No. 870245. We also acknowledge financial support from the Czech Science Foundation (grant no. 24-10008S). The views expressed here are those of the authors and not necessarily those of our institutions. All remaining errors are solely our responsibility.

# 1 Introduction

This paper combines machine learning based analysis of investor sentiment with econometric investigation of relations between this sentiment and performance indicators of green bond exchange traded funds. It investigates the impact of sentiment in news data related to the industry on the pricing dynamics of fixed-income exchange traded funds (ETFs) on the secondary market. Its objective is to fill the literature gap by investigating the still relatively small but growing part of ESG industry of green bond ETF, how it behaves compared to traditional assets.

Furthermore, to ensure that findings are not driven by ETF-specific characteristics, the empirical tests are replicated separately on a second green bond ETF. This step supports the external validity of the results and provides additional insights into how fund structure and market behaviour interact with sentiment-driven dynamics.

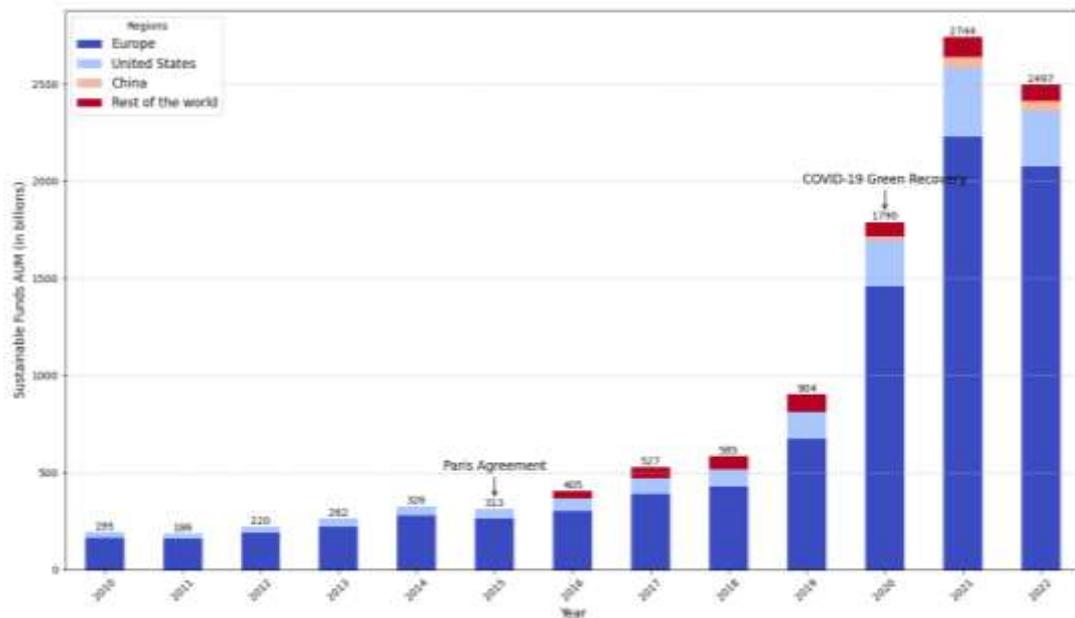
We outline the research design, data sources, and econometric techniques used in this study. It begins with data collection followed by a detailed account of how sentiment scores were derived using natural language processing (NLP), lastly it introduces the Vector Autoregression (VAR) and GARCH frameworks used to examine dynamic relationships and volatility behaviour.

We present the empirical findings in three stages. It begins with the output of the sentiment analysis, followed by an investigation into the statistical properties of the time series and the estimation of VAR models to assess potential relationships and causality. The empirical part concludes with GARCH model estimations, evaluating whether sentiment contributes to volatility clustering and time-varying volatility in green bond ETFs.

## 2 Green Funds

When searching for statistics, we found that the total amount of green assets is hardly separated from the sustainable industry numbers nor consistently collected. So firstly, the growth of the whole sustainable sector is depicted on the numbers of sustainable funds. Figure 1 illustrates the growth of global sustainable assets under management (AUM) from 2010 to 2022. The rise has been substantial, reaching approximately 2.5 trillion U.S. dollars in volume in 2022 (United Nations Conference on Trade and Development 2023). Key milestones, such as the launch of the United Nations Principles for Responsible Investment in 2006, the Paris Agreement in 2015, and the COVID-19-driven green recovery in 2020, were added to highlight significant points where interest in sustainable investing surged. Secondly, between 2014 and 2022, the issuance of sustainable bonds experienced rapid exponential growth but has stabilized in recent years. By 2022, the total value surpassed 900 billion U.S. dollars globally growing fivefold between 2017 and 2022. Of the total almost 600 billion is assigned to green bonds, the oldest market for sustainable bonds. Lastly, UNCTAD recognise voluntary carbon markets which attained market volume of 2 billion U.S. dollars in 2021 when it nearly quadrupled from 2020. Figure 1 clearly shows enormous regional disparity in green/sustainable funds and AUM between Europe and US (and other regions as well).

Figure 1: Sustainable funds and assets under management, 2012–2022

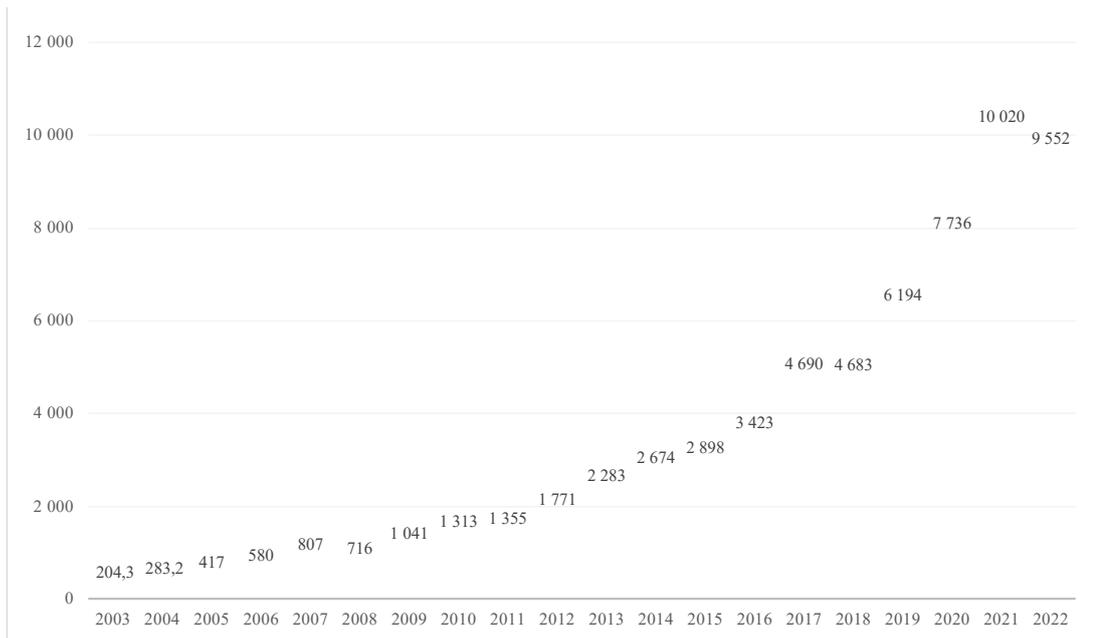


Source: World Investment Report 2023, own adaptation

Out of green funds we focus on ETFs. Our empirical analysis aims to further investigate whether the relationship between investor sentiment and overall green market represented as different ETF returns is positive or negative, and additionally how does the sentiment influence the volatility of the returns – is it consistent with the coefficient of the sentiment with respect to green returns?

From the beginning of the 21<sup>st</sup> century, the value of assets under ETFs management grew markedly from 203 billion US dollars in 2003 to almost 10 trillion US dollars in 2022 (see Figure 2). The number of ETFs reached 8 754 in 2022 (Statista Research Department 2023). It is therefore no surprise that such investment rise draws attention not only of investors but also many researchers.

Figure 2: Development of ETF asset value 2003-2022



Source: Statista, own adaptation

## **3 Methodology**

In investigating the influence of investor sentiment on the returns of green assets incorporated in selected green bond Exchange-Traded Funds (ETFs), our methodology comprises three key steps. First, the data collection is undertaken to gather relevant information on both investor sentiment and the historical financial performance data of green bond ETFs. Next, we conduct sentiment analysis using Natural Language Processing (NLP) method to gauge the prevailing sentiments within the international journal community. Finally, we employ statistical analysis techniques, including regression analysis, to identify any significant correlations or causal relationships between investor sentiment and the performance of ETFs.

### **3.1 Data Collection**

To all gathered data a specific time interval has been selected, the considered period is from 1<sup>st</sup> January 2017 to 31<sup>st</sup> December 2024. Such time span enables a comparison of the market under different shocks, for example Covid pandemic in 2020.

For this study, English news data were downloaded from the global articles database – Factiva. That is particularly because of its comprehensive collection of news articles, company reports, and other financial publications. All sources included there are captured over time, so it is useful for identifying trends and shifts in investor sentiment. Also, Factiva offers advanced search engines with filtering across sectors, date ranges, and sources that comes in handy. In total, 97 160 of raw English written articles were gathered.

The approach described in study of Toulová (2025) was mostly followed. As a search word, “green bond” was taken into consideration after few unsuccessful attempts to get reasonable data with a general word “green”. Almost 100 000 articles were downloaded and pre-processed as follows.

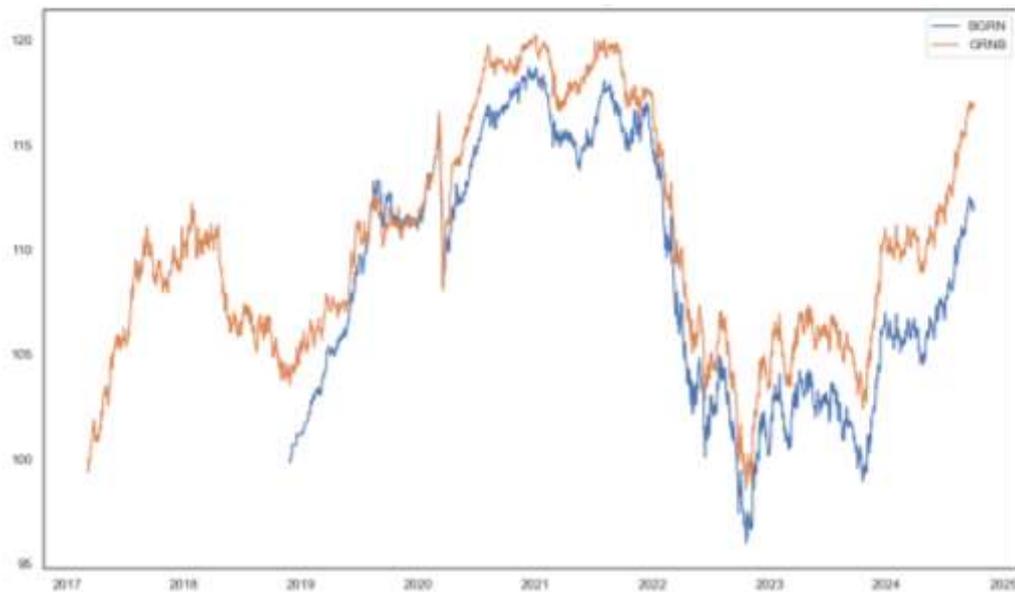
First, we got acquainted with all 31 downloaded columns that included for example name of the publisher, date, or language. Then, we selected 3 main ones for further analysis – HD (headline), LP (abstract), and TD (text). The median of the words in each variable was: 11 words in headlines, 53 words in abstract and 669 words in full text. Naturally, the abstract was selected to be analysed for the sentiment as it includes



municipalities, and corporations to finance projects with environmental benefits, such as renewable energy or energy efficiency. Its benchmark index is Bloomberg MSCI Global Green Bond Select Index.

- **VanEck Vectors Green Bond ETF (GRNB)** seeks to track the S&P Green Bond Select Index, which also includes bonds issued by governments, municipalities, and corporations worldwide to finance projects that have a positive environmental impact. It has been available since 2017.

Figure 3: Green bonds ETFs normalized prices in time (in US dollars)



Source: own adaptation

Both green bond ETFs showed a high correlation of 0.77, indicating that their price movements are strongly related. GRNB slightly outperformed BGRN in terms of returns as of the end of the period – 31.10.2024, however, BGRN provided a higher dividend yield.

### 3.2 Sentiment Analysis

Sentiment analysis, a pivotal task in natural language processing (NLP), involves extracting and classifying emotions and opinions from text data. This chapter delves into two primary approaches for performing sentiment analysis: building an NLP model from scratch and leveraging a pre-trained model, specifically FinBERT, for financial sentiment analysis.

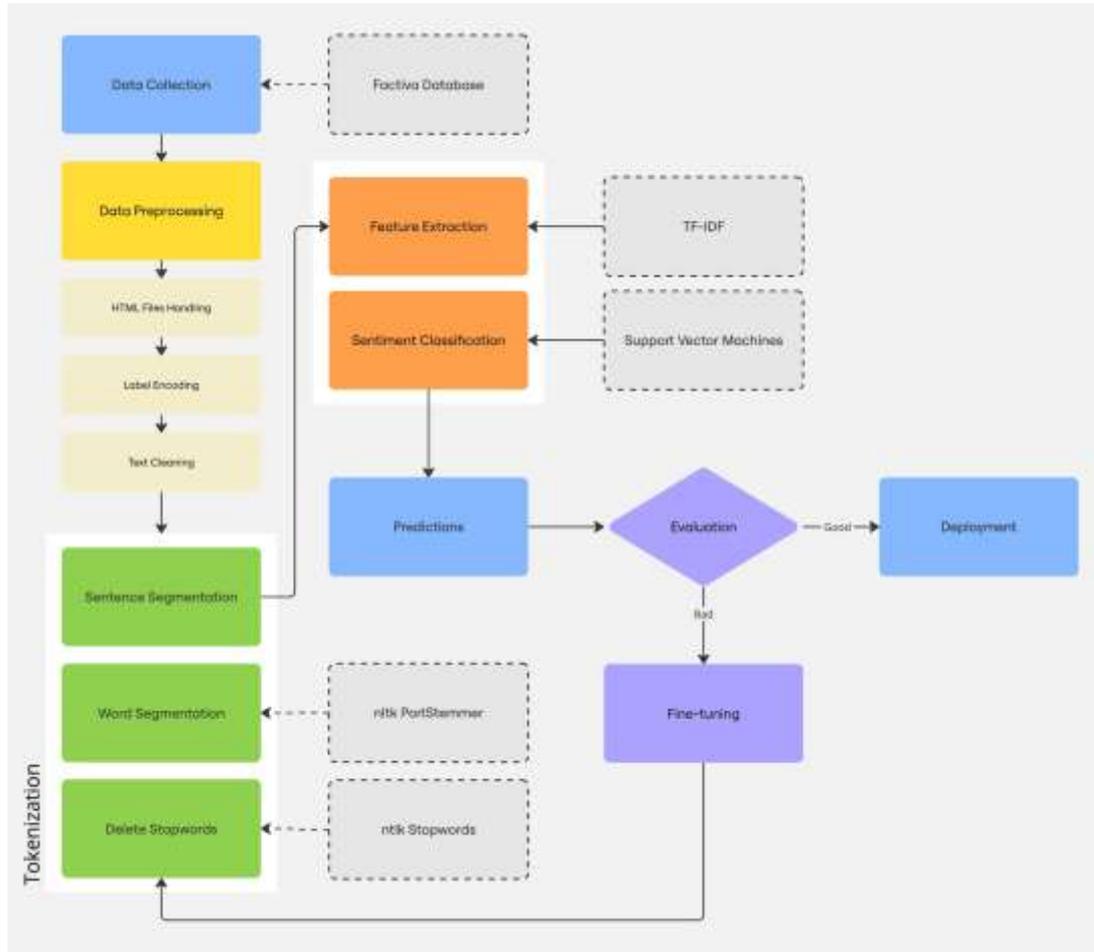
### 3.2.1 NLP Model from Scratch

First, the fundamental multiple-step analysis was done by hand. Such text analysis to determine the sentiment or emotion expressed in a piece of text includes the following steps: (i) **Tokenization**, where the text is segmented into discrete units known as tokens, (ii) **Feature Extraction** which means discover intrinsic characteristics of the analyse text using certain extraction methods, such as Bag of Words or Word2Vec, (iii) **Sentiment Classification** that is tracked down by machine learning model trained to classify the sentiment, predominantly employed ones are Naïve Bayes Classifier, Support Vector Machines, or Random Forests. (iv) **Evaluation and Fine-tuning** is subsequent to model training to access the model's performance, also refinement is essential to maintain the model's effectiveness, particularly as linguistic patterns evolve, and finally (v) **Deployment** (OpenAI 2024). For this study, more specific instructions from (Raj 2021) were followed as depicted in diagram in Figure 4. The results were, unfortunately, insufficient on the tested dataset due to small amount of financial training data and therefore poor performance results. Find the compared statistics in 3.2.3 Evaluation and Comparison.

### 3.2.2 Pre-trained Models

Consequently, already pre-trained and fine-tuned models were considered leading to better sentiment classification performance together with minimum computational resource need. The search for an appropriate NLP model ended up using the transformers library, specifically the FinBERT model (Araci 2019). The reason for choosing to include the FinBERT model into the practical part is due to a fact that such pre-trained models offer a powerful and efficient alternative which is proved for example by Shen and Zhang (2024). FinBERT, a variant of BERT (Bidirectional Encoder Representations from Transformers), is specifically fine-tuned for financial text, making it highly suitable for our sentiment analysis that uses economic articles as the source of a sentiment. Utilizing FinBERT showed faster deployment, and it also achieved superior performance due to the extensive pre-training on vast datasets.

Figure 4: Diagram of NLP model creation



Source: own adaptation

As a second integrated pre-trained model was included RoBERTa Base with general purpose, fine-tuned for sentiment analysis.

### 3.2.3 Evaluation and Comparison

Classification results of the above-described models can be observed in Table 1. There are general performance metrics such as

- accuracy – a percentage of correct predictions,
- precision – a proportion of true positive predictions to total positive predictions,
- recall (also called sensitivity) - proportion of true positive predictions to actual positives, and
- F1-score – a harmonic mean of precision and recall, which is useful for imbalanced datasets.

Our original NLP model showed an accuracy on the tested dataset of nearly 54%, whereas pretrained FinBERT model correctly decided about the sentiment in 89%. Lastly, RoBERTa model’s accuracy was 66%. The order repeats in almost all other calculated metrics which confirms the best model for financial new data – the FinBERT model.

Besides general comparison metrics, we are interested in a proportion of each predicted sentiment to the total. A positive or negative tone of a message was predicted by our original NLP model in 45 % of all articles, the rest almost 55 % were classified as neutral. The heavily pre-trained FinBERT model that assigned neutral sentiment to 53 % cases, the rest was classified with a specific tone. The proportion of neutral sentiment was expected around 50 % since we trained and tested the model on fact-based news data. We conclude that similar output is further assumed on the data from Factiva database.

Table 1: NLP models comparison metrics

Metric		Our original model	FinBERT	RoBERTa
<b>Accuracy</b>		53,78%	88,93%	66,65%
<b>Precision</b>	Negative	35,00%	80,00%	79,00%
	Neutral	66,00%	96,00%	67,00%
	Positive	40,00%	81,00%	63,00%
<b>Recall (Sensitivity)</b>	Negative	31,00%	97,00%	30,00%
	Neutral	61,00%	86,00%	87,00%
	Positive	48,00%	92,00%	39,00%
<b>F1-score</b>	Negative	33,00%	88,00%	43,00%
	Neutral	64,00%	91,00%	76,00%
	Positive	43,00%	86,00%	48,00%
<b>Proportion of predicted sentiment</b>	Negative	10,89%	15,08%	4,68%
	Neutral	54,83%	52,95%	77,67%
	Positive	34,28%	31,96%	17,64%

## 4 Results

### 4.1 NLP Model Output

A pre-trained FinBERT model was employed to classify the sentiment of news articles related to green bonds, retrieved from the Factiva database. The sentiments were categorized as negative, neutral, and positive with its respective scores. Initially, these scores were treated as scalar sentiment values; however, it was later clarified that they represent classification confidences (from 0 to 1) rather than continuous sentiment magnitudes. Also, the second approach of mapping each label to its numerical value (-1, 0, and 1) was rejected as it created too coarse values.

To better reflect the model's intent, we decided to assign each article a signed sentiment score based on the predicted label with the highest confidence: +score for positive, -score for negative, 0 for neutral. This approach was selected as best because it captures valuable nuance from the FinBERT model while preserving directional interpretation. Because many days had multiple articles with its predicted sentiment, we computed an average sentiment for each day, so each day has one value. In total, 2,697 unique publication days in period from 2017-01-01 to 2024-09-30 were obtained.

A histogram was plotted to show distribution of the average sentiment, see Figure 6. Since the peak is centred slightly to the right, it is considered right-skewed, indicating that most articles have a mildly positive sentiment. There is very thin left tail, meaning that very few articles have strongly negative sentiment. This could indicate a general optimism or constructive focus in green news reporting, possibly due to the positive framing of sustainability efforts, innovations, and environmental progress.

After merging the sentiment on an ETF time-series total of 6 missing sentiment values appeared, which happened due to the fact that there were no articles downloaded on the trading days, therefore they were imputed using nearest-neighbour interpolation. In the Figure 5, the sentiments are represented by distinct colours. Across all years, there is a notable proportion of neutral sentiment, which dominates most years. This indicates that many articles have balanced or non-polarized tones.

The volume of the news articles quadrupled in the observed period highlighting the increase in the ESG topics.

More details concerning the sentiment analysis follow in the next subchapter.

Figure 5: Predicted sentiment distribution by years

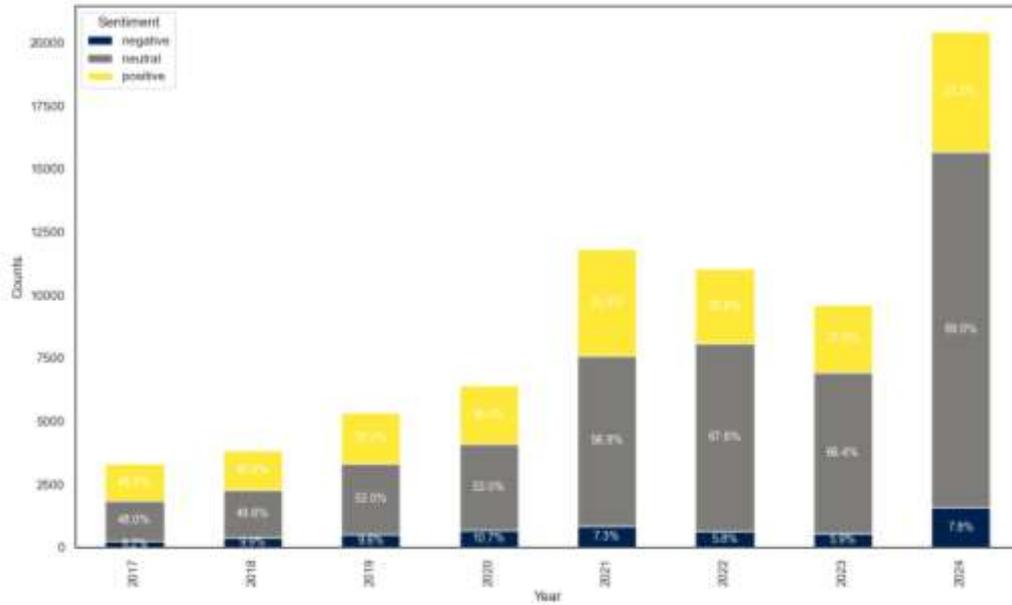
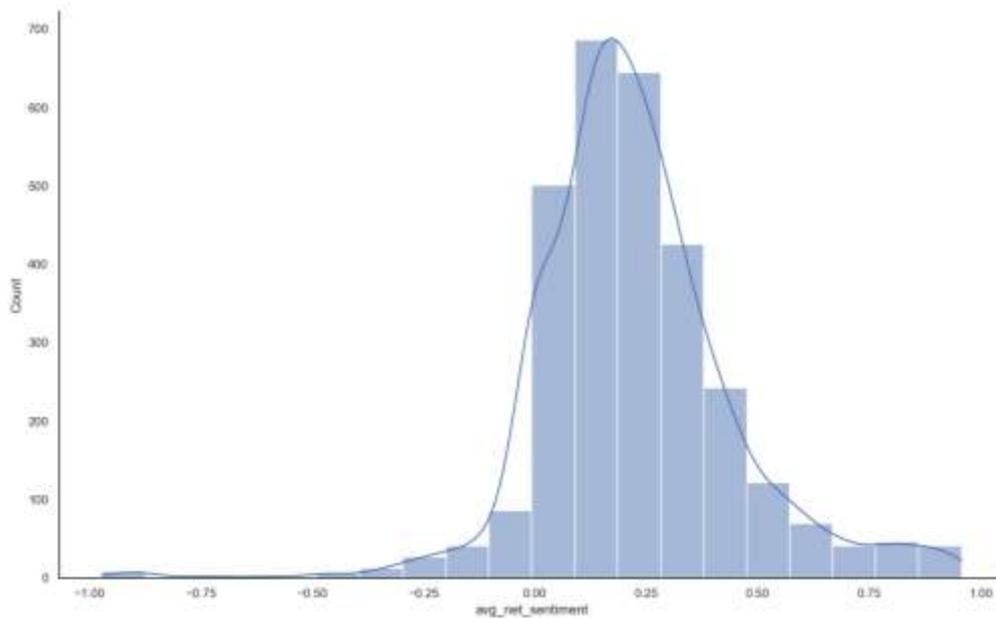


Figure 6: Distribution of average sentiment



## 4.2 Estimating the Relationship Between Sentiment and ETFs

In this section, an analysis of the relationship between the ETF market and its main determinants is conducted. Specifically, the study aims to find answer to the main question if the sentiment in green bond-related news influences the returns and volatility of green bond ETFs.

**H<sub>1</sub>:** *News sentiment has a statistically significant impact on green bond ETF returns.*

**H<sub>2</sub>:** *Green bond ETF returns exhibit*

- a) volatility clustering*
- b) time-varying volatility.*

**H<sub>3</sub>:** *News sentiment significantly affects the volatility of green bond returns.*

Furthermore, to ensure that findings are not driven by ETF-specific characteristics, the empirical tests are replicated on a second green bond ETF. This step enhances the external validity of the results and provides additional insights into how fund structure and market behaviour interact with sentiment-driven dynamics.

This chapter presents the empirical findings from modelling the relationship between green bond ETF returns and news sentiment using both VAR and GARCH frameworks. The VAR analysis explores whether sentiment carries predictive power for ETF returns when controlling for key macroeconomic variables, while the GARCH models examine how sentiment contributes to the time-varying nature of return volatility. Together, these models provide a two-dimensional view as it assesses not only potential return impacts but also how sentiment may amplify risk.

### 4.2.1 Stage 0: Pre-model Analysis

Table 2 provides a summary of key statistical metrics for all time-series used in VAR modelling. For all time-series except for the average sentiment daily close prices are observed. Non-numeric and missing values were excluded from the analysis.

GRNB consistently shows lower mean prices than BGRN, both ETFs exhibit relatively low standard deviations, indicating moderate daily price variability. The

average sentiment score, ranging between  $-1$  and  $1$ , shows a positive bias (based on the mean =  $0.29$ ), implying generally favourable news during the sample period. The VIX displays a wide range and high variability, consistent with its nature as a market volatility index.

Table 2: Statistics of selected variables

	GRNB	BGRN	Average Sentiment	VIX	TNX	GSPC
count	1,905	1,469	2,698	2,200	2,199	2,200
mean	22.61	45.74	0.21	18.47	2.46	3,430.26
min	20.20	40.37	-0.97	9.14	0.50	1,829.08
25%	21.73	43.38	0.10	13.20	1.64	2,642.30
50%	22.51	45.57	0.19	16.48	2.36	3,221.25
75%	23.48	48.31	0.31	21.74	3.16	4,226.70
max	24.65	49.93	0.95	82.69	4.99	5,762.48
std	1.09	2.53	0.21	7.60	1.08	977.67
stationarity	log ✓	log ✓	✓	log ✓	log ✓	log ✓

All series were tested for **stationarity** using Augmented Dickey-Fuller test and results confirmed that log transformations of returns are stationary by construction as well as the average sentiment, allowing for VAR modelling without any differencing.

**Autocorrelation** analysis was performed on the log returns of ETF prices, which are generally stationary by construction. A visualization of partial autocorrelation function (PACF) was created. This helps identify the direct effect of a lag  $k$  on the current value after controlling for other lags. It revealed no significant spikes beyond lag 0, suggesting that the log return series exhibits white noise behaviour – a common characteristic in efficient financial markets. However, when we analysed volatility in order to reject or confirm  $H_2$ , it showed dependence over time (see Figure 7 and Figure 8). This indicates volatility clustering, a typical feature of financial time-series, where large (or small) price changes are likely to be followed by similarly large (or small) changes. To test these characteristics Ljung-Box Q-Statistic test on squared returns was performed. The null hypothesis states that the data are independently distributed, hence there is no autocorrelation. The test statistics and their respective p-values are in the table below. The null hypothesis is rejected therefore, the results justify not only attention to volatility modelling but also confirms posed hypothesis  $H_2$  which will be later re-tested by fitting GARCH(1,1) model for stronger evidence.

Table 3: Ljung-Box test

Lag	BGRN	GRNB
1	24.16 (0.01)	84.21 (0.00)
2	60.90 (0.00)	113.82 (0.00)
3	88.47 (0.00)	149.30 (0.00)
4	118.33 (0.00)	183.73 (0.00)
5	124.66 (0.00)	212.27 (0.00)
6	133.07 (0.00)	223.42 (0.00)
7	138.91 (0.00)	227.98 (0.00)
8	148.13 (0.00)	231.72 (0.00)
9	151.97 (0.00)	242.02 (0.00)
10	155.00 (0.00)	245.00 (0.00)

Lastly, multicollinearity was assessed using the Variance Inflation Factor (VIF) before fitting each model. All variables used in the model showed VIF not higher than 2.54, which falls under the general rule of thumb that VIF exceeding 4 requires correction.

Figure 7: Partial autocorrelation functions of squared returns of BGRN

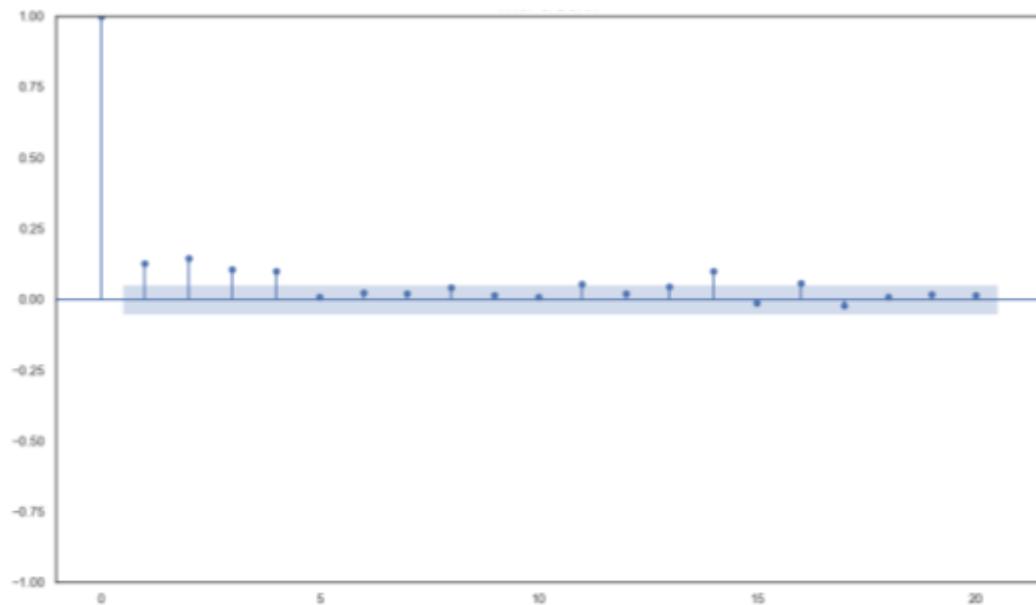
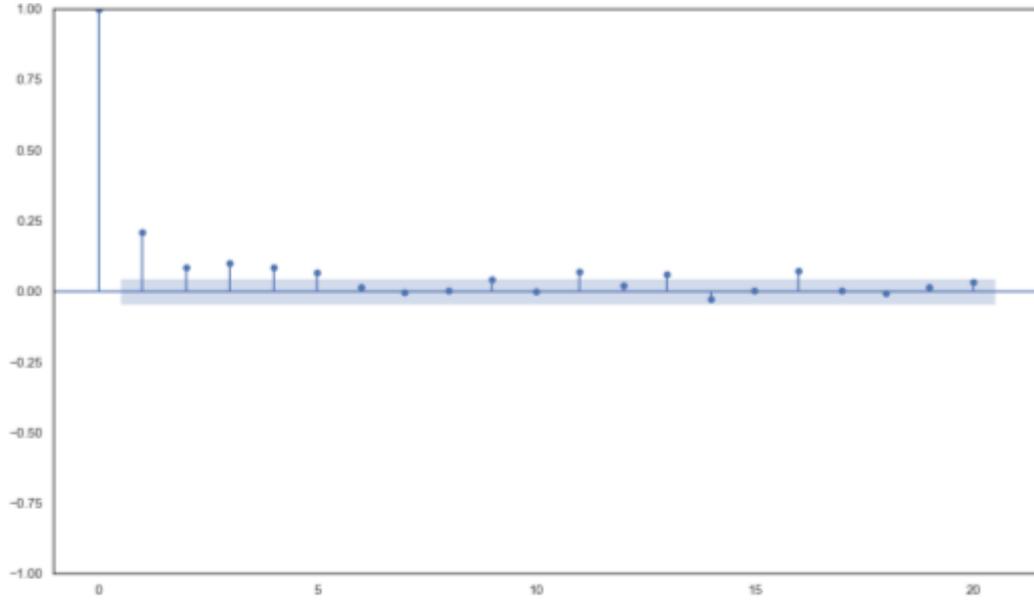


Figure 8: Partial autocorrelation functions of squared returns of GRNB



#### 4.2.2 Stage 1: VAR Estimation

In this first modelling stage, a vector autoregression framework was applied to examine the dynamic relationship between green bond ETF returns and investor sentiment. Since VARs don't perform well with too many variables because of overfitting and reduces power, we added three macroeconomic control variables - the interest rates, stock market index, and volatility index. The optimal lag length was determined using standard information criteria (AIC, BIC). A wide range of model specifications was estimated, utilizing various variables. In total, three main VAR model were found appropriate to investigate in detail. All three include as many macroeconomic variables as is eligible. For example, when creating an interaction term *Sentiment\_x\_VIX*, the volatility index itself was dropped not to cause overfitting.

The first part focuses on modelling the VanEck Vectors Green Bond ETF

(GRNB). For the first (full) model, let  $y_t = \begin{bmatrix} GRNB_t \\ Sent_t \\ TNX_t \\ GSPC_t \\ VIX_t \end{bmatrix}$  be the vector of endogenous

variables. Then proceeding from equation (1) the formula for GRNB in VAR(1) would be:

$$GRNB_t = \alpha_0 + \alpha_1 GRNB_{t-1} + \alpha_2 Sent_{t-1} + \alpha_3 TNX_{t-1} + \alpha_4 GSPC_{t-1} + \alpha_5 VIX_{t-1} + \varepsilon_t$$

By adding the rest of four similar equations create a system of five interrelated equations. All variables must be stationary which was proved by ADF test. Consequently, tests for homoscedasticity and serial correlation were satisfied. Unfortunately, the residuals were not proved to be normally distributed in any of the models. However, the models were estimated as it was the only violation of the assumptions. Lastly, the stability of the model was successfully tested by depicting the eigenvalues of the companion matrix, all lied outside the unit circle. Following the same process the other two models were analysed with similar outputs (see Table 4).

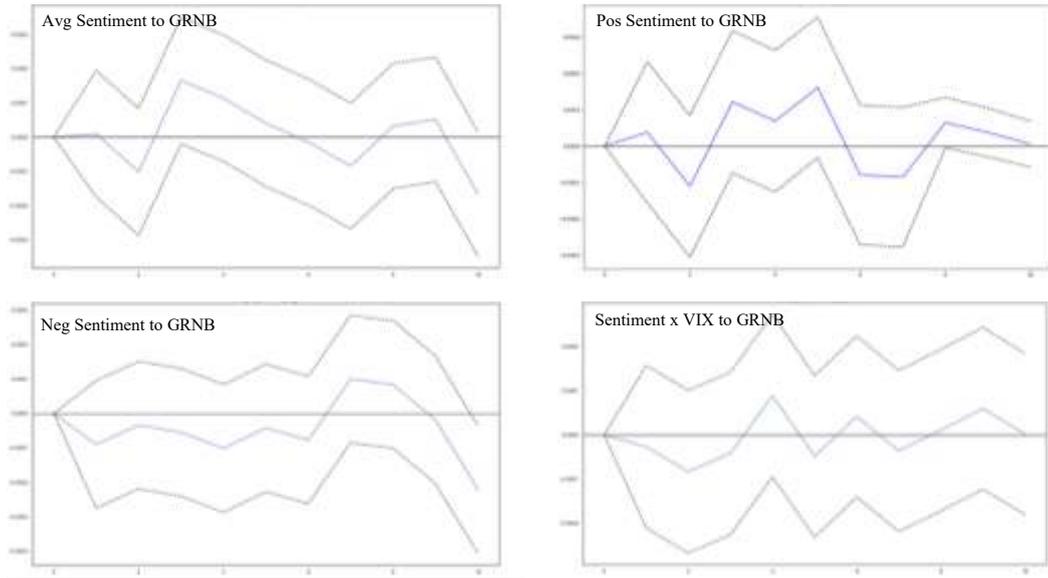
Table 4: Summary of VAR models including GRNB

Model	Included variables	Sentiment variable	AIC	Significant lags (Sent)	Granger causality	IRF
1	GRNB, VIX, TNX, GSPC, avg_sent	avg_sent	-37.48	Lag 3 (p = <b>0.042</b> ), lag 10 (p = <b>0.063</b> )	No	Positive short-term effect
2	GRNB, sent_Pos, sent_Neg, VIX, TNX, GSPC	sent_Pos, sent_Neg	-45.51	None	No	Negligible / expected direction
4	GRNB, GSPC, Sent VIX	Sent_x_VIX	-35.85	None	No	No clear effect

From the VAR models' summary tables, there were no consistent evidence that investor sentiment derived from news mentioning green bonds would significantly influence GRNB returns. Although, in Model 1 the sentiment variable appears statistically significant ( $p \approx 0.05$ ), it did not pass conventional thresholds. Its explanatory power remained weak across FEVD and IRF analyses (see Figure 9). The response of average sentiment appears from the visual positive at multiple horizons, particularly around periods 2, 5, and 7, suggesting that average sentiment has some modest but consistent short-term effect on GRNB returns. Both asymmetric responses show expected reaction, the negative is hinting at a negative market reaction to pessimistic sentiment. Lastly, the interaction term yields a mostly positive effect peaking after period 4, and suggesting that sentiment under high volatility conditions may be interpreted differently – a potential signal of risk premium adjustments. Overall, all shock responses are at very low levels around 0.0005.

Granger causality tests further confirmed the absence of predictive power. These findings are evidence for  $H_1$  resulting in statistically inconclusive impact of different types of sentiment on the green bond ETF returns.

Figure 9: Orthogonal IRF – GRNB model



To conclude the first part, while different specifications slightly varied in fit (as indicated by AIC), sentiment did not emerge as a robust driver of VanEck Vector Green Bond ETF returns in a linear VAR framework.

The next part focuses on modelling the iShares Green Bond ETF (BGRN) within the above-described approach. As it was mentioned, the assumption is that the results will be very similar as the returns showed high correlation between the two green ETFs. If there was a difference it would suggest that shorter time span reveals different relationship, since BGRN has trading history almost 2 years shorter than GRNB. Hence, it would signify to try to subset GRNB and observe the influence of investor sentiment under different market situations.

The results from the models' summary tables are very similar – in two models the sentiment variable approached significance – the `avg_net_sentiment` variable in Model 4 at lags 3 and 10 ( $p \approx 0.09$ ) and the interaction term `Sentiment × VIX` in Model 6 at lags 4 and 5 ( $p \approx 0.07$ ) – but the results are not convincing. Therefore, the focus turned towards depicting IRF to see if there are any visual differences. The sentiment from the

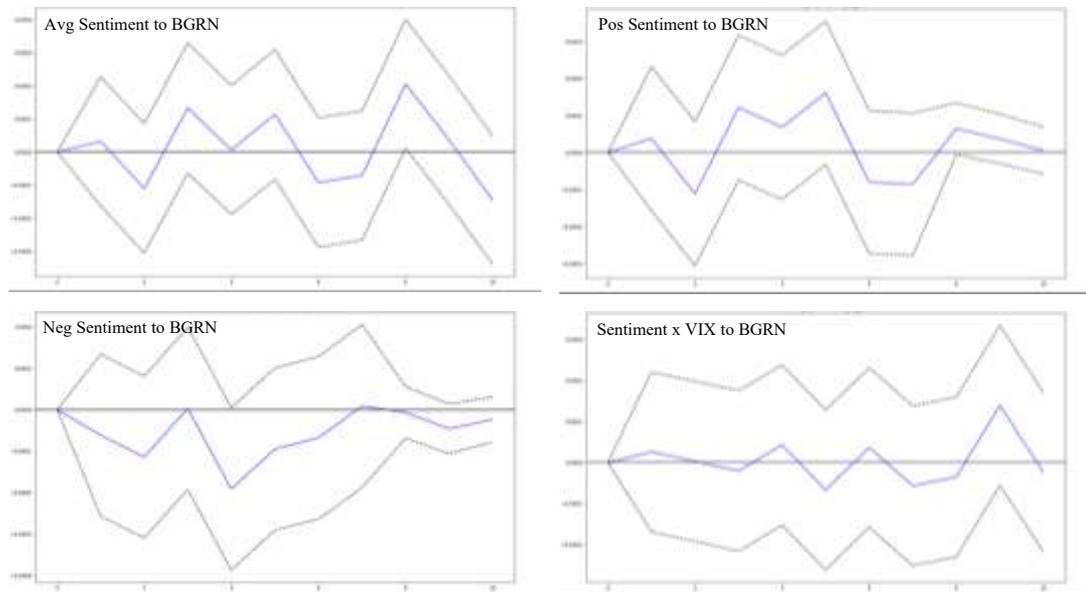
Figure 10 in largely insignificant similarly to the plots of GRNB. The direction of the shock is intuitive; however, the responses are weak. BGRN seems to integrate sentiment better when market uncertainty is high, while GRNB shows weak

responsiveness. This could reflect higher sensitivity of BGRN to broader market risk sentiment.

Table 5: Summary of VAR models including BGRN

Model	Included variables	Sentiment variable	AIC	Significant lags (Sent)	Granger causality	IRF
4	BGRN, VIX, TNX, GSPC, avg_sent	avg_sent	-37.34	Lag 8 (p = <b>0.088</b> ), lag 10 (p = <b>0.010</b> )	No	Mild, positive effect
5	BGRN, sent_Pos, sent_Neg, VIX, TNX, GSPC	sent_Pos, sent_Neg	-45.38	None	No	Negligible / expected direction
6	BGRN, GSPC, Sent_VIX	Sent_x_VIX	-34.69	Lag 4 (p = <b>0.070</b> ), lag 5 (p = <b>0.062</b> )	No	Low reponse

Figure 10: Orthogonal IRF – BGRN model



Both outputs support the rejection of the proposed hypothesis  $H_1$  resulting in not proven significant influence of the news sentiment on the selected green bond ETFs. Based on the previous findings, the lack of effect in the mean equation, but visible volatility clustering in the above-displayed PACF of squared returns suggests estimation with GARCH-type models.

### 4.2.3 Stage 2: GARCH Estimation

To explore whether investor sentiment influences returns or volatility, sentiment variables were included in GARCH(1,1) model as exogenous regressors in the mean equation. This approach allows testing whether sentiment not only influences return levels but potentially correlates with periods of increased or decreased volatility.

Firstly, the model will be estimated for GRNB time series as did before, followed by results of modelling on BGRN where we again assume very similar outcomes.

The initial model, including the interaction term *Sentiment\_x\_VIX* was first tested, but results showed no statistical significance. This suggests that sentiment adjusted for the whole market uncertainty (proxied by the VIX) does not significantly predict return dynamics in this context. Subsequently, it was replaced by the *avg\_net\_sentiment* variable. In addition, the distribution of residuals exhibited heavy tails, which violates the normality assumption therefore, the conditional distribution of errors was specified as a Student's t-distribution.

The model structure with  $X_t$  as investor sentiment is as follows:

- Mean equation:  $y_t = \mu + \beta X_t + \varepsilon_t$ ,  $\varepsilon_t = z_t \sqrt{h_t}$ , where  $z_t \sim t_\nu(0,1)$
- Variance equation:  $h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$

After correcting for the scale of the dependent variable, the model results (Table 6) indicate that the average net sentiment coefficient is positive (0.0579) but statistically insignificant ( $p = 0.233$ ).

Table 6: Results of GARCH(1,1) – GRNB model

AR-X - GARCH Model Results					
Dep. Variable:	GRNB_log_return	R-squared:			-0.001
Mean Model:	AR-X	Adj. R-squared:			-0.002
Vol Model:	GARCH	Log-Likelihood:			-263.796
Distribution:	Standardized Student's t	AIC:			539.591
Method:	Maximum Likelihood	BIC:			571.341
		No. Observations:			1468
Date:	Sun, May 18 2025	Df Residuals:			1466
Time:	20:34:33	Df Model:			2
Mean Model					
	coef	std err	t	P> t	95.0% Conf. Int.
Const	0.0138	1.178e-02	1.169	0.243	[-9.325e-03, 3.686e-02]
avg_net_sentiment	0.0579	4.853e-02	1.193	0.233	[-3.720e-02, 0.153]
Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.
omega	7.4384e-04	4.077e-04	1.824	0.068	[-5.533e-05, 1.543e-03]
alpha[1]	0.0728	1.721e-02	4.227	0.000	[3.902e-02, 0.106]
beta[1]	0.9231	1.773e-02	52.061	0.000	[ 0.888, 0.958]

This suggests what was expected that sentiment does not have a strong contemporaneous impact on GRNB returns. The constant term is also not significant, further reinforcing the weak explanatory power of the mean equation. The very low R-squared (-0.001) is typical for high-frequency return models and not unexpected in financial time series, where most variation is captured in the conditional variance. On the other hand, the volatility model performs well. Both  $\alpha$  (ARCH term) and  $\beta$  (GARCH term) are statistically significant and positive, with values of 0.0728 and 0.9231, respectively. This implies that volatility is highly persistent, as is typical in financial return series, where shocks tend to decay slowly over time. The sum of  $\alpha$  and  $\beta$  is close to 1, indicating near-integrated volatility.

Consequently, Figure 11 shows the conditional standard deviation estimated by the model for each time point. There is a high spike in 2020 where the market was under Covid-19 stress. Also, volatility clusters can be observed throughout the year 2022 and 2023 where the Russian Ukrainian conflict hit. This justifies the use of GARCH modelling over constant variance models as well as it again confirms the second hypothesis  $H_2$  that the returns exhibit volatility clustering and time-varying volatility.

As a final step in this model, volatility residuals diagnostics are performed by Ljung-Box test and standardized residual plots (see Figure 12) to see whether residuals of the model are well-behaved with no remaining ARCH effects. Standardized residuals Ljung-Box ( $p = 0.075$ ) show slight autocorrelation, but not statistically significant at the 5% level. So, the mean dynamics are sufficiently captured by the AR-X component. For the squared residuals – Ljung-Box ( $p = 0.629$ ) reveal no evidence of remaining ARCH effects. In terms of mean and variance dynamics the model is well-specified.

Figure 11: Annualized conditional volatility of GARCH(1,1) - GRNB model

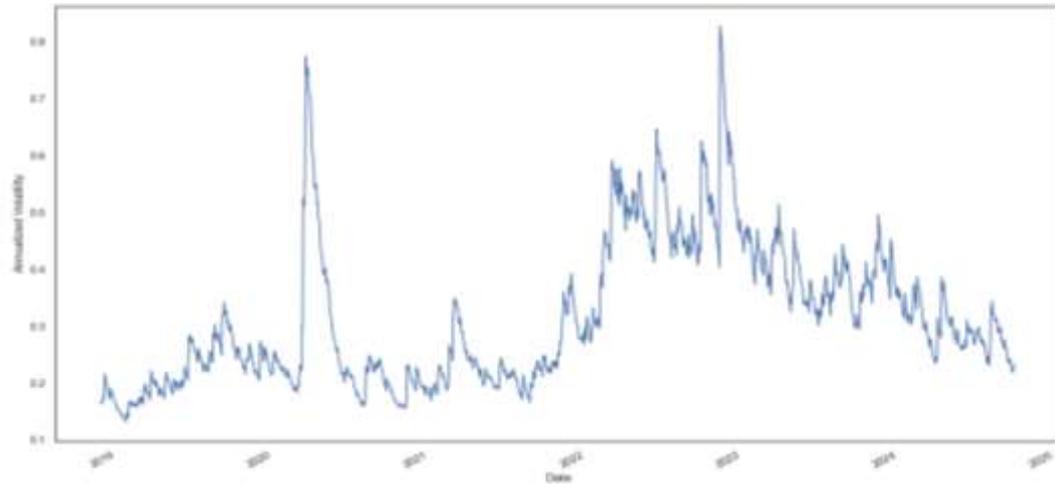
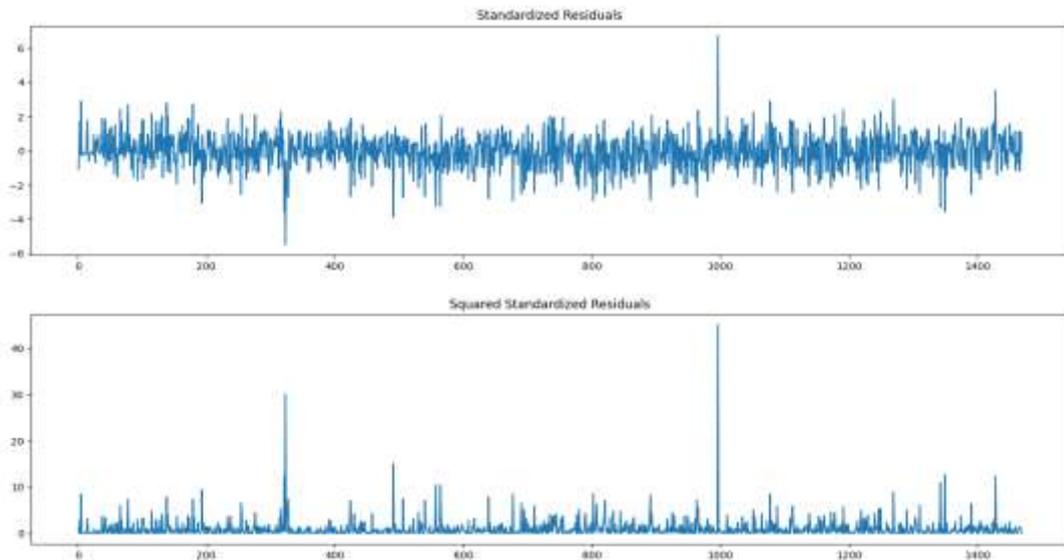


Figure 12: Residual diagnostics for GARCH(1,1) - GRNB model



To examine whether sentiment explains volatility dynamics beyond the GARCH specification, the estimated conditional standard deviations from the GARCH(1,1) - GRNB model were regressed on the average sentiment with OLS. The approximation was used since the Python *arch* package does not support direct estimation of GARCH-X models (with sentiment in the variance equation). The results in Table 7 show a statistically significant negative relationship between sentiment and conditional volatility ( $\beta = -0.204$ ,  $p < 0.001$ ). This suggests that higher investor sentiment is associated with lower conditional volatility, which in line with our intuition indicates that optimism in the market is linked with greater stability. Finally,

the two-step approach supports the third research hypothesis **H<sub>3</sub>** that news sentiment significantly explains the volatility of green bond ETF returns.

As a bonus and because we expect delayed investor reactions, the first model was re-estimated using lagged sentiment as an exogenous regressor (see Table 8). When the average net sentiment is lagged by one day, its coefficient becomes statistically significant at the 5% level. This indicates that sentiment does not instantaneously affect returns but may instead have a delayed influence.

To check for robustness, the OLS regression was repeated using lagged sentiment, and yielded qualitatively similar results, with a nearly identical coefficient and significance level. This reinforces the conclusion that sentiment has a measurable, and slightly persistent effect on volatility.

Table 7: Approximate GARCH-X results

OLS Regression Results						
Dep. Variable:	cond_vol	R-squared:	0.036			
Model:	OLS	Adj. R-squared:	0.036			
Method:	Least Squares	F-statistic:	54.96			
Date:	Sun, 18 May 2025	Prob (F-statistic):	2.07e-13			
Time:	22:20:24	Log-Likelihood:	980.62			
No. Observations:	1467	AIC:	-1957.			
Df Residuals:	1465	BIC:	-1947.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.3542	0.006	58.607	0.000	0.342	0.366
avg_net_sentiment	-0.2050	0.028	-7.414	0.000	-0.259	-0.151
Omnibus:	197.222	Durbin-Watson:	0.092			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	282.146			
Skew:	1.000	Prob(JB):	5.41e-62			
Kurtosis:	3.786	Cond. No.	8.83			

Table 8: Results of GARCH(1,1) – GRNB model with lagged sentiment

AR-X - GARCH Model Results					
Dep. Variable:	GRNB_log_return	R-squared:	-0.002		
Mean Model:	AR-X	Adj. R-squared:	-0.002		
Vol Model:	GARCH	Log-Likelihood:	-262.504		
Distribution:	Standardized Student's t	AIC:	537.007		
Method:	Maximum Likelihood	BIC:	568.753		
		No. Observations:	1467		
Date:	Sun, May 18 2025	Df Residuals:	1465		
Time:	21:33:41	Df Model:	2		
Mean Model					
	coef	std err	t	P> t	95.0% Conf. Int.
Const	5.2582e-03	1.163e-02	0.452	0.651	[-1.753e-02, 2.805e-02]
sentiment_lag1	0.1026	4.743e-02	2.164	3.047e-02	[9.674e-03, 0.196]
Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.
omega	7.3127e-04	3.936e-04	1.858	6.315e-02	[-4.008e-05, 1.503e-03]
alpha[1]	0.0741	1.722e-02	4.304	1.680e-05	[4.035e-02, 0.108]
beta[1]	0.9221	1.750e-02	52.691	0.000	[ 0.888, 0.956]

To validate the robustness of the previous GARCH model results, the analysis was replicated on a second ETF – BGRN. The model specifications and estimation procedures were kept consistent with the initial analysis. The outcomes obtained for BGRN closely mirror those found in the previous models and statistics, confirming the stability and reliability of the modelling approach. Given the similarity of results, detailed tables and figures for BGRN are omitted to avoid redundancy.

### 4.3 Discussion of Results

The presented analysis aimed to assess the influence of investor sentiment on the returns and volatility of green bond ETFs, specifically focusing on the GRNB/BGRN index. The analysis combined a VAR model framework with GARCH-family models to capture both return dynamics and time-varying volatility. The discussion below interprets the empirical findings in relation to each of the three research hypotheses.

**H<sub>1</sub>:** *News sentiment has a statistically significant impact on green bond ETF returns.*

The first hypothesis was not supported by the empirical results of VAR models. The VAR models, designed to detect dynamic interactions between variables, did not reveal any statistically significant influence of news sentiment on green bond returns. Neither the average sentiment index nor interaction terms involving the VIX provided predictive power in this framework.

This finding was largely corroborated by the GARCH(1,1) models with sentiment included as an exogenous regressor in the mean equation. When average sentiment with no lag was used, the coefficient was not statistically significant although the model was correctly specified. However, when a one-period lag of sentiment was introduced, the coefficient became positive and significant at the 5% level. This suggests a possible delayed effect of sentiment on returns, and although the economic significance appears modest and does not fully support the hypothesis in its original form, we can conclude that the hypothesis is partially rejected.

**H<sub>2</sub>:** *Green bond ETF returns exhibit*

- a) *volatility clustering*
- b) *time-varying volatility.*

The second hypothesis was strongly supported by the results of the GARCH modelling. The estimated GARCH(1,1) model clearly showed volatility clustering and persistence, with both  $\alpha$  (ARCH) and  $\beta$  (GARCH) parameters statistically significant and within expected bounds. The sum of these parameters approached unity, indicating a high degree of volatility persistence.

Moreover, even first diagnostic tests such as the Ljung-Box test on squared residuals of the returns or the PACF plot in the pre-model analysis indicated autocorrelation and showed dependence over time. Additionally, the Ljung-Box test also confirmed that the GARCH model effectively captured the conditional heteroskedasticity in the return series which validate the presence of time-varying volatility in green bond ETF returns.

**H<sub>3</sub>:** *News sentiment significantly affects the volatility of green bond returns.*

The third hypothesis was confirmed. Although sentiment variables were not directly included in the volatility equation of the GARCH model, a two-step approach

was used as a workaround: conditional variance estimates from the GARCH model were extracted and then regressed on news sentiment.

This regression revealed a statistically significant and negative relationship between sentiment and volatility. Specifically, higher average net sentiment was associated with lower conditional volatility. This suggests that positive investor sentiment contributes to market stability, reducing perceived risk in green bond markets. This result held both for present and lagged sentiment values, indicating robustness.

In conclusion:

- **H<sub>1</sub>** is partially rejected: the evidence does not support an immediate impact of sentiment on returns (as originally hypothesized), but does suggest a delayed influence, which supports a weaker form of the hypothesis.
- **H<sub>2</sub>** is confirmed: green bond ETF returns show clear signs of volatility clustering and time-varying volatility.
- **H<sub>3</sub>** is confirmed: sentiment has a significant and negative relationship with return volatility.

These results indicate that while sentiment may not serve as a direct return predictor in green bond markets, it does have important implications for risk perception and volatility dynamics.

## Conclusions

The growing relevance of sustainable investing and the rapid development of the green industry have underscored the importance of understanding the unique factors influencing green financial instruments. This paper addressed that by examining how investor sentiment, captured from news data, impacts the pricing dynamics – both in returns and volatility – of green bond ETFs. It aimed to bridge a gap in the literature by exploring the behaviour of these fixed-income ESG assets in the secondary market.

Three hypotheses were tested primarily on VanEck Green Bond ETF to answer the research question, and the results offer different conclusions: **H<sub>1</sub> was partially rejected**. The VAR model found no significant impact of sentiment on returns. However, the GARCH model with lagged sentiment revealed a statistically significant positive effect, suggesting that sentiment may influence green bond prices with a delay. This highlights a behavioural component in the market where investors respond to sentiment gradually rather than immediately. **H<sub>2</sub> was confirmed**. The GARCH(1,1) estimation strongly supported the presence of volatility clustering and time-varying volatility in green bond ETF returns, validating the use of conditional heteroskedasticity models. This finding aligns with general facts observed in wider financial markets. **H<sub>3</sub> was confirmed**. Regressing the conditional volatility on sentiment scores revealed a significant negative relationship – higher sentiment is associated with lower volatility. This finding implies that positive sentiment contributes to market stability and may reduce perceived risk, reinforcing the importance of investor psychology in green financial markets.

Additionally, as planned the results were replicated on a second green bond ETF - iShares Green Bond ETF, enhancing the external validity and showing that sentiment-driven effects are not unique to a specific fund structure.

These findings may have important implications for multiple stakeholders. For example, investors and portfolio managers could integrate the sentiment into risk models or used to inform trading strategies in the green bond space since there is confirmed the delayed yet significant influence of sentiment and its stabilizing effect on volatility. As green finance becomes more integrated into the global economy, for policy makers and regulators understanding how the information environment

influence price and volatility dynamics becomes crucial, as they can help calm markets and support investor confidence. Also, as we confirmed the reactions are delayed so there is a need for standardized, timely, and accessible disclosures to help investors react more efficiently. This paper contributes to the growing body of work at the cross-section of ESG investing, sentiment analysis, and financial econometrics. The use of NLP-derived sentiment in econometric modelling sets the stage for more detailed investigations across asset classes or regions.

Some limitations should be acknowledged. The sentiment measure did not account for intra-day market responses. The ETFs studied, while representative, cannot fully capture the global green bond universe. Future research could explore high-frequency sentiment data, apply machine learning models to detect non-linear effects, or investigate cross-asset spillovers within ESG markets.

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