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ESG VOLATILITIES THROUGH CRISES IN THE WORLD'S HAPPIEST COUNTRY

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Acknowledgement

"In God's plan, nothing happens by chance." - Saint John Paul II

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Love,
Hong Bao Ngoc Nguyen Lukinmaa
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Abstract

There have been recently many adverse events happened to the financial world, such as the COVID-19 pandemic in 2019, the rise in inflation from 2021 to 2022, Ukraine war in 2022, and the current global recession. In the world's happiest country Finland, ESG Sustainable Investing is so popular that it has become one of the most favourable research topics here. However, is it worth to consistently invest in ESG entities in Finland, especially in crises?

This paper has examined the daily return series of Finland stock market index (OMX Helsinki 25), the actively managed mutual fund EVLI Finland Select, and 61 Finnish companies from 1.1.2015 to 5.5.2022. The econometric models of ARCH, GARCH, or EGARCH have been applied to estimate the variance and the conditional volatility of all observations. As a result, it can be concluded that the Finnish market benchmark OMXH25 was more efficient and less volatised than not only most of the ESG companies, but also the EVLI Finland Select in crises. Considering the ESG Combined Scores 2020 from Refinitiv Eikon, a highly scored ESG company seemed not to volatilise better than a lower ranking one in Finland for this period.

Keywords
ESG returns, ESG Sustainable Investing, volatility, time series analysis, ARCH, GARCH, EGARCH, ESG Combined Scores, Total Return Index (RI), daily returns, crisis

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1 INTRODUCTION

Finland has been recognized as the happiest country in the world for the past five years, and it has continuously topped in various ESG (environmental, social, and governance) rankings. Thus, Finland is a typical research object for ESG performance. The objective of this study is to analyse and compare the performance of the highest-scoring ESG companies in Finland, the actively managed mutual fund EVLI Finland Select, and Finland stock market index (OMX Helsinki 25) during times of crisis, specifically from 2015 to 2022. During this time, there were many difficulties in the financial industry, such as the COVID-19 pandemic in 2019, the rise in inflation from 2021 to 2022, Ukraine war in 2022, and the current global recession. In these turbulent times, the author would like to know whether ESG companies and funds in Finland would provide higher returns and smaller volatility than the benchmark index OMX Helsinki 25 or not.

Diverse academic studies on the profitability of ESG for investors have produced contradictory findings. Ouchen (2021) has recently proved that an ESG portfolio will be less volatile than the S&P 500 benchmark in the United States, excluding the COVID-19 disaster. On the other hand, Ouchen (2021) must admit that there is no absolute proof to prove the positive relationship between ESG and its performance since published studies have shown both negative and positive effects. Specifically, Cornell (2021) stated that ESG investing might promote social benefits and reduce the cost of equity capital, but it also diminishes the expected returns for investors. Besides, both Brunet (2019) and Giese and Lee (2019) agreed that there is no consensus regarding the favourable effects of ESG on performance. In contrast to the US market, Deng and Cheng (2019) argued that ESG improvement has incredibly increased the stock value of companies in China. Similarly, Morea, Donato, et al. (2022) revealed that ESG characteristics positively affect stock performance in Europe. However, it is challenging to find the published research focusing only on Finland in this scope. Therefore, this research has been conducted only for the Finnish market by comparing the daily return series of 61 Finnish high-scored ESG firms, the EVLI Finland Select fund, and the market benchmark OMX Helsinki 25. Last year, EVLI won the SFR "Responsible Investment Award 2021" for its superior knowledge of responsible investing (ESG) in Finland's asset management. Thus, it makes sense to think of this actively managed mutual fund as a good ESG portfolio in Finland. Furthermore, the data has been purposely collected from 2015 to 2022 because there are plenty of crises in this period. It is stimulating to observe how ESG entities react in these hectic times.

Accordingly, there are three main purposes in this study. For the first instance, it is essential to inspect the stock performance of 61 Finnish ESG companies, the EVLI Finland Select fund, and the benchmark market OMX Helsinki 25 during the crisis time from 1.1.2015 to 5.5.2022. The second target is to analyse the returns of the ESG portfolio in comparison to the market index in Finland in these seven years. In other words, the author will compare the conditional volatilities of these ESG returns to the benchmark one. Finally, among the ESG companies collected from Refinitiv Eikon, the author would like to compare their performances in accordance with their ESG Combined Scores. Therefore, the research questions of this thesis are:

"Would ESG returns volatilise smaller than the Finnish benchmark ones in crises? Would a top-notch ESG rating company perform better than a lowly scored one in Finland during this crisis period?"

It is compelling to find the answer for these questions because ESG Ranking has always been a crucial factor for investors, especially in Finland and Nordic countries.

The methodologies of this research are empirical and applied econometric methods. The sample of data includes 61 Finnish companies, the actively managed mutual fund EVLI Finland Select, and the Finland stock market index (OMX Helsinki 25). Firstly, the total return indices (RI) of these samples were collected from the Refinitiv Eikon system for the period between 1.1.2015 and 5.5.2022. These 61 firms in Finland were particularly chosen and graded by the ESG Combined Score List 2020 of Refinitiv Eikon. Among this list, the ESG Combined Scores have been decreasingly aligned from 90.05 to 11.01. Additionally, these companies must be registered as "Active" not only in Equity Status but also in ESG Status on the Refinitiv Eikon system. Last, the list of 61 high scored ESG companies was sorted by getting rid of all the small securities and foreign stocks. The daily return series from the total return indices has been conducted for time series analysis in the statistical software program EViews. In applied econometrics, time series analysis is a useful method for forecasting, estimating the dynamic causal effects, modelling volatility in the stock market, or testing economic theories. These characteristics are good for the research goals, and EViews is one of the best tools for analysing time series.

As mentioned before, time series analysis is the key methodology in this thesis. Besides, the author has chosen ARCH (Autoregressive Conditional Heteroscedasticity), GARCH (Generalized Autoregressive Conditional Heteroscedasticity), and the exponential GARCH (EGARCH) to analyse the daily return variances for the research goals. Back to 1982, ARCH model was developed by the famous scholar Robert Engle who also won the Nobel Memorial Prize 2003 in Economic Sciences, "for methods of analysing economic time series with time-varying volatility “. Whereas GARCH, which is an extension of ARCH, was introduced by Bollerslev in 1986 (BOLLERSLEV, 1986). In comparison with ARCH model, GARCH typically requires less parameters and easier to identify or estimate. However, some time series in this study fit better with 1-lag ARCH or ARCH (1); whereas the others otherwise perfectly fit with GARCH (1,1) or GARCH (1 autoregressive component, 1 lag). Exceptionally, EGARCH(1,1) was conducted for the daily returns of EVLI Finland Select together with the Finland stock market index (OMX Helsinki 25) in this research.

Base on the knowledge from the Applied Econometric course and reading from Engle and Bollerslev research papers (BOLLERSLEV, 1986), the author believes that it is reasonable for considering the conditional standard deviation from the GARCH Variance Series as the main elements of volatility. In other words, the higher conditional standard deviation, the more volatilised returns are. Therefore, it is essential to carefully follow the five steps of ARCH/GARCH modelling in EViews: (1) estimating the mean equation, (2) checking for ARCH or GARCH effects, (3) determining and estimating ARCH or GARCH models, (4) conducting model diagnostics (heteroskedasticity and autocorrelation tests), and (5) making GARCH Variance. As the last step for the empirical results, the conditional standard deviation outcomes have been collected at the same time with other indicators from the GARCH Variance Series. The target is to compare the volatility volume and rate between the ESG returns and the Finnish benchmark index one. Together with the ESG Combined Scores extracted from Refinitiv Eikon, it would be good enough to fulfil the thesis purposes for observing which companies with lower ESG scores still performed better than the others.

Overall, this thesis is structured as follows: (2) the literature review, (3) the methodology, (4) the findings, (5) the discussion and conclusions, (7) the appendix, and (8) the references.

The second chapter Literature Review represents the theories and knowledge of corporate social responsibility (CSR); Sustainable, responsible, and impact investing (SRI); and Environmental, social, and governance (ESG) Sustainable Investing. Theoretically, these concepts have supported and promoted sustainable investing in ESG companies, especially in hectic times. Moreover, there are numerous research papers escalating these ideas. Nevertheless, it is still worth mentioning the contradictory findings of relevant research studies about ESG volatility in crises. Overall, this is the theoretical framework of the thesis for answering the research questions.

In the third chapter, the methodology of ARCH, GARCH, and EGARCH used in the thesis has been briefly covered. Besides, the research data description is mentioned at the end of this chapter.

Next, the fourth chapter covers the findings of this research. This chapter includes basic graph analysis, and the empirical results of estimating ARCH, GARCH or EGARCH models on the daily return time series. Moreover, the last part of this chapter is about the conditional volatility of 61 Finnish companies considering ESG Combined Score Ranking in 2020.

As a result, the last chapter is discussions and conclusions where all the research questions are answered and summarised. Finally, the appendix and references are attached for further reading and resources on this topic.

2 LITERATURE REVIEW

2.1 An overview about Corporate Social Responsibility (CSR) and Sustainable, responsible & impact investing (SRI)

In this research, Environmental, social, and governance (ESG) Sustainable Investing is the main conceptual framework. However, it is necessary to mention the relevant or original concepts related to ESG, such as CSR and SRI here. The first concept is corporate social responsibility (CSR) particularly explained by two well-known models: Carroll's CSR Pyramid and The Triple Bottom Line (3BL).

2.1.1 Carroll's CSR Pyramid

The terminology corporate social responsibility (CSR) was initially introduced in the 1960s by famous scholars like Keith Davis, Joseph McGuire, Adolph Berle, William Frederick, and Clarence Walton (Carroll A. B., 1999). However, Lockett et al. (2006) and many other CSR experts considred Carroll's CSR Pyramid as the most well-known model of CSR.

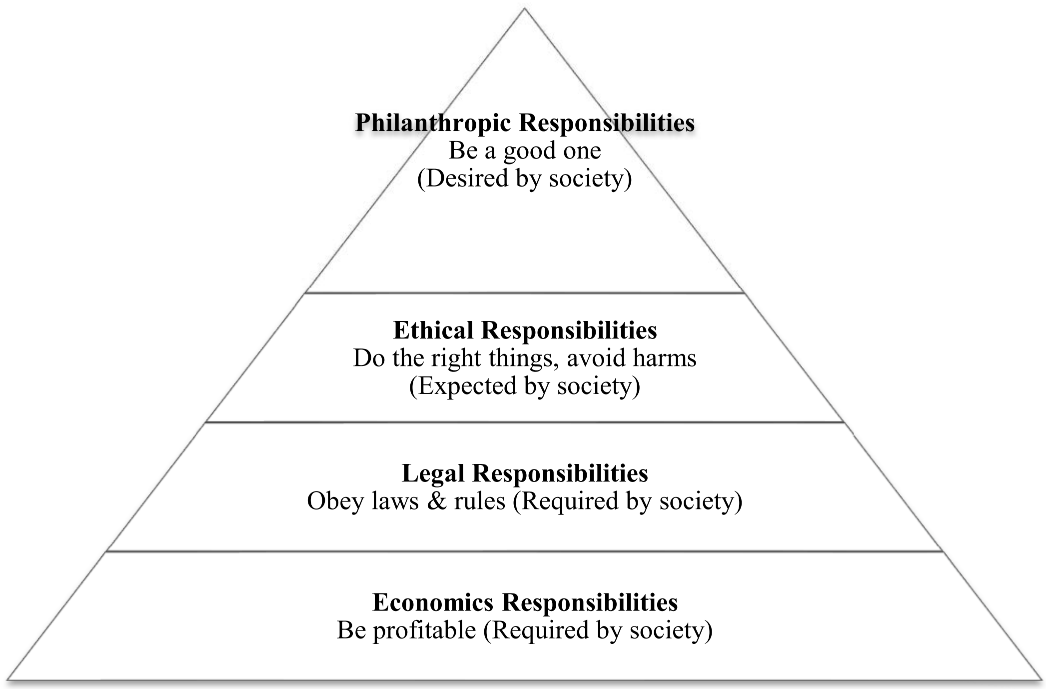


Figure 1. Carroll's CSR pyramid (adapted from Carroll A. B., 2016, p. 5)

Briefly, there are four responsibilities of a firm outlined in Archie Carroll's Pyramid of CSR model from bottom to top: Economic responsibilities, Legal responsibilities, Ethical responsibilities, and Philanthropic responsibilities. Firstly, the economic responsibilities are the fundamental responsibilities in Carroll's Pyramid. It is necessary for businesses to operate profitably. Practically, a profitable corporate contributes to the social economy by paying taxes, creating jobs, and adding economic values. Secondly, businesses ought to be obliged by federal, state, or local laws and regulations in the legal responsibilities. A few requiring terms could be clarified as follows: performing in consistent with governments and laws' expectations, complying with local rules and orders, being law-abiding corporate citizens, fulfilling legal obligations to societal stakeholders, and meeting legal requirements in providing goods and services. Next, the third level in Carroll's Pyramid is the ethical responsibilities, which means that businesses are expected to act with moralities and ethics by society. Alternatively, practices, norms, activities, and standards are conducted by corporates even though they are not required by laws, but are expected, nonetheless. Finally, the philanthropic responsibilities are the highest level in Carroll's Pyramid and go even further beyond compliance with laws and regulations, or ethics. These philanthropic responsibilities are desired by society and more discretionary or voluntary on business's part.

These responsibilities seem divided and separated by levels, however, they are integrated and unified to support for the norms of "ethics." Alternatively, ethics permeates Carroll`s pyramid. (Carroll A. B., 2016)

2.1.2 The Triple Bottom Line (3BL)

The Triple Bottom Line (3BL) concept is the theory about the three core values that business should focus to achieve in consistent with Corporate Social Responsibility (CSR). It was originally introduced by the renowned British management consultant and sustainability guru John Elkington in 1994. Besides, his excellent accomplishment "Cannibals With Forks: The Triple Bottom Line of 21st Century Business" published in 1999 is a must-read book for any business students. (Elkington, 1999)

The three bottom lines (3BL) are: organization's financial goals, organization's social goals, and organization's environmental goals. In details, the first bottom line, which is the financial or economic goals, implies about profit maximization in the short term or long term, productivity improvement, and relevant responsibilities to societal stakeholders (for instance, suppliers, employees, competitors, customers, or business partners). The firm is required to operate efficiently and profitably to contribute economic values to society, such as paying taxes, creating jobs, or increasing Gross Domestic Production (GDP) for nations. Additionally, the firm is also required to treat fairly and respect its societal stakeholders. Next, the second bottom line is organization's social goals. These goals require firms to preserve and foster health; respect not only laws and regulations, but also social customs and cultural heritages; also engage selectively in cultural and political life. In summary, this bottom line acquires firms to respect the local culture, rules, and orders in specified societies even though these might not be the original culture in these corporates. It is consistent with the idea of a saying "When in Rome, do as the Romans do." Lastly, the third bottom line is about organization's environmental goals, which is committed to "sustainable development." The firm is expected to grow or make profits with the least negative impacts to environment or without environmental harming.

Concisely, both Carroll's CSR Pyramid and the Triple Bottom Line (3BL) models provide good understanding of CSR definition and how CSR has been actively applied in modern businesses nowadays. From these basic knowledges of CSR, it would be easier to link to further concepts such as Sustainable, responsible, and impact investing (SRI) or Environmental, social, and governance (ESG) Sustainable Investing.

2.1.3 Environmental, social, and governance (ESG) in terms of Sustainable, responsible, and impact investing (SRI)

The Forum of Sustainable and Responsible Investment (US SIF) has defined Sustainable, responsible, and impact investing (SRI) as "an investment discipline that considers ESG factors to generate long-term competitive financial returns and positive societal impact".

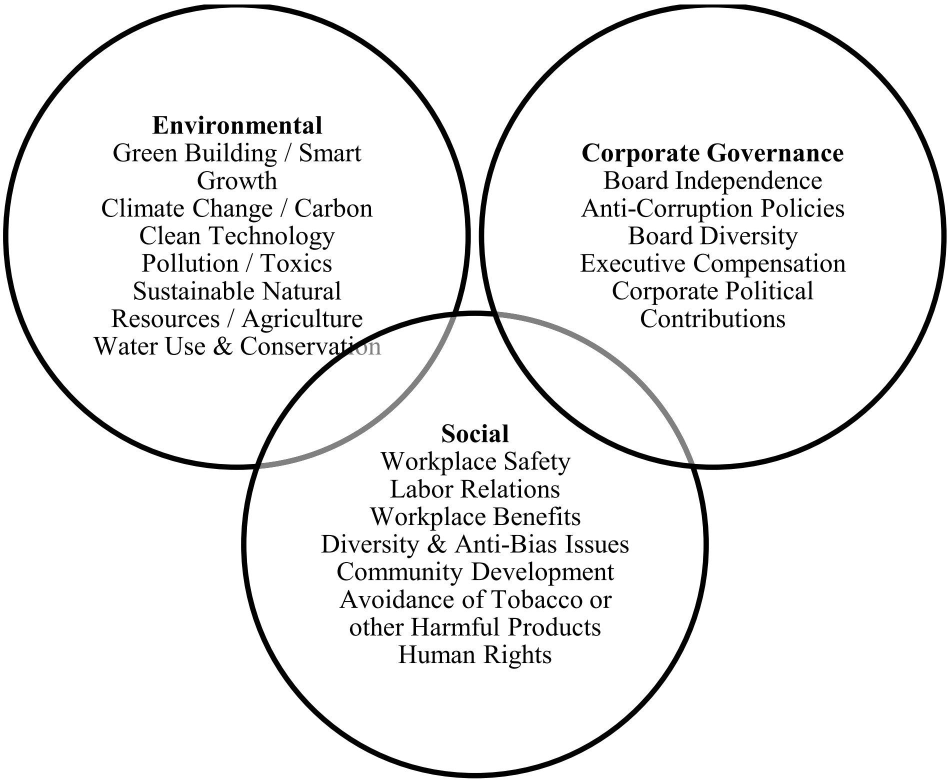


Figure 2. Examples of ESG Sustainable Investing (adapted from US SIF website, Examples of ESG criteria used by sustainable investors)

Figure 2 illustrated typical examples of ESG Sustainable Investing. In fact, SRI is the primary form of ESG Sustainable Investing. Nowadays, CSR, SRI and ESG Investing, which closely relate to each other, have become increasingly important in investing and financial decisions. Moreover, researchers are always curious to find out whether ESG Sustainable Investing performs well, especially in crises. Thus, it is worth to cover the literature review on this specific scope in the next part.

2.2 The relation between ESG Sustainable Investing and its performance in crises

According to the Forum of Sustainable and Responsible Investment (US SIF), multiple research studies have indicated that organizations with robust corporate social responsibility (CSR) policies and practices are solid investments. Particularly, some well-known organizations have been mentioned such as Oxford University, Deutsche Asset & Wealth Management, Morgan Stanley Institute for Sustainable Investing, TIAA - CREF Asset Management, and the United Nations Environment Programme Finance Initiative and so on. Among others, these institutions have published research studies with similar findings for supporting CSR, SRI or ESG in financial and investment decisions (Harty, D., & Clark, R. , 2018). In 2015, for instance, Deutsche Asset & Wealth Management and Hamburg University undertook the most complete evaluation of academic research on this topic, a meta-analysis of over 2,000 empirical studies. Most of the research indicate a positive association between ESG standards and firm financial performance, according to their findings (Gunnar Friede, Timo Busch & Alexander Bassen, 2015). Furthermore, the Morgan Stanley Institute for Sustainable Investing has conducted a study of ESG-focused mutual funds and ETFs, which results that "no financial trade-off in the returns of sustainable funds compared to traditional funds, and they demonstrate lower downside risk." Especially, throughout a period of extreme volatility, this study assertively addressed that "strong statistical evidence that sustainable funds are more stable." (Stanley, 2021)

In contrast, it might be too overconfident to conclude that sustainable funds are perfectly safer than others in crises. Karaibrahimoglu (2010) proved that the number and extent of CSR projects had adversely been affected by the global fiscal crisis 2008 even though there was a greater demand for social projects during this crisis. This study sample included 100 companies among the Fortune 500 from the United States, Europe, and other countries. Besides, Sjöström (2011) concluded that it would be imprudent to make a categorical statement about the investment return of SRI products based on a single or a small number of studies (as some academics and professionals were doing). Sjöström (2011) has impressively gone through 21 peer-reviewed academic studies on the topic of the investment performance of SRI products to find out whether SRI generates higher or lower (or similar) financial return than other investments. Moreover, Cornell (2021) proved in his analysis that ESG investing might promote social benefits and reduce the cost of equity capital, but it also diminishes the expected returns for investors in highly rated firms. Furthermore, Cornell (2021) has mentioned one interesting opinion about ESG ratings, which is “stocks with high ESG ratings should provide lower, not higher, expected returns”.

Contributing further on this topic, Ouchen (2021) has recently utilised the complexed methodology of econometrics such as ARCH process and its extensions (GARCH and EGARCH models), in addition to the Markov-switching GARCH and EGARCH models in his research studies about ESG volatility. As a result, his research has shown that the daily returns of MSCI USA ESG Select were less volatile than the one of S&P 500 benchmark in the United States from 1.6.2005 to 31.12.2020, excluding the COVID-19 disaster. Despite answering “Yes” to the main research question “Is the ESG portfolio less turbulent than a market benchmark portfolio?,” Ouchen (2021) must admit that there is no absolute proof to concretely conclude the positive relationship between ESG and its performance since the published studies have controversially shown both negative and positive effects. No matter where the research area is, the US stock market here, this research is still a typical example for analysing and comparing the volatility of ESG portfolio to the benchmark one by using the Markov-switching GARCH process.

These excellent studies have motivated the author to make research on a topic about ESG returns and volatility analysis comparing with the benchmark index in Finland. Because the author believes that ESG companies do not perform better than other counterparts, especially in crisis time, this research would help to prove it. Besides, ARCH and GARCH models in time series analysis would be applied as the key methodology for this thesis. Unfortunately, it is still challenging to find a perfectly similar article to these ideas for the Finnish stock market. On the other hand, there are more relevant research studies about this topic for the U.S. stock market such as what Ouchen (2021) studied. Therefore, this thesis might help to fill in the gap of studying ESG volatilities of Finland in crisis times.

3 METHODOLOGY OF THE ECONOMETRIC STUDY

There are three models applied in this research: Autoregressive Conditional Heteroscedasticity (ARCH), Generalized Autoregressive Conditional Heteroscedasticity (GARCH), and the Exponential GARCH (EGARCH). These are the most popular econometric models in estimating the variance. In this thesis, they are chosen to estimate the variance of daily returns series in the Finnish market. The advantage of these models in comparison with other previous econometric ones is that the variance can vary with time, which makes sense in reality. The following parts briefly introduce the key theories of methodology and a succinct description of the empirical data in this thesis.

3.1 Autoregressive Conditional Heteroscedasticity (ARCH) Model

Engle (1982) introduced ARCH model in his prestigious paper "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". Since the 1980s, this volatility modelling has generated significant interests in the financial market research. Particularly, ARCH is a type of heteroscedasticity, whose basic idea is that large shocks are more likely to be followed by large shocks and small shock by small ones. In other words, the concept ARCH refers to series with volatility changing over time (Heteroscedasticity) conditional to previous lags autocorrelation (Autoregressive Conditional). Besides, the volatility models are performed over stationary time series (mean), but with a non-constant variance. In ARCH modelling, the variance depends on past squared innovations. (ENGLE, 1982)

The ARCH(q) model has the mean equation y_t, with the constants θ_t and the error terms ϵ_t as follows:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \ldots + \theta_n y_{t-n} + \epsilon_t,$$

The next equation corresponds the conditional relationship between the errors and the previous information, which is written as:

$\epsilon_t | I_{t-1} N(0, h_t)$

In ARCH process, the conditional variance is not constant, but depends on q lags of squared errors:

$$h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \alpha_2 \epsilon^2_{t-2} + \cdots + \alpha_q \epsilon^2_{t-n},$$

Moreover, the variances must be guaranteed to be positive ($\alpha_0 > 0$ and $\alpha_i > 0$) and their sum must not exceed 1 ($0 \leq \sum_{i=1}^{i=n} \alpha_I < 1$). In addition, the lag values should be in decreasing order to verify that the recent past has more influences than the older events ($\alpha_1 > \alpha_2 > ... > \alpha_n$).

Thus, the ARCH(1) model's conditional variance h_t is written as follows:

$$h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \eta_t,$$

Where ϵ_t is the error term from the mean equation, η_t is the white noise (IID), and the square of h_t is the conditional volatility or standard deviation. The error terms are uncorrelated, which is that $E[\epsilon_t, \epsilon_{t-i}]$ equals to 0. Furthermore, the positive and less-than-1 variance conditions for ARCH(1) model are $\alpha_0 > 0$, $0 < \alpha_1 < 1$.

3.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

GARCH (Generalized Autoregressive Conditional Heteroscedasticity), which is an extended version of ARCH, was introduced by Bollerslev in 1986 (BOLLERSLEV, 1986). GARCH models enable the conditional variance to be modelled as an ARMA process. They incorporate autoregressive and moving average components in the heteroskedastic variance. In comparison with ARCH model, GARCH typically requires less parameters and easier to identify or estimate. Overall, GARCH models provide a parsimonious alternative to high order ARCH models.

According to Bollerslev (1986), GARCH(p,q) model has q as the lag length for ”moving average component” and p as the autoregressive component. Besides, the GARCH mean equation y_t, with the constants θ_t and the error terms ϵ_t is expressed as follows:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \ldots + \theta_n y_{t-n} + \epsilon_t,$$

Similarly, the error terms of GARCH(p,q) model also are as follows:

$$\epsilon_t | I_{t-1} N(0, h_t),$$

Nevertheless, GARCH(p,q) model includes both ARCH terms ($\sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2$) and the MA terms ($\sum_{i=1}^{p} \beta_i \, h_{t-i}$) in the following conditional variance equation.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i},$$

As same as ARCH(q) case, the positive and decaying variance conditions of GARCH(p,q) are represented as:

$$\alpha_0 > 0,\ \alpha_i > 0,\ \beta_i > 0 \text{ and } 0 \leq \sum_{i=1}^{i=n} \alpha_i + \sum_{i=1}^{i=n} \beta_i < 1,$$

Accordingly, the GARCH(1,1) conditional variance h_t is written as follows:

$$h_t = \alpha_0 + \alpha_1 \, \epsilon_{t-1}^2 + \beta_1 h_{t-1},$$

The positivity condition to ensure the positive variance h_t is that $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$. In addition, the stationarity condition is that $\alpha_1 + \beta_1 < 1$.

3.3 <u>Exponential GARCH (EGARCH) Model</u>

Continuously on the path of improving the initial ARCH model, Nelson (1991) proposed the exponential GARCH (EGARCH) model where the conditional variance equation also includes the exponential terms $(\frac{\varepsilon_{t-i}}{h_{t-i}^{0.5}})$ in the right-hand side. This model is believed to eliminate three following limitations of the previous GARCH model: the condition of non-negativity constraints, the negative relationship between volatility and returns in assumption, and the determination whether shocks to conditional variance "persist" or not. (Brooks, 2014)

The log-linear conditional variance equation of EGARCH(1,1) is written as follows:

$$Log(h_t) = \alpha_0 + \alpha_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \alpha_2\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \beta_1 \log(h_{t-1}),$$

3.4 Empirical process to estimate the ARCH or GARCH Models

To estimate ARCH or GARCH Models, there are two main parts: identifying mean equation and estimating variance equation (D'Amico, 2021).

Firstly, the mean equation results from stationarity check and mean equation estimating. In this initial step, it is essential to conduct graph analysis, correlogram and formal unit root tests such as Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). As a result, these steps help to conclude whether the time series are stationary or not. The stationarity condition needs fulfilling to estimate the mean equation. Next, the mean equation is formed by selecting an ARIMA(p,d,q) model. Thanks to the correlogram, the orders of "p" and "q" are gradually chosen.

Secondly, the output of variance equation is created by checking the existence of ARCH or GARCH effects and estimating the ARCH or GARCH Model. It is necessary to perform Heteroscedasticity Test with ARCH option to confirm the existence of ARCH or GARCH effects. A proper ARCH or GARCH Model needs to be estimated well enough to mitigate the ARCH or GARCH effects and remove the autocorrelation. In other words, there is no significant lags in this model. Therefore, model diagnostics must be cautiously conducted after estimating the ARCH or GARCH Model.

3.5 Empirical data description

After carefully going through the literature review, the author decided to choose the Finnish stock market index (OMX Helsinki 25) as the research object representing for the benchmark index. Besides, the actively managed mutual fund EVLI Finland Select and the list of 61 companies ranked by ESG Combined Scores in 2020 are considered as the representative research objects for ESG Finland. All thesis data were collected from 1.1.2015 to 5.5.2022 and legally extracted from the Refinitiv Eikon system.

As mentioned before, the sample of data includes 61 Finnish companies, the actively managed mutual fund EVLI Finland Select, and the Finland stock market index (OMX Helsinki 25). In the first instance, the total return indices (RI) of these samples were collected from the Refinitiv Eikon system for the selected period between 1.1.2015 and 5.5.2022. These 61 firms in Finland were particularly chosen and graded by the ESG Combined Score List 2020 of Refinitiv Eikon. Among this list, the ESG Combined Scores have been decreasingly aligned from 90.05 to 11.01. In addition, these companies must be registered as “Active” not only in Equity Status but also in ESG Status on the Refinitiv Eikon system. Next, the list of 61 high scored ESG companies was sorted by getting rid of all the small securities and foreign stocks. Finally, the daily return series from the total return indices has been conducted for time series analysis methods of ARCH and GARCH in the statistical software program EViews. In applied econometrics, time series analysis is a useful method for forecasting, estimating the dynamic causal effects, modelling volatility in the stock market, or testing economic theories. These characteristics perfectly fit the research target of analysing the daily return variance, and EViews is currently one of the most popular statistical tools nowadays.

Extracted from Refinitiv Eikon resources, Finland represents the list of 61 ESG companies graded by ESG Combined Scores 2020 from top to bottom in the Finnish market. Besides, this ESG order of these companies has been maintained for further empirical analysis throughout the research.

Table 1. List of 61 ESG Companies in Finland (Refinitiv Eikon)

ESG Rank	Company Name	ESG Combined Scores 2020
1	Stora Enso	90.05
2	Outokumpu	88.15
3	Wärtsilä	80.83
4	Huhtamaki	79.26
5	Cargotec	77.47
6	Orion B	76.37
7	Fortum	75.69
8	Finnair	75.43
9	Valmet	75.39
10	Kesko	74.49
11	Nordea Bank	73.19
12	Nokian Renkaat	73.11
13	Neste	71.53
14	Sanoma	70.64
15	Metsa Board	68.97
16	Metso Outotec	68.57
17	Kemira	68.23
18	Kone	66.85
19	YIT	65.88
20	Stockmann	65.67
21	Verkkokauppa.Com	65.52
22	Tietoevry	64.49
23	Caverion	63.82
24	Elisa	62.29
25	Fiskars	61.89
26	Oriola	60.31
27	Citycon	59.32
28	Aktia Bank	58.80
29	Uponor	58.06
30	Alma Media	56.94
31	Digia	56.88
32	Suominen	54.53
33	Hkscan	53.88
34	Bittium	52.82
35	Marimekko	52.10
36	Etteplan	50.75
37	Atria	49.79
38	Nokia	49.33
39	Upm-Kymmene	48.16
40	Basware	47.00
41	Exel Composites	46.12
42	Sampo	45.49
43	Lassila & Tikanoja	44.14
44	Vaisala	43.97
45	Konecranes	41.98
46	Scanfil	41.55
47	Withsecure	41.16
48	Incap	40.45
49	Olvi	40.07
50	Glaston	33.87
51	Ponsse	33.45
52	Raute	33.09
53	Teleste	31.66
54	Solteq	29.96
55	Alandsbanken	28.48
56	Aspo	26.24
57	Rapala Vmc	22.82
58	Siili Solutions	18.97
59	Viking Line	16.89
60	Noho Partners	11.01
61	Nixu	NA

4 FINDINGS

4.1 Basic graphical and statistical analysis of time series

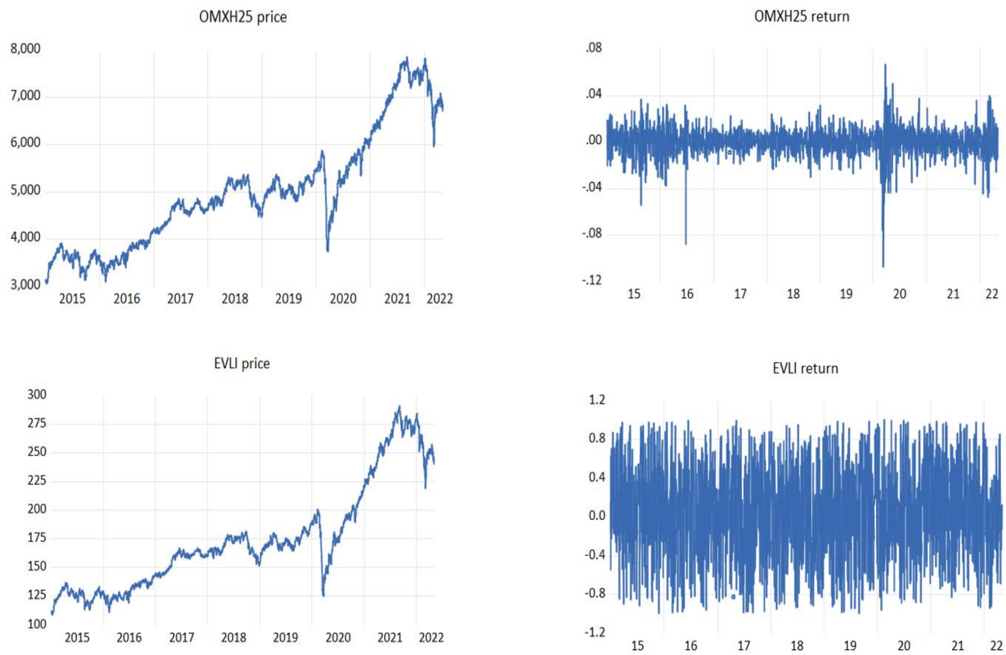


Figure 3. Daily prices and returns of the market benchmark portfolio OMXH25 and the ESG portfolio "EVLI Finland Select"

The above Figure 3 is the graphical examination of the benchmark portfolio OMX Helsinki 25 (OMXH25) and the ESG portfolio “EVLI Finland Select” in the period 1.1.2015 - 5.5.2022. Overall, both daily price graphs on the left side have the positive trend despite the substantial COVID-19 drop in 2020. Nevertheless, the daily price graphs are not likely to distinguish between the benchmark portfolio and the ESG EVLI one. Not considering the formal stationarity tests yet, these graphics could clearly show that the daily price time series on the left side are non-stationary, which consists of trends and intercepts. In contrast, the return time series on the right side look graphically stationary because they have no trends or intercepts. Therefore, it is better to make time series analysis on natural logarithms of returns in the research design because these logarithm values are closer to normal distribution, have elasticity interpretation, remove quadratic trend, and efficiently reflect long-term mean returns. Based on the natural-log return graphs, it is clearly noticeable to observe the benchmark outliers in crisis times such as the years 2015, 2016, and 2020. These are the most interesting characteristics in modelling return time series.

The below Table 2 indicates the descriptive statistics of daily returns OMX Helsinki 25 (OMXH25) and EVLI Finland Select (EVLI) from 1.1.2015 to 5.5.2022.

Table 2. Descriptive Statistics of the daily return time series OMXH25 and EVLI Finland Select

	OMXH25_RETURN	EVLI_RETURN
Mean	0.000422	0.052799
Median	0.00092	0.127985
Maximum	0.066647	0.998836
Minimum	-0.10666	-0.993543
Std. Dev.	0.012037	0.475919
Skewness	-0.858317	-0.096911
Kurtosis	10.50996	2.25644
Jarque-Bera	4547.414	45.24308
Probability	0.000000	0.000000
Sum	0.775196	97.09754
Sum Sq. Dev.	0.266312	416.3052
Observations	1839	1839

Based on these outcomes, it is obvious to see not only the higher mean return of ESG portfolio than the benchmark one, but also the higher volatility of this ESG representative in the crisis period. Besides, both series have positive Kurtosis values (leptokurtic), which feature a sharper peak and thicker tails than a normal distribution. In other words, the EVLI Finland Select portfolio is likely to have more extreme observations in both tails relative to the normal distribution in this period. These series are likewise nonlinear since its distribution is skewed to the left due to a negative asymmetric coefficient Skewness. Thus, the return volatility is more sensitive in an adverse shock than a positive one.

Conducting the same graphical examination for 61 ESG companies in Finland, there are also a clear trend and intercept that belongs to the daily price time series, which refuses the stationarity of these series. On the other hand, the return time series of these 61 companies look stationary without trends or intercepts and suitable for further empirical analysis in the period 1.1.2015 - 5.5.2022.

4.2 Empirical results of ARCH/GARCH and EGARCH modelling

4.2.1 Unit root tests

As mentioned before, the graphical examination and correlogram might help analysts to expect whether time series are stationary or not. However, it is essential to conduct formal unit root tests as the beginning of ARCH or GARCH process. These formal test names are Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS).

As the results, Table **3** summarizes the unit root test outcomes performed on the daily price and return (Re) time series of all research objects: OMXH25, EVLI, and 61 ESG companies in Finland. Overall, these formal unit root tests are particularly consistent with the previous graphical examination to conclude about the stationarity characteristic. Obviously, the daily price time series are not statistically stationary at all even though there are a few exceptional cases that only KPSS test could reject the null hypothesis to confirm the non-stationary status of these price series. On the other hand, the daily return time series has been statistically significant to be stationary by these unit root tests. Thus, only daily return time series are qualified enough for further ARCH/GARCH estimation.

Table 3. Unit Root Test Results

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
OMXH25	(c)	2.68617	0.2425	-2.855461	0.1776	(c)	0.4678*	0.1460
OMXH25_Re	(a)	41.4846*	0.0000	-41.52570*	0.0000	(b)	0.03433	0.4630
EVLI	(c)	-2.08494	0.5534	-2.273306	0.4479	(c)	0.6127*	0.1460
EVLI_Re	(a)	-41.1882*	0.0000	-41.50851*	0.0000	(b)	0.14285	0.4630
Stora Enso	(c)	-2.33349	0.4149	-2.389407	0.3850	(c)	0.3300*	0.1460
StoraEnso_Re	(a)	42.6358*	0.0001	42.64076*	0.0001	(b)	0.04408	0.4630
Outokumpu	(c)	-1.71912	0.7427	-1.779074	0.7148	(c)	0.4799*	0.1460
Outokump_Re	(a)	-41.2746*	0.0000	-41.28415*	0.0000	(b)	0.07928	0.4630
Wärtsilä	(c)	-1.81163	0.6990	-1.813664	0.6980	(c)	0.7146*	0.1460
Wärtsilä_Re	(a)	-41.8464*	0.0000	-41.84679*	0.0000	(b)	0.15814	0.4630
Huhtamaki	(c)	-3.16899	0.0910	-3.320482	0.0632	(c)	0.2281*	0.1460
Huhtamak_Re	(a)	-40.9423*	0.0000	-40.95083*	0.0000	(b)	0.12909	0.4630
Cargotec	(c)	-2.11472	0.5367	-2.066376	0.5637	(c)	0.4795*	0.1460
Cargotec_Re	(a)	-40.9519*	0.0000	-40.92045*	0.0000	(b)	0.11380	0.4630
Orion	(c)	-2.44947	0.3536	-2.551829	0.3029	(c)	0.2329*	0.1460
Orion_Re	(a)	-43.2880*	0.0001	-43.28806*	0.0001	(b)	0.08534	0.4630
Fortum	(c)	-1.85161	0.6790	-2.328057	0.4179	(c)	0.1976*	0.1460
Fortum_Re	(a)	-40.7036*	0.0000	-40.93174*	0.0000	(b)	0.08163	0.4630
Finnair	(c)	-1.61449	0.7873	-1.602428	0.7921	(c)	0.9987*	0.1460
Finnair_Re	(a)	-43.8768*	0.0001	-43.88882*	0.0001	(b)	0.36793	0.4630
Valmet	(c)	-2.41821	0.3698	-2.433272	0.3620	(c)	0.4786*	0.1460
Valmet_Re	(a)	-43.3992*	0.0001	-43.40124*	0.0001	(b)	0.05408	0.4630
Kesko	(c)	-1.73711	0.7345	-1.735298	0.7353	(c)	0.8719*	0.1460
Kesko_Re	(a)	-42.8835*	0.0001	-42.88739*	0.0001	(b)	0.05123	0.4630
Nordea Bank	(c)	-1.59959	0.7932	-1.704906	0.7490	(c)	0.5206*	0.1460

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
Nordea_Re	(a)	-41.6219*	0.0000	-41.67041*	0.0000	(b)	0.07085	0.4630
Nokian Renkaat	(c)	-1.71021	0.7467	-1.778149	0.7152	(c)	0.4181*	0.1460
NokRenka_Re	(a)	-43.9851*	0.0001	-43.98949*	0.0001	(b)	0.44182	0.4630
Neste	(c)	-2.43573	0.3607	-2.357561	0.4019	(c)	0.45906	0.1460
Neste_Re	(a)	-42.9209*	0.0001	-42.92390*	0.0001	(b)	0.10526	0.4630
Sanoma	(c)	-2.47005	0.3432	-2.637904	0.2633	(c)	0.3482*	0.1460
Sanoma_Re	(a)	-44.4367*	0.0001	-44.42711*	0.0001	(b)	0.06258	0.4630
Metsä	(c)	-1.92040	0.6433	-1.834785	0.6875	(c)	0.4017*	0.1460
Metsä_Re	(a)	-44.9159*	0.0001	-44.91419*	0.0001	(b)	0.06769	0.4630
Metso Outotec	(c)	-2.16651	0.5076	-2.182855	0.4984	(c)	0.4536*	0.1460
MOutotec_Re	(a)	-42.7358*	0.0001	-42.73581*	0.0001	(b)	0.04568	0.4630
Kemira	(c)	-3.9796*	0.0095	-3.90064*	0.0122	(c)	0.1723*	0.1460
Kemira_Re	(a)	-44.6498*	0.0001	-44.65504*	0.0001	(b)	0.02245	0.4630
Kone	(c)	-1.29140	0.8895	-0.949548	0.9487	(c)	0.4540*	0.1460
Kone_Re	(a)	-32.8198*	0.0000	-44.02977*	0.0001	(b)	0.20185	0.4630
YIT	(c)	-3.5877*	0.0311	-3.62788*	0.0277	(c)	0.4837*	0.1460
YIT_Re	(a)	-43.3875*	0.0001	-43.39857*	0.0001	(b)	0.14628	0.4630
Stockmann	(c)	-2.09722	0.5465	-2.006889	0.5966	(c)	0.5254*	0.1460
Stockman_Re	(a)	-38.1544*	0.0000	-38.14272*	0.0000	(b)	0.12066	0.4630
Verkkokauppa	(c)	-1.53459	0.8176	-1.488848	0.8334	(c)	0.5889*	0.1460
Verkko_Re	(a)	-40.0832*	0.0000	-40.09718*	0.0000	(b)	0.16922	0.4630
Tietoevry	(c)	-3.7283*	0.0207	-3.80779*	0.0163	(c)	0.4557*	0.1460
Tietoevry_Re	(a)	-43.9629*	0.0001	-43.95951*	0.0001	(b)	0.07264	0.4630
Caverion	(c)	-3.6257*	0.0279	-3.85965*	0.0139	(c)	0.4097*	0.1460

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
Caverion_Re	(a)	-41.5763*	0.0000	-41.61846*	0.0000	(b)	0.05091	0.4630
ELISA	(c)	-3.30782	0.0652	-3.010083	0.1296	(c)	0.4385*	0.1460
ELISA_Re	(a)	-43.0784*	0.0001	-43.61241*	0.0001	(b)	0.09780	0.4630
Fiskars	(c)	-1.65973	0.7687	-1.704037	0.7494	(c)	0.6452*	0.1460
Fiskars_Re	(a)	-44.2683*	0.0001	-44.26918*	0.0001	(b)	0.09659	0.4630
Oriola	(c)	-3.33145	0.0615	-3.064526	0.1152	(c)	0.6101*	0.1460
Oriola_Re	(a)	-42.6777*	0.0001	-43.06936*	0.0001	(b)	0.10093	0.4630
Citycon	(c)	-3.32259	0.0629	-3.479193	0.0419	(c)	0.10427	0.1460
Citycon _Re	(a)	-42.4849*	0.0001	-42.48487*	0.0001	(b)	0.02681	0.4630
Aktia Bank	(c)	-3.15712	0.0936	-3.094217	0.1079	(c)	0.7681*	0.1460
Aktia_Re	(a)	-21.9847*	0.0000	-45.34812*	0.0001	(b)	0.02404	0.4630
Uponor	(c)	-1.72619	0.7395	-1.752713	0.7272	(c)	0.7959*	0.1460
Uponor_Re	(a)	-40.2577*	0.0000	-40.21572*	0.0000	(b)	0.07444	0.4630
Alma Media	(c)	-3.31396	0.0642	-3.241058	0.0768	(c)	0.4197*	0.1460
Alma_Re	(a)	-44.9092*	0.0001	-44.93930*	0.0001	(b)	0.08831	0.4630
Digia	(c)	-1.89013	0.6592	-1.781474	0.7136	(c)	1.1138*	0.1460
Digia _Re	(a)	-44.8986*	0.0001	-44.87559*	0.0001	(b)	0.13189	0.4630
Suominen	(c)	-1.63638	0.7784	-1.593260	0.7957	(c)	0.7811*	0.1460
Suominen _Re	(a)	-45.8157*	0.0001	-45.85001*	0.0001	(b)	0.12477	0.4630
Hkscan	(c)	-2.93083	0.1528	-3.073180	0.1130	(c)	0.3687*	0.1460
Hkscan_Re	(a)	-40.5601*	0.0000	-40.64578*	0.0000	(b)	0.12900	0.4630
Bittium	(c)	-3.4654*	0.0434	-3.48929*	0.0408	(c)	0.5436*	0.1460
Bittium_Re	(a)	-41.9002*	0.0000	-41.88890*	0.0000	(b)	0.19733	0.4630
Marimekko	(c)	-2.11482	0.5366	-2.110666	0.5390	(c)	1.0032*	0.1460
Marimekk_Re	(a)	-45.1954*	0.0001	-45.17471*	0.0001	(b)	0.11355	0.4630

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
Etteplan	(c)	-2.51511	0.3207	-2.340452	0.4112	(c)	0.6259*	0.1460
Etteplan_Re	(a)	-45.3201*	0.0001	-45.32030*	0.0001	(b)	0.07372	0.4630
Atria	(c)	-2.31838	0.4231	-2.398073	0.3804	(c)	0.4378*	0.1460
Atria_Re	(a)	-42.5202*	0.0001	-42.56989*	0.0001	(b)	0.14037	0.4630
Nokia	(c)	-2.89657	0.1638	-2.958990	0.1443	(c)	0.3485*	0.1460
Nokia _Re	(a)	-28.4039*	0.0000	-42.82743*	0.0001	(b)	0.04844	0.4630
UPM-Kymmene	(c)	-3.19015	0.0866	-3.160743	0.0928	(c)	0.2970*	0.1460
UpmKym_Re	(a)	-32.2427*	0.0000	-42.20621*	0.0001	(b)	0.06723	0.4630
Basware	(c)	-2.71553	0.2303	-2.742026	0.2196	(c)	0.3303*	0.1460
Basware _Re	(a)	-42.2839*	0.0001	-42.29446*	0.0001	(b)	0.05603	0.4630
Exel Compo	(c)	-1.84559	0.6821	-1.946442	0.6294	(c)	0.7168*	0.1460
Exel_Re	(a)	-44.6522*	0.0001	-44.71008*	0.0001	(b)	0.13532	0.4630
Sampo	(c)	-2.68824	0.2416	-2.912161	0.1587	(c)	0.3844*	0.1460
Sampo_Re	(a)	-41.4128*	0.0000	-41.47523*	0.0000	(b)	0.03564	0.4630
L&T	(c)	-3.60286	0.0298	-3.60997*	0.0292	(c)	0.4841*	0.1460
L&T_Re	(a)	-44.8008*	0.0001	-44.78867*	0.0001	(b)	0.15913	0.4630
Vaisala	(c)	-2.59256	0.2838	-2.683484	0.2436	(c)	0.73534	0.1460
Vaisala_Re	(a)	-48.0715*	0.0001	-47.99262*	0.0001	(b)	0.03710	0.4630
Konecranes	(c)	-2.33915	0.4119	-2.474892	0.3407	(c)	0.3682*	0.1460
Konecran _Re	(a)	-40.4873*	0.0000	-40.55257*	0.0000	(b)	0.07249	0.4630
Scanfil	(c)	-2.43784	0.3596	-2.373332	0.3935	(c)	0.7374*	0.1460
Scanfil _Re	(a)	-45.5794*	0.0001	-45.579430	0.0001	(b)	0.04575	0.4630
Withsecure	(c)	-2.28568	0.4411	-2.159757	0.5113	(c)	0.5523*	0.1460
Withsecur_Re	(a)	-45.5359*	0.0001	-45.65398*	0.0001	(b)	0.06804	0.4630
Incap	(c)	-0.61043	0.9779	-0.603748	0.9783	(c)	0.93283	0.1460

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
Incap _Re	(a)	-41.7506*	0.0000	-41.94361*	0.0000	(b)	0.12407	0.4630
Olvi	(c)	-0.50540	0.9833	-0.857676	0.9588	(c)	0.4731*	0.1460
Olvi_Re	(a)	-35.0368*	0.0000	-47.08287*	0.0001	(b)	0.26992	0.4630
Glaston	(c)	-2.72246	0.2275	-2.866403	0.1738	(c)	0.39637	0.1460
Glaston _Re	(a)	-45.9981*	0.0001	-45.95556*	0.0001	(b)	0.09908	0.4630
Ponsse	(c)	-2.30094	0.4327	-2.304938	0.4305	(c)	0.2588*	0.1460
Ponsse _Re	(a)	-44.2563*	0.0001	-44.24952*	0.0001	(b)	0.23589	0.4630
Raute	(c)	-1.09692	0.9280	-1.055015	0.9345	(c)	1.0521*	0.1460
Raute_Re	(a)	-43.5811*	0.0001	-43.68051*	0.0001	(b)	0.8158*	0.4630
Teleste	(c)	-3.27380	0.0709	-3.56313*	0.0333	(c)	0.5019*	0.1460
Teleste _Re	(a)	-48.3918*	0.0001	-48.20123*	0.0001	(b)	0.24535	0.4630
Solteq	(c)	-1.56851	0.8051	-1.500567	0.8295	(c)	0.7552*	0.1460
Solteq _Re	(a)	-46.7082*	0.0001	-46.92520*	0.0001	(b)	0.15917	0.4630
Alandsbanken	(c)	-1.17813	0.9137	-0.953164	0.9483	(c)	1.1337*	0.1460
Alandsban_Re	(a)	-37.2428*	0.0000	-60.35320*	0.0001	(b)	0.16523	0.4630
Aspo	(c)	-1.98786	0.6071	-2.213581	0.4812	(c)	0.3218*	0.1460
Aspo _Re	(a)	-28.1619*	0.0000	-42.41323*	0.0001	(b)	0.17740	0.4630
Rapala Vmc	(c)	-1.39753	0.8617	-1.446620	0.8470	(c)	0.9105*	0.1460
Rapala_Re	(a)	-47.4165*	0.0001	-47.38257*	0.0001	(b)	0.22816	0.4630
Siili Solutions	(c)	-2.20228	0.4875	-2.224047	0.4753	(c)	0.4264*	0.1460
Siili_Re	(a)	-44.4684*	0.0001	-44.44633*	0.0001	(b)	0.13326	0.4630
Viking Line	(c)	-2.64873	0.2585	-2.920236	0.1562	(c)	0.3027*	0.1460
Viking_Re	(a)	-29.9853*	0.0000	-55.23776*	0.0001	(b)	0.16334	0.4630
Noho Partners	(c)	-2.31468	0.4252	-2.544926	0.3062	(c)	0.8054*	0.1460
Noho_Re	(a)	-27.2549*	0.0000	-41.25861*	0.0000	(b)	0.11174	0.4630

Variables	Augmented Dickey-Fuller Test			Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test		
	Model	ADF t-Statistic	Critical Prob.	Adjusted t-Statistic	Critical Prob.	Model	LM statistics	Critical value at 5%
Nixu	(c)	-1.53904	0.8160	-1.417759	0.8558	(c)	1.0559*	0.1460
Nixu _Re	(a)	-44.9908*	0.0001	-45.10802*	0.0001	(b)	0.35670	0.4630

* = 0.05 level of significance
Model (a): neither trend nor constant
Model (b): no trend and with constant
Model (c): with trend and constant

4.2.2 ARCH/GARCH modelling results

Table 4 summarises the ARCH/GARCH modelling outcomes such as the conditional variance factors (α_0, α_1, β_1), the log likelihood ratio Log(L), and the Akaike information criterion (AIC) of all daily return series in the period 1.1.2015-5.5.2022. As a note for comparing which ARCH or GARCH model is preferable, then a more sufficient ARCH or GARCH model would have a higher Log(L) and a smaller AIC for better estimation of time series. Moreover, the ARCH and GARCH estimations are Normal (Gaussian) error distribution in this research.

After conducting hundreds of ARCH/GARCH estimation on the selected observations in EViews, it is concluded that some daily return series fit better with ARCH(1) and others prefer GARCH(1,1). Exceptionally, there is only one case, where it is impossible to estimate ARCH/GARCH for the daily return EVLI Finland Select. No matter how to adjust the number of ARCH/GARCH lags and orders, the series did not fit well with any estimations because there were no ARCH effects in this observation and the ARCH parameter of the conditional variance was not qualified enough to be positive. Accordingly, it is essential to apply EGARCH model for the daily return series of EVLI Finland Select since the GARCH condition of non-negativity constraints would be relaxed in EGARCH. Thanks to the outcomes of ARCH/GARCH modelling, the GARCH Variance Series would be later obtained to perform the conditional volatility of these time series. This is also the key analysis of this thesis to find out answers for the research question: Would ESG returns volatilise smaller than the Finnish benchmark ones in crises?

Table 4. ARCH/GARCH modelling results for the daily return series from 1.1.2015 to 5.5.2022

Variables	ARCH(1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \eta_t$; GARCH(1,1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \beta_1 h_{t-1}$, where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	Model	α_0	α_1	β_1	Log(L)	AIC
OMXH25_Re	GARCH(1,1)	0.000023*	0.149928*	0.599928*	5717.47	-6.214873
EVLI_Re	_	_	_	_	_	_
StoraEnso_Re	GARCH(1,1)	0.000024*	0.083331*	0.860871*	4660.66	-5.040240
		(2.35e-05)				
Outokumpu_Re	GARCH(1,1)	0.000010*	0.018164*	0.971771*	3759.29	-4.066405
Wärtsilä_Re	ARCH(1)	0.000399*	0.086291*		4515.80	-4.91105
Huhtamaki_Re	GARCH(1,1)	0.000077*	0.128878*	0.604721*	4971.48	-5.376810
Cargotec_Re	ARCH(1)	0.000446*	0.258503*			
Orion_Re	GARCH(1,1)	0.000056*	0.231403*	0.660460*	4763.54	-5.216602
Fortum_Re	ARCH(1)	0.000191*	0.367748*		5007.68	-5.422963
Finnair_Re	GARCH(1,1)	0.000033*	0.144149*	0.839270*	4043.03	-4.373813
Valmet_Re	GARCH(1,1)	0.000033*	0.082269*	0.834456*	4676.58	-5.065705
		(3.26e-05)				
Kesko_Re	GARCH(1,1)	0.000017*	0.077752*	0.858579*	5087.88	-5.526790
		(1.66e-05)				
Nordea_Re	GARCH(1,1)	0.000016*	0.114873*	0.823476*	5150.11	-5.570233
		(1.61e-05)				
NokiaRenkaat_Re	GARCH(1,1)	0.000008*	0.071384*	0.914344*	4684.28	-5.076806
		(8.30e-06)				
Neste_Returns	GARCH(1,1)	0.000123*	0.193559*	0.535316*	4593.71	-4.967744
Sanoma _Re	GARCH(1,1)	0.000048*	0.103339*	0.808621*	4466.23	-4.829698
		(4.76e-05)				
Metsä_Re	ARCH(1)	0.000365*	0.170360*		4549.26	-4.926024

Variables	ARCH(1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \eta_t$; GARCH(1,1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \beta_1 h_{t-1}$, where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	Model	α_0	α_1	β_1	Log(L)	AIC
MetsoOutotec_Re	GARCH(1,1)	0.000026*	0.098024*	0.888226*	3897.24	-4.229613
Kemira_Re	GARCH(1,1)	0.000058*	0.245432*	0.584006*	5017.63	-5.426776
		(5.79e-05)				
Kone_Re	GARCH(1,1)	0.000018*	0.100415*	0.815207*	5276.64	-5.710340
		(1.80e-05)				
YIT_Re	GARCH(1,1)	0.000137*	0.340358*	0.404827*	4605.00	-4.985366
Stockmann_Re	GARCH(1,1)	0.000035*	0.075300*	0.889629*	4059.57	-4.389358
		(3.49e-05)				
Verkkokauppa_Re	GARCH(1,1)	0.000083*	0.207819*	0.584264*	4773.04	-5.161922
		(8.34e-05)				
Tietoevry_Re	ARCH(1)	0.000187*	0.171450*		5090.06	-5.509269
Caverion_Re	ARCH(1)	0.000424*	0.171551*		4497.62	-4.872693
Elisa_Re	ARCH(1)	0.000159*	0.171462*		5360.75	-5.808835
Fiskars_Re	GARCH(1,1)	0.000062*	0.149899*	0.599899*	5158.12	-5.591017
		(6.15e-05)				
Oriola_Re	ARCH(1)	0.000206*	0.171429*		4860.95	-5.289710
Citycon_Re	GARCH(1,1)	0.000078*	0.149937*	0.599937*	5299.86	-5.747948
		(7.76e-05)				
Aktia Bank_Re	GARCH(1,1)	0.000019*	0.149883*	0.599883*	5151.99	-5.645623
Uponor_Re	GARCH(1,1)	0.000068*	0.149747*	0.599747*	4325.47	-4.682351
Alma Media_Re	ARCH(1)	0.000286*	0.171475*		4711.34	-5.104491
Digia_Re	GARCH(1,1)	0.000073*	0.149792*	0.599792*	4530.43	-4.928567
Suominen_Re	GARCH(1,1)	0.000115*	0.149798*	0.599798*	4526.66	-4.895142
Hkscan_Re	GARCH(1,1)	0.000102*	0.149866*	0.599866*	4808.24	-5.216985
Bittium_Re	GARCH(1,1)	0.000100*	0.149772*	0.599772*	4462.75	-4.860145

Variables	ARCH(1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \eta_t$; GARCH(1,1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \beta_1 h_{t-1}$, where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	Model	α_0	α_1	β_1	Log(L)	AIC
Marimekko_Re	GARCH(1,1)	0.000104*	0.149758*	0.599758*	4363.04	-4.798506
Etteplan_Re	ARCH(1)	0.000280*	0.171429*		4545.68	-4.946279
Atria_Re	ARCH(1)	0.000181*	0.171452*		5104.15	-5.548590
Nokia_Ret	ARCH(1)	0.000332*	0.171429*		4388.05	-4.748694
Upm-Kymmene_Re	ARCH(1)	0.000207*	0.171429*		4850.46	-5.249685
Basware_Returns	ARCH(1)	0.000543*	0.171429*		3866.85	-4.211390
Exel Composite_Re	ARCH(1)	0.000246*	0.171447*		4776.80	-5.167082
Sampo_Re	GARCH(1,1)	0.000036*	0.149889*	0.599889*	5399.39	-5.936585
L&T_Re	GARCH(1,1)	0.000047*	0.149911*	0.599911*	5287.82	-5.734879
Vaisala_Re	GARCH(1,1)	0.000079*	0.149821*	0.599821*	4606.06	-5.049461
Konecranes_Re	GARCH(1,1)	0.000127*	0.149784*	0.599784*	4417.68	-4.777125
Scanfil_Re	ARCH(1)	0.000274*	0.171484*		4818.96	-5.212730
Withsecure_Re	GARCH(1,1)	0.000155*	0.149793*	0.599793*	4386.81	-4.743707
Incap_Re	GARCH(1,1)	0.000112*	0.149558*	0.599558*	4031.01	-4.358432
Olvi_Re	GARCH(1,1)	0.000051*	0.149902	0.599902	5292.62	-5.724552
Glaston_Re	GARCH(1,1)	0.000046*	0.149743*	0.599743*	4527.99	-4.896580
Ponsse_Re	GARCH(1,1)	0.000036*	0.149801*	0.599801*	4608.72	-4.989392
Raute_Re	GARCH(1,1)	0.000091*	0.149868*	0.599868*	4825.71	-5.253085
Teleste_Re	GARCH(1,1)	0.000058*	0.149859*	0.599859*	4946.51	-5.349765
Solteq_Re	ARCH(1)	0.000470*	0.171465*		4262.02	-4.617155
Alandsbanken_Re	ARCH(1)	0.000393*	0.171504*		4562.06	-4.934555
Aspo_Re	ARCH(1)	0.000159*	0.171429*		5205.75	-5.631564
Rapala Vmc_Re	GARCH(1,1)	0.000102*	0.149824*	0.599824*	4712.76	-5.096652
Siili Solutions_Re	ARCH(1)	0.000304*	0.171521*		4840.91	-5.239343
Viking Line_Re	GARCH(1,1)	0.000068*	0.149878*	0.599878*	5034.22	-5.444739

Variables	ARCH(1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \eta_t$; GARCH(1,1): $y_t = \theta_0 + \theta_1 y_{t-1} + \epsilon_t$; $h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \beta_1 h_{t-1}$, where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	Model	α_0	α_1	β_1	Log(L)	AIC
Noho Partners_Re	GARCH(1,1)	0.000099*	0.149731*	0.599731*	4471.99	-4.835939
Nixu_Re	ARCH(1)	0.000445*	0.171566*		4475.81	-4.841159

* = 0.05 level of significance

4.2.3 ARCH/GARCH Conditional Volatility

The below Table 5 has briefly covered descriptive statistics of conditional volatility from all observations. As mentioned before, the GARCH Variance Series would be determined after estimating the ARCH/GARCH lags and orders. As a result, obtaining the conditional standard deviations of each series would contribute to investigate how the daily return volatility performed in this crisis period 1.1.2015-5.5.2022.

Besides, Figure 4 has illustrated the conditional standard deviation and median values of OMXH25 and 61 Finnish companies through crises. The higher conditional standard deviation is, the higher volatility of daily return series is. Thus, it makes sense that the market benchmark OMXH25 were more stable and less volatised than most of the ESG companies for this period. The only exception is Kone daily return series, which is statistically less volatised than the market benchmark OMXH25 in this case.

Table 5. Conditional Volatility of the daily return time series

	GARCH Variance Series					
Conditional Volatility	Model	Min	Median	Mean	Max	Std. Dev.
OMXH25_Re	GARCH(1,1)	0.00006 (5.68E-05)	0.00008 (8.35E-05)	0.00011	0.00200	0.000104
EVLI_Re	_	_	_	_	_	_
StoraEnso_Re	GARCH(1,1)	0.00019	0.00035	0.00041	0.00298	0.000234
Outokumpu_Re	GARCH(1,1)	0.00057	0.00090	0.00106	0.00320	0.000439
Wärtsilä_Re	ARCH(1)	0.00040	0.00041	0.00044	0.00212	0.000121
Huhtamaki_Re	GARCH(1,1)	0.00020	0.00024	0.00029	0.00198	0.000152
Cargotec_Re	ARCH(1)	0.00045	0.00049	0.00059	0.01002	0.000417
Orion_Re	GARCH(1,1)	0.00011	0.000270	0.00039	0.01036	0.000481
Fortum_Re	ARCH(1)	0.00019	0.00022	0.00030	0.00768	0.000330
Finnair_Re	GARCH(1,1)	0.00023	0.00064	0.00109	0.02943	0.001950
Valmet_Re	GARCH(1,1)	0.00021	0.00034	0.00040	0.00322	0.000214
Kesko_Re	GARCH(1,1)	0.00013	0.00021	0.00027	0.00348	0.000249
Nordea Bank _Re	GARCH(1,1)	0.00010	0.00020	0.00026	0.00312	0.000233
Nokian Renkaat_Re	GARCH(1,1)	0.00012	0.00031	0.00052	0.00822	0.000757
Neste_Re	GARCH(1,1)	0.000270	0.00036	0.00046	0.00492	0.000374 (3.74E-04)
Sanoma _Re	GARCH(1,1)	0.00028	0.00042	0.00052	0.00439	0.000358 (3.58E-04)
Metsa Board_Re	ARCH(1)	0.00037	0.00039	0.00044	0.0046	0.000196
Metso Outotec_Re	GARCH(1,1)	0.00035	0.00073	0.00108	0.02164	0.001316
Kemira_Re	GARCH(1,1)	0.00014	0.00022	0.00031	0.00397	0.000284 (2.84E-04)
Kone_Re	GARCH(1,1)	0.00010	0.00018	0.00021	0.00090	0.000100 (9.98E-05)
YIT_Re	GARCH(1,1)	0.00023	0.00033	0.00049	0.00534	0.000478
Stockmann_Re	GARCH(1,1)	0.00028	0.00062	0.00089	0.01179	0.000898
Verkkokauppa_Re	GARCH(1,1)	0.00020	0.00029	0.00039	0.00618	0.000366
Tietoevry_Re	ARCH(1)	0.00019	0.00020	0.00023	0.00199	0.000120
Caverion_Re	ARCH(1)	0.00042	0.00044	0.00050	0.00378	0.000204 (2.04E-04)

Conditional Volatility	GARCH Variance Series					
	Model	Min	Median	Mean	Max	Std. Dev.
Elisa_Re	ARCH(1)	0.00016	0.00017	0.00019	0.00383	0.000120
Fiskars_Re	GARCH(1,1)	0.00009 (8.73E-05)	0.00020	0.00025	0.00219	0.000158
Oriola_Re	ARCH(1)	0.00021	0.00022	0.00026	0.00257	0.000146 (1.46E-04)
Citycon_Re	GARCH(1,1)	0.00020	0.00023	0.00027	0.00353	0.000187
Aktia Bank_Re	GARCH(1,1)	0.00005 (4.86E-05)	0.00009 (8.59E-05)	0.00013	0.00253	0.000153
Uponor_Re	GARCH(1,1)	0.00017	0.00026	0.00036	0.00599	0.000345
Alma Media _Re	ARCH(1)	0.00029	0.00030	0.00035	0.00427	0.000174 (1.74E-04)
Digia _Re	GARCH(1,1)	0.00018	0.00026	0.00034	0.00448	0.000257 (2.57E-04)
Suominen_Re	GARCH(1,1)	0.00029	0.00038	0.00047	0.00374	0.000298 (2.98E-04)
Hkscan_Re	GARCH(1,1)	0.00026	0.00032	0.00039	0.00413	0.000229 (2.29E-04)
Bittium_Re	GARCH(1,1)	0.00025	0.00033	0.00044	0.00550	0.000376
Marimekko_Re	GARCH(1,1)	0.00026	0.00037	0.00046	0.00389	0.000294
Etteplan_Re	ARCH(1)	0.00028	0.0003	0.00035	0.00287	0.000171
Atria_Re	ARCH(1)	0.00018	0.00019	0.00022	0.00141	0.000089 (8.88E-05)
Nokia_Returns	ARCH(1)	0.00033	0.00035	0.00042	0.01252	0.000425
Upm-Kymmene _Returns	ARCH(1)	0.00021	0.00022	0.00026	0.00313	0.000154
Basware_Returns	ARCH(1)	0.00054	0.00056	0.00068	0.07546	0.001892
Exel Composites_Re	ARCH(1)	0.00025	0.00026	0.00031	0.00527	0.000216
Sampo_Re	GARCH(1,1)	0.00005 (4.87E-05)	0.00012	0.00017	0.00461	0.000252
L&T_Re	GARCH(1,1)	0.00012	0.00016	0.00019	0.00177	0.000121 (1.21E-04)
Vaisala_Re	GARCH(1,1)	0.00020	0.00028	0.00035	0.00264	0.000192
Konecranes_Re	GARCH(1,1)	0.00023	0.00043	0.00051	0.00440	0.000304
Scanfil_Re	ARCH(1)	0.00027	0.00029	0.00033	0.00285	0.000145

Conditional Volatility	GARCH Variance Series					
	Model	Min	Median	Mean	Max	Std. Dev.
Withsecure_Re	GARCH(1,1)	0.00039	0.00050	0.00059	0.00502	0.000323
Incap_Re	GARCH(1,1)	0.00028	0.00040	0.00059	0.00857	0.000614
Olvi_Re	GARCH(1,1)	0.00013	0.00017	0.00021	0.00384	0.000172
Glaston_Re	GARCH(1,1)	0.00012	0.00019	0.00029	0.00973	0.000405
Ponsse_Re	GARCH(1,1)	0.00006 (5.72E-05)	0.00016	0.00022	0.00281	0.000208
Raute_Re	GARCH(1,1)	0.00013	0.00029	0.00035	0.00267	0.000205
Teleste_Re	GARCH(1,1)	0.00015	0.00020	0.00026	0.00261	0.000179
Solteq_Re	ARCH(1)	0.00047	0.00049	0.00058	0.00706	0.000374
Alandsbanken_Re	ARCH(1)	0.00039	0.00041	0.00047	0.00623	0.000230
Aspo_Re	ARCH(1)	0.00016	0.00017	0.00020	0.00326	0.000145
Rapala Vmc_Re	GARCH(1,1)	0.00014	0.00031	0.00041	0.005490	0.000374
Siili Solutions_Re	ARCH(1)	0.00030 (3.04E-04)	0.00032	0.00036	0.006910	0.000189
Viking Line_Re	GARCH(1,1)	0.00017	0.00023	0.00028	0.001700	0.000145
Noho Partners_Re	GARCH(1,1)	0.00011	0.00034	0.00046	0.008200	0.000489
Nixu_Returns	ARCH(1)	0.00045	0.00046	0.00053	0.009720	0.000285

* = 0.05 level of significance

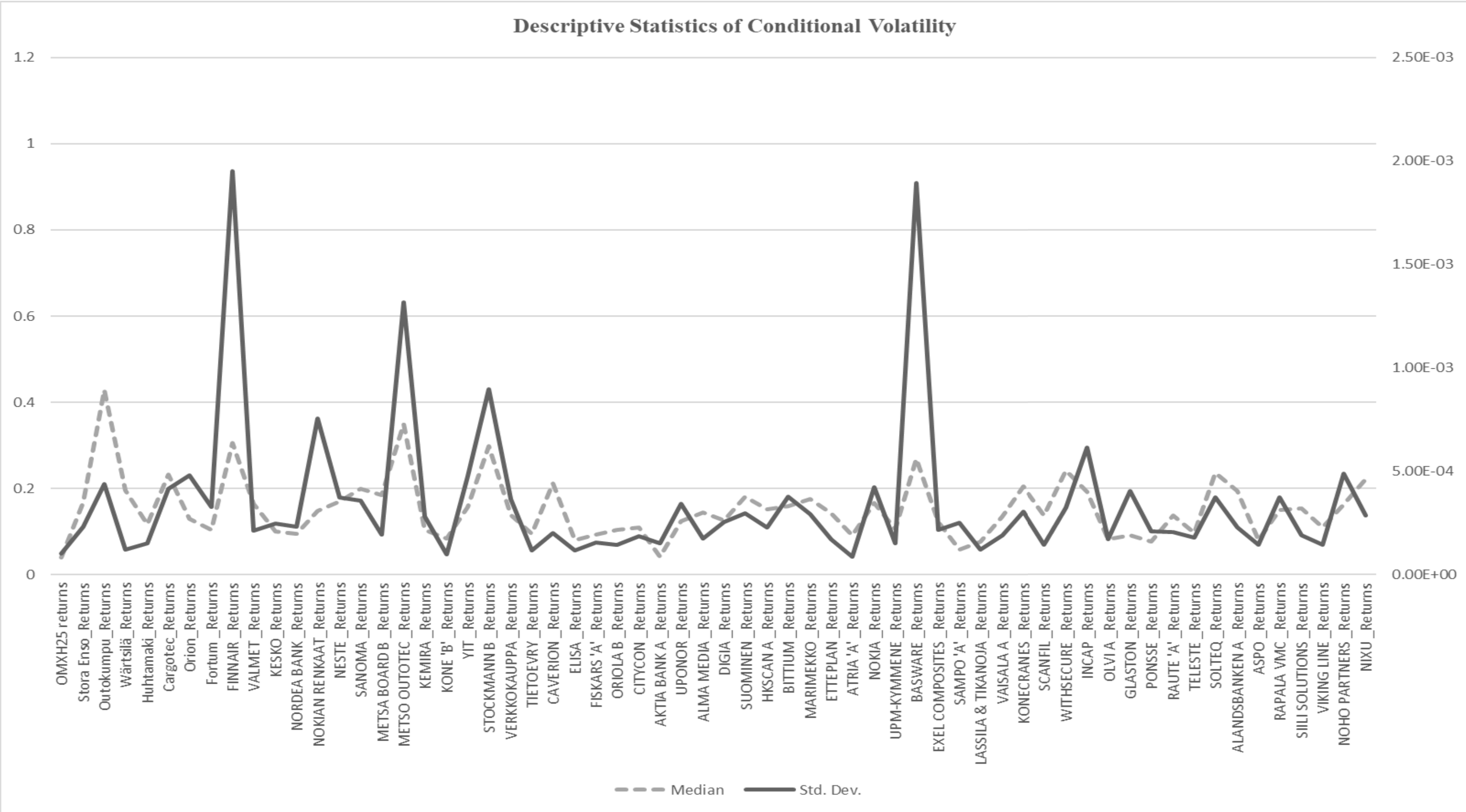


Figure 4. Descriptive Statistics of Conditional Volatility

4.2.4 EGARCH modelling results of OMXH25 and EVLI Finland Select

Because the daily return series of EVLI Finland Select did not satisfy the positive constraint coefficients of GARCH model, it is compulsory to conduct the exponential GARCH (EGARCH) modelling on this observation. Considering the Finnish market benchmark portfolio, the same EGARCH process has been taken for the daily return series of OMXH25 to compare with the ESG portfolio EVLI in the period 1.1.2015-5.5.2022. In addition, the EGARCH modelling is nEGARCH(1,1) with normal (Gaussian) error distribution here.

As the result, table 6 below represents the EGARCH outcomes with single regime model and the conditional volatility indicators for these two series. Moreover, Figure 5 illustrates the conditional volatility volume withdrawn from the EGARCH Variance Series, which helps to clearly see the higher volatility of daily return series EVLI than OMXH25 in this crisis time.

Table 6. EGARCH single-regime model for the market benchmark OMXH25 and the ESG portfolio EVLI Finland Select

Variables	nEGARCH(1,1) $Log(h_t) = \alpha_0 + \alpha_1\left\|\frac{\varepsilon_{t-1}}{h_{t-1}}\right\| + \alpha_2\left\|\frac{\varepsilon_{t-1}}{h_{t-1}}\right\| + \beta_1 \log(h_{t-1})$					
	α_0	α_1	α_2	β_1	Log(L)	AIC
OMXH25_Re	-0.503592*	0.192759*	-0.121183*	0.961131*	5801.366	-6.305077
EVLI_Re	-2.955481*	0.002008	0.013763	-0.972468*	-1214.032	1.346974

Conditional Volatility	EGARCH Variance Series				
	Min	Median	Mean	Max	Standard Deviation
OMXH25_Re	0.0000182 (1.82E-05)	0.0000943 (9.43E-05)	0.000139	0.002201	0.000159
EVLI_Re	0.185463	0.223795	0.22416	0.267925	0.014549

* = 0.05 level of significance

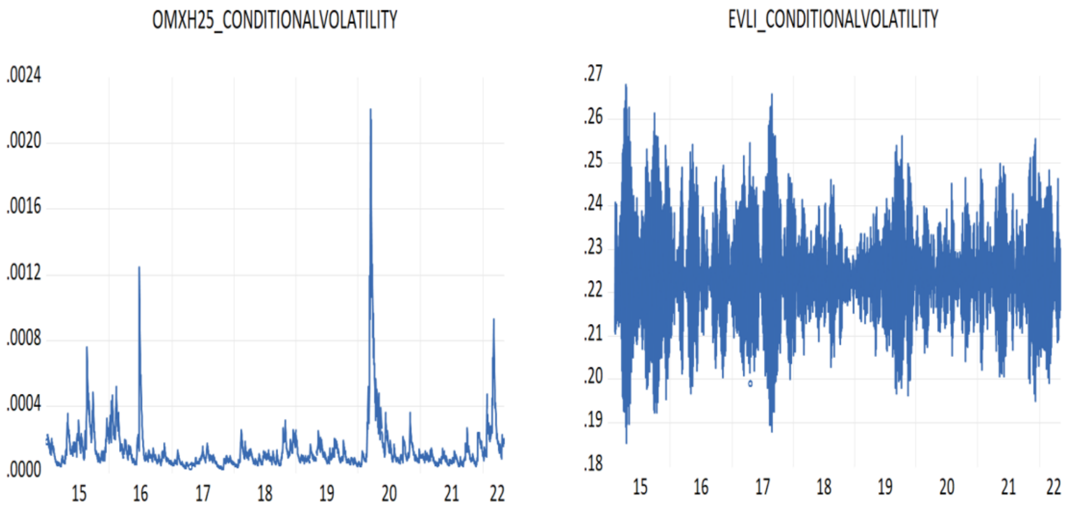


Figure 5. Conditional Volatility of the market benchmark OMXH25 and the ESG portfolio EVLI Finland Select

4.2.5 ESG Combined Scores (2020) versus Conditional Volatility (2015-2022)

One of the research questions is whether a top-notch ESG rating company performed better than a lowly scored one in Finland during this crisis period. Figure 6, which is the illustration between ESG Combined Scores (2020) and the conditional standard deviation from 1.1.2015 to 5.5.2022, could be a great support to solve this research problem. Basing on this chart, it would be challenging to conclude that the higher ESG scores were, the better the companies strived in crises because the results were mixed. Accordingly, a top-notch ESG rating could not assure the stability of returns in these crises. For instance, if comparing Stora Enso (1st rank with 90.05 points in ESG Combined Scores 2020) with Viking Line (59th rank with 16.89 points), then it is statistically significant that Viking Line volatility was smaller than the number one ESG company (The conditional standard deviation: Stora Enso 0.000234 vs Viking Line 0.000145).

Furthermore, it is interesting to see a highly correlated relationship between Stora Enso and UPM-Kymmene daily returns with a substantial coefficient of 0.83. Figure 7 and Table 7 represent that these two variables are directly proportional and positively correspond to each other. Nonetheless, Stora Enso (1st rank with 90.05 points in ESG Combined Scores 2020) was statistically significant to have greater conditional volatility than UPM-Kymmene (39th rank with 48.16 points), which indicates in Figure 8.

Therefore, a highly scored ESG company seemed not to volatilise better than a lower ranking one in Finland from 1.1.2015 to 5.5.2022.

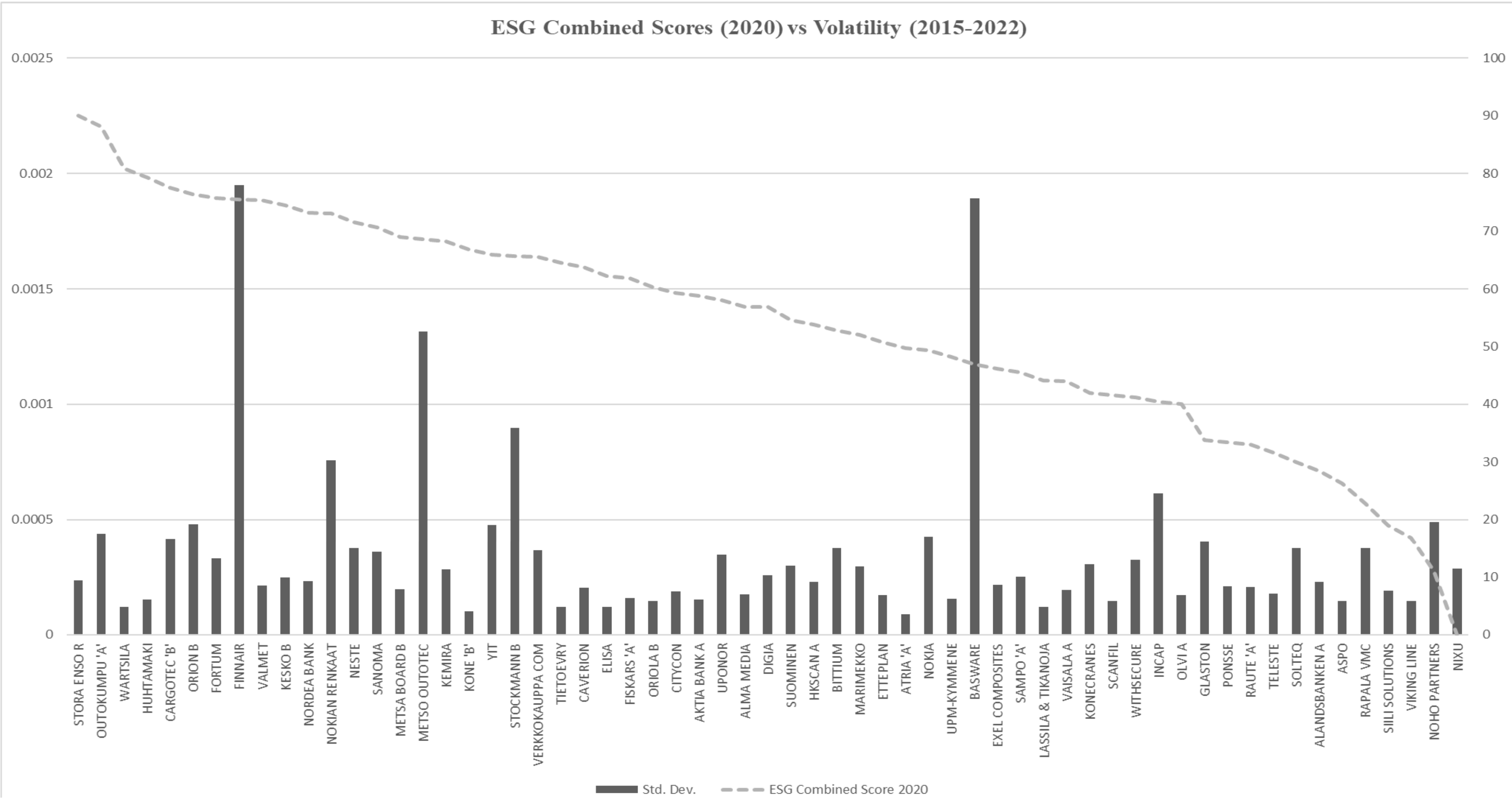


Figure 6. ESG Combined Scores (2020) vs Conditional Volatility (2015-2022)

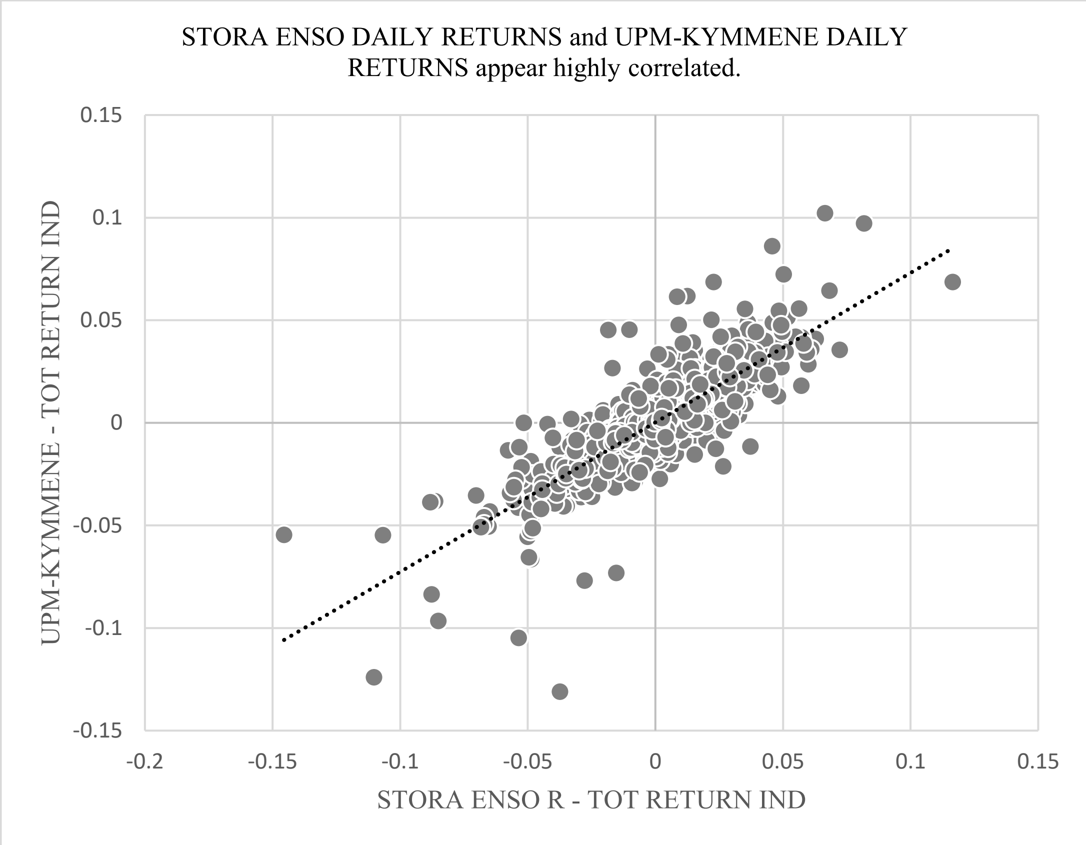
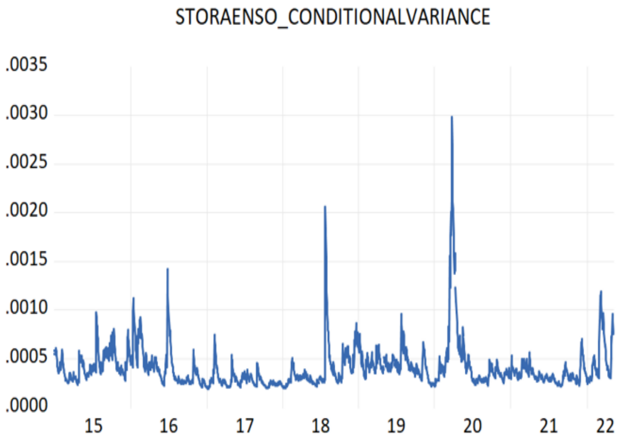


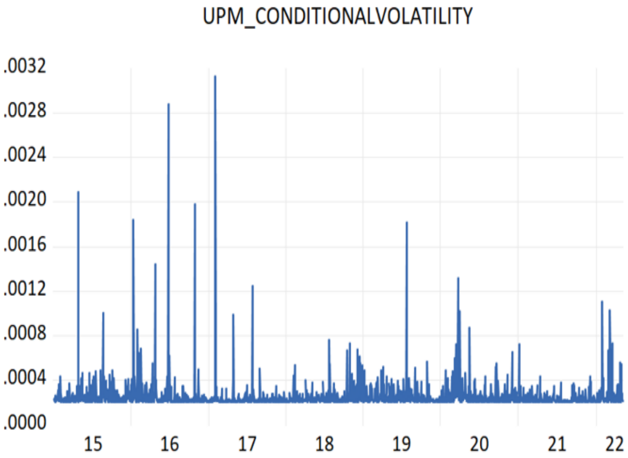
Figure 7. Stora Enso and UPM-Kymmene highly correlated relationship

Table 7. Stora Enso and UPM-Kymmene Correlation and Covariance

CORRELATION	Stora Enso Returns	UPM-Kymmene Returns
Stora Enso Returns	1	
UPM-Kymmene Returns	0.831177597	1

COVARIANCE	Stora Enso Returns	UPM-Kymmene Returns
Stora Enso Returns	0.000409798	
UPM-Kymmene Returns	0.00029863	0.000315024





	CONDITIONALVARIANCE	
	Stora Enso	**UPM-Kymmene**
Mean	**0.000413**	**0.000261**
Median	**0.000353**	**0.000223**
Maximum	**0.002983**	**0.003129**
Minimum	**0.000194**	**0.000207**
Std. Dev.	**0.000234**	**0.000154**
Skewness	**4.188520**	**10.29748**
Kurtosis	**30.08576**	**148.5169**
Jarque-Bera	**61860.11**	**1661349**
Probability	**0.000000**	**0.000000**
Sum	**0.763634**	**0.481158**
Sum Sq. Dev.	**0.000101**	**0.0000437 (4.37E-05)**
Observations	**1847**	**1846**

Figure 8. Conditional Volatility of Stora Enso and UPM-Kymmene

5 DISCUSSIONS AND CONCLUSIONS

This thesis has been written to solve these following research problems: Would ESG returns volatilise smaller than the Finnish benchmark ones in crises? Would a top-notch ESG rating company perform better than a lowly scored one in Finland during this crisis period?

The research sample includes the market benchmark OMX Helsinki 25 (OMXH25), the actively managed mutual fund EVLI Finland Select (EVLI), and 61 Finnish companies ranked in ESG Combined Score 2020 of Refinitiv Eikon. Besides, the crisis period has been chosen from 1.1.2015 to 5.5.2022 when there were many adverse events happened, such as the COVID-19 pandemic in 2019, the rise in inflation from 2021 to 2022, Ukraine war in 2022, and the current global recession. The research purpose is to apply ARCH, GARCH, and EGARCH models in estimating and analysing the conditional variance series of daily returns. In addition, the literature review has shown a mixed results of supporting ESG Sustainable Investing, especially in crises. Therefore, this thesis has been conducted to fill in the gap of analysing ESG volatilities in crisis for the Finnish market. Moreover, the studies help to point out which Finnish companies are doing a decent job in returns together with ESG Ranking in this volatilised time. Furthermore, the outcomes of this thesis might be considered by investors for investing and financial decisions, particularly in ESG Sustainable Investing.

The overall results of this research could be interpreted as follows. In the first instance, most daily return series fit well with either ARCH(1) or GARCH(1,1) model. There is only one exception of EVLI Finland Select where EGARCH(1,1) has been conducted to remove the GARCH non-negativity constraint condition. Thanks to the initial modelling estimations, the conditional volatility has been withdrawn from GARCH Variance Series. In ARCH and GARCH conditional volatility, the Finnish market benchmark OMXH25 were more efficient and less volatised than most of the ESG companies for this period. Exceptionally, Kone daily return series seem to be statistically more stable than the market benchmark OMXH25 in this case. At the same time for EGARCH modelling, the volatility of daily return series EVLI is higher than the market benchmark OMXH25 in this crisis time.

Secondly, a superior ESG rating may not guarantee stable returns during these crises. In other words, a high-scoring ESG company did not appear to be less volatile than a lower-scoring one in the period 1.1.2015-5.5.2022. A typical example is Stora Enso and Viking Line here where the later one has strived better in crises than the ESG winner Stora Enso. Additionally, there is a high correlation between Stora Enso and UPM-Kymmene in daily returns even though the later one has surprisingly volatilised smaller than Stora Enso. Observing Figure 6 also helps us to have an overview about the volatility of Finnish ESG companies in this time. It has been seen clearly that the top 20 ESG companies seem to fluctuate even in higher volume than the lower ESG ranking ones.

In conclusion, the research outcomes have been in aligned with the author's initial expectation that ESG companies do not perform better than other counterparts, especially in crisis time. Despite hard-working efforts, the research has still had lots of imperfections, such as the knowledge gaps about the econometric models, the consideration about endogenous and exogenous effects on daily returns in crises, the limitations of econometric estimating, and the unexpected factors that might change the research nature.

6 APPENDIX

The ARCH/GARCH conditional volatility graphs of all daily return time series

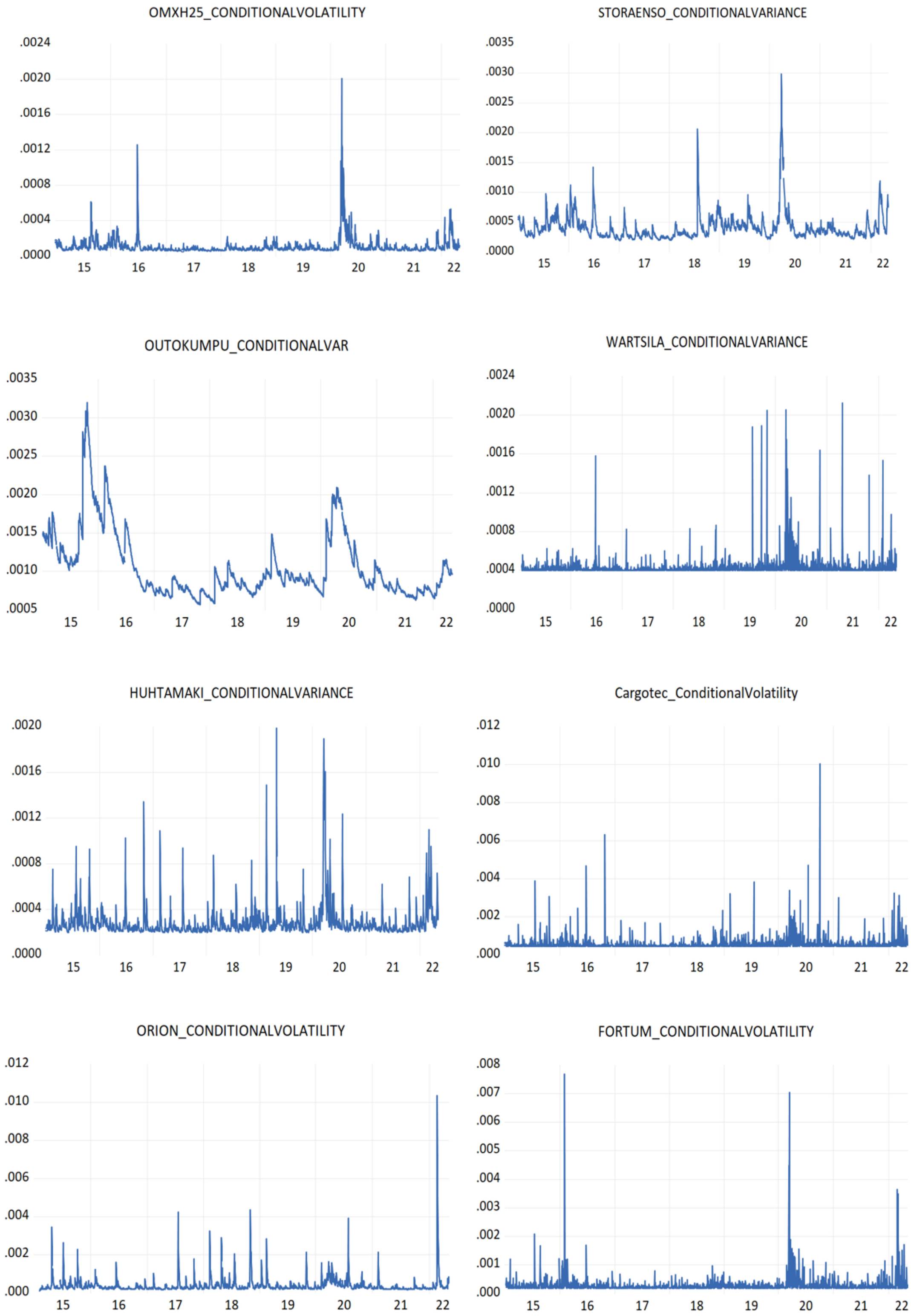
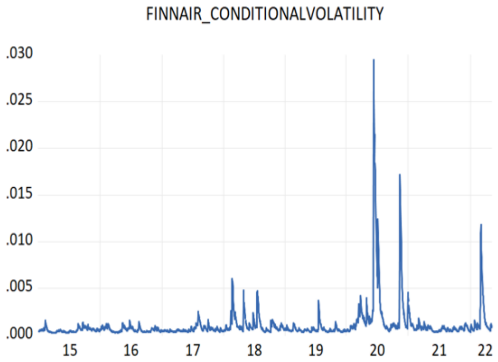


Figure 9. The ARCH/GARCH conditional volatility graphs of all daily return time series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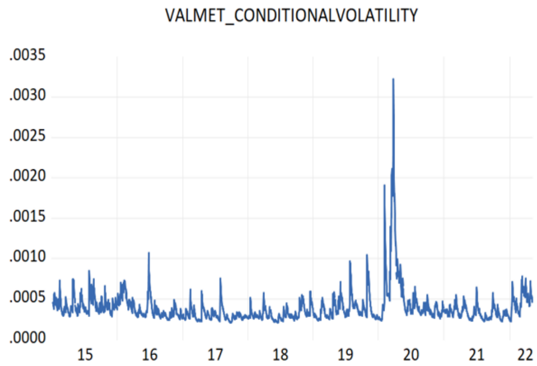
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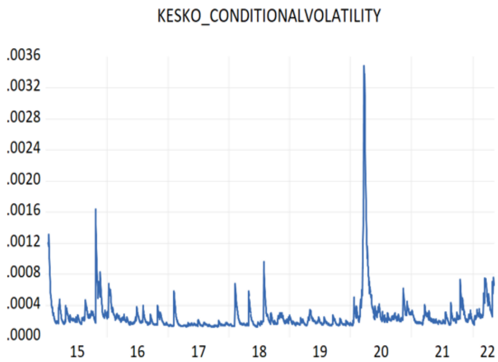
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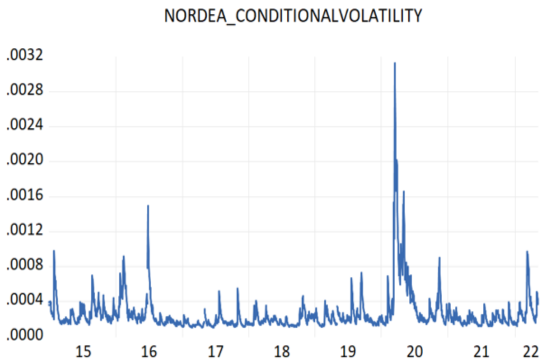
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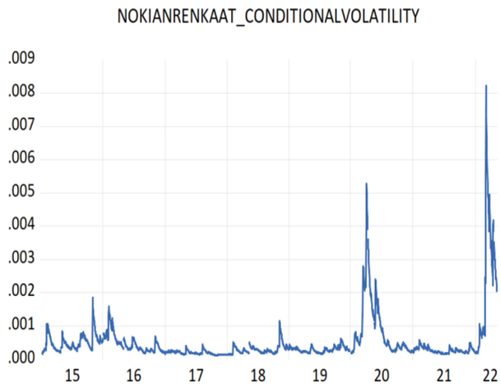
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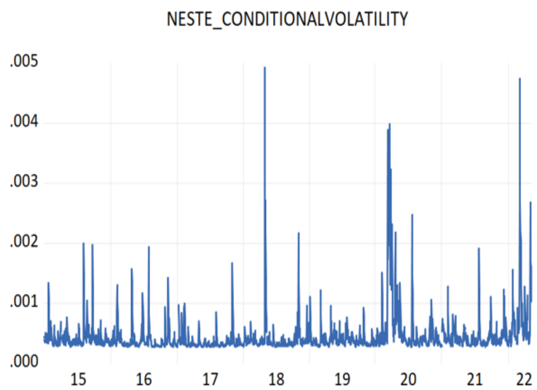
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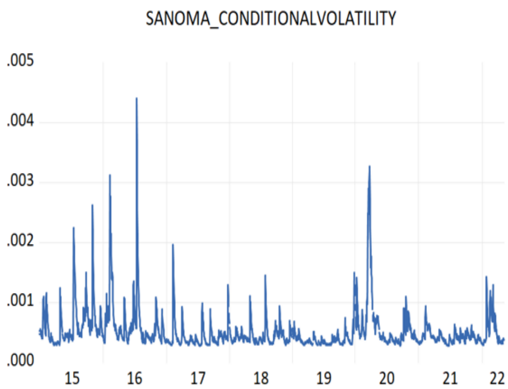
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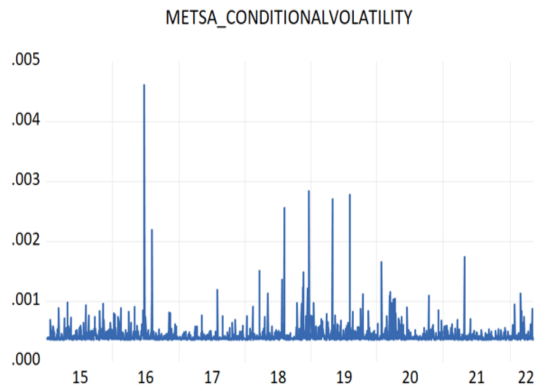
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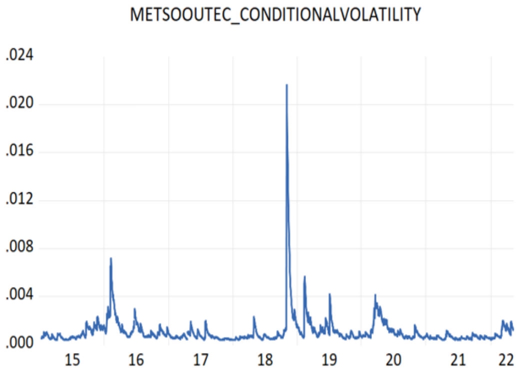
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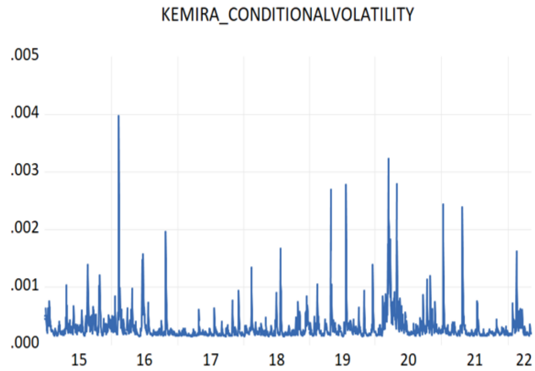
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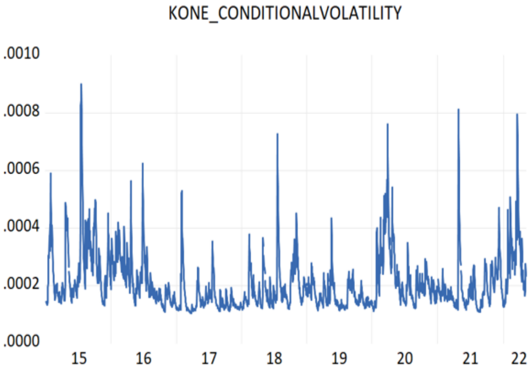
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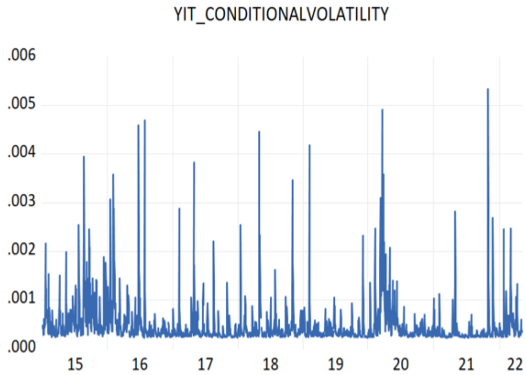
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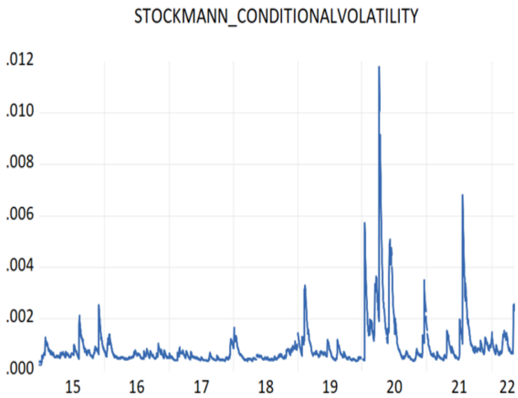
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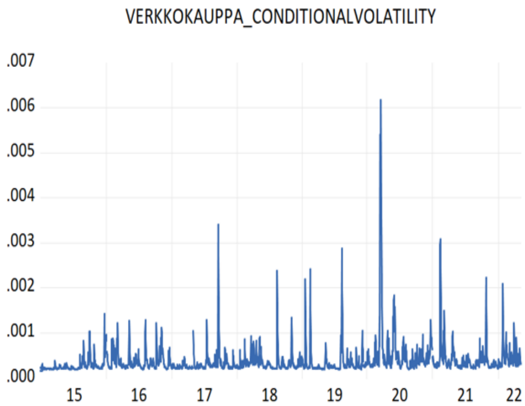
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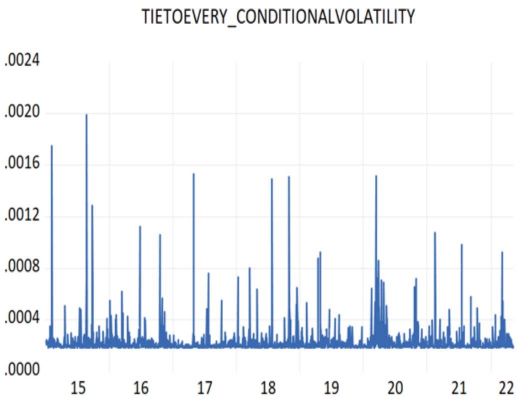
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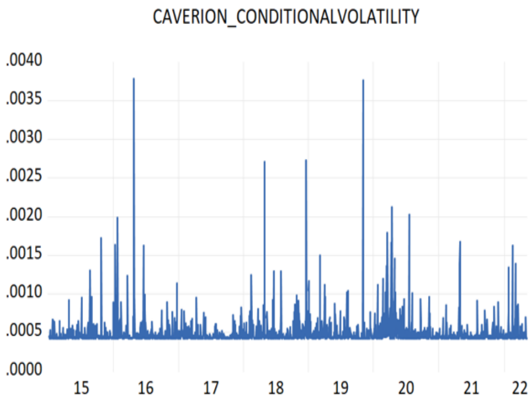
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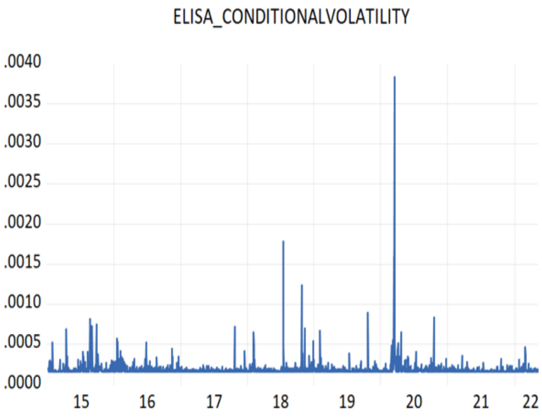
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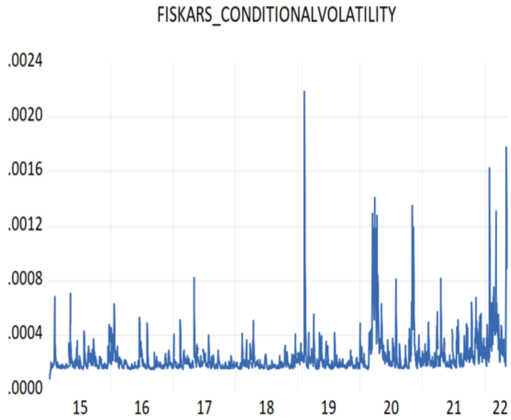
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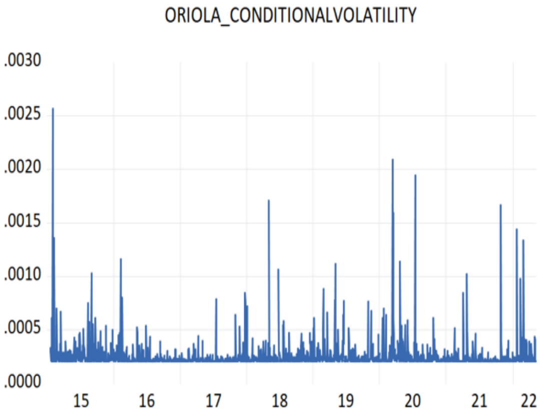
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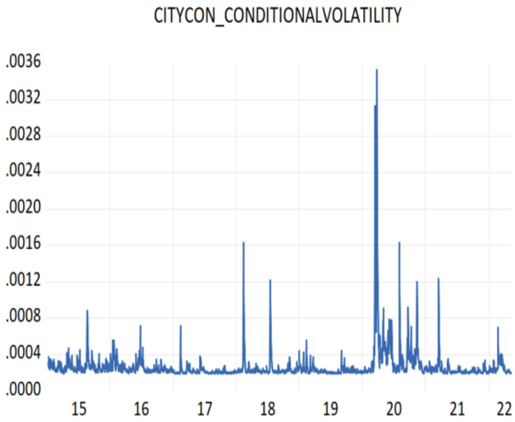
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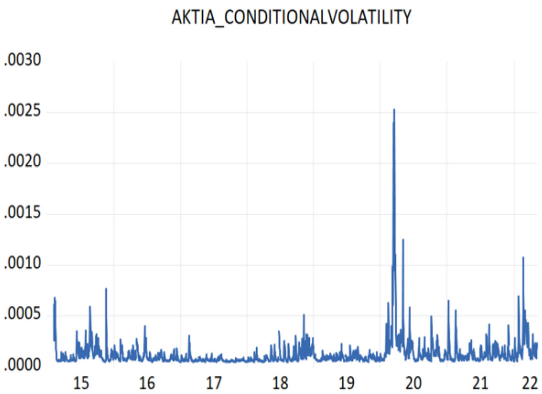
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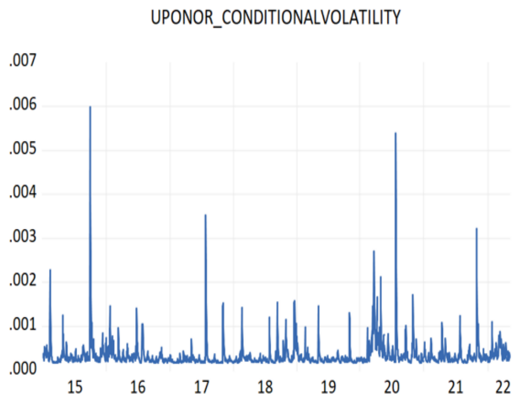
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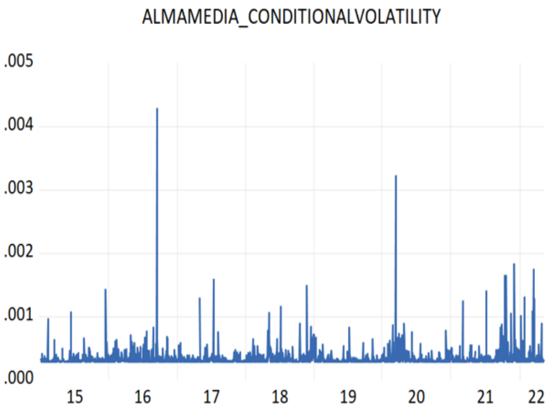
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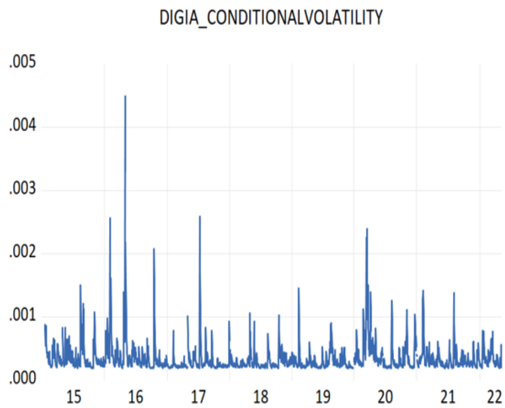
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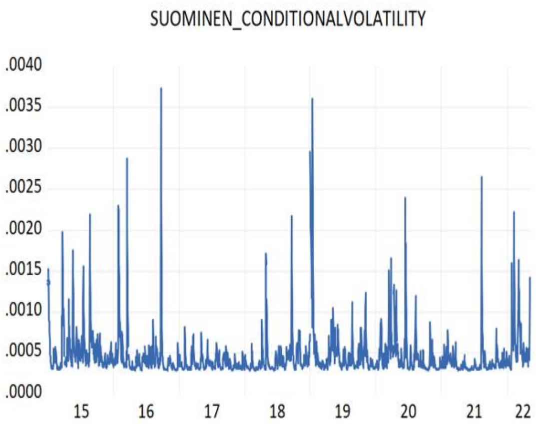
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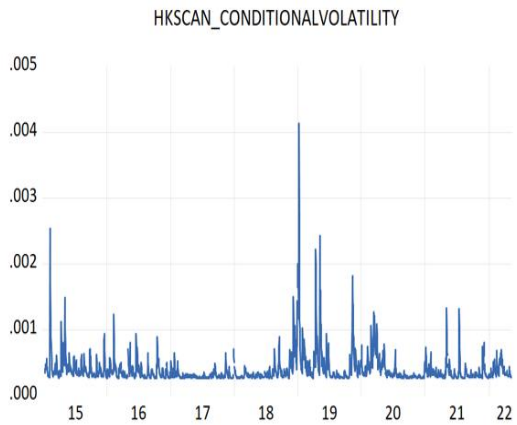
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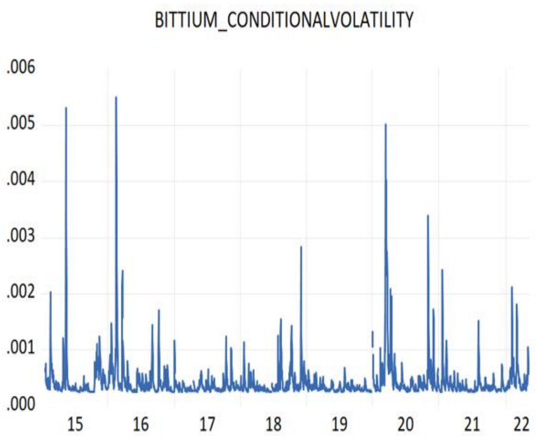
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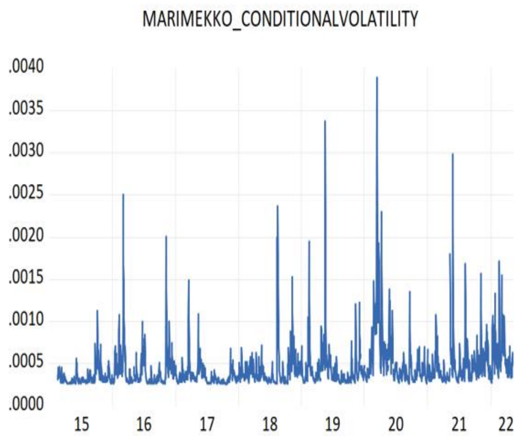
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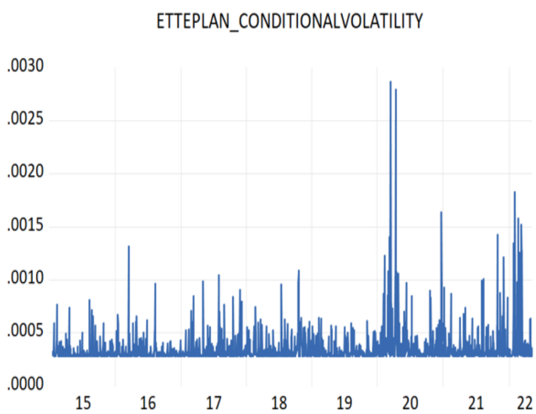
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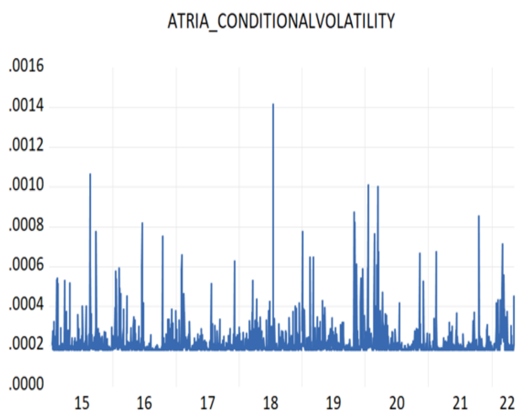
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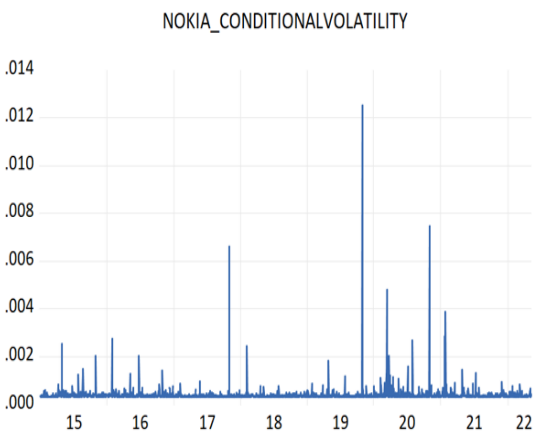
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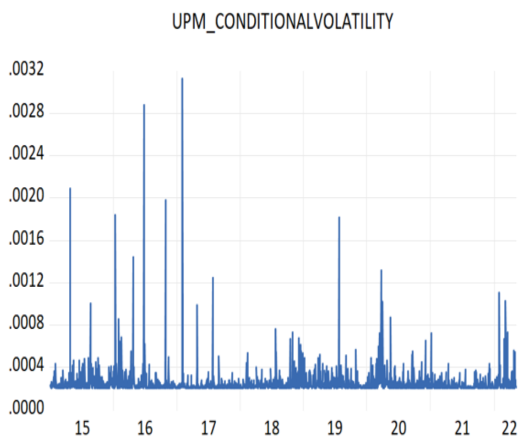
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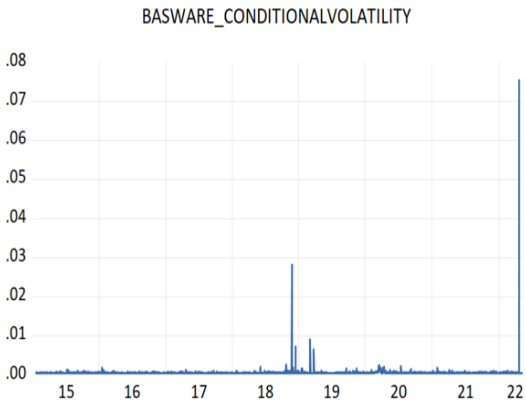
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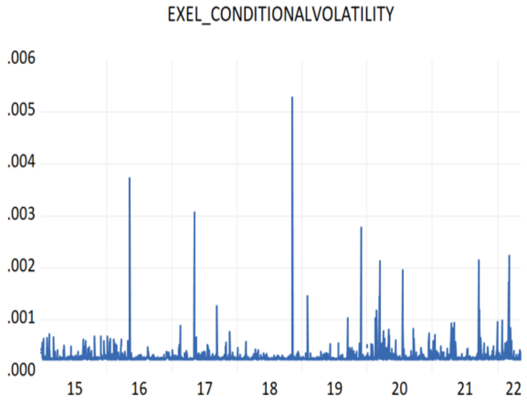
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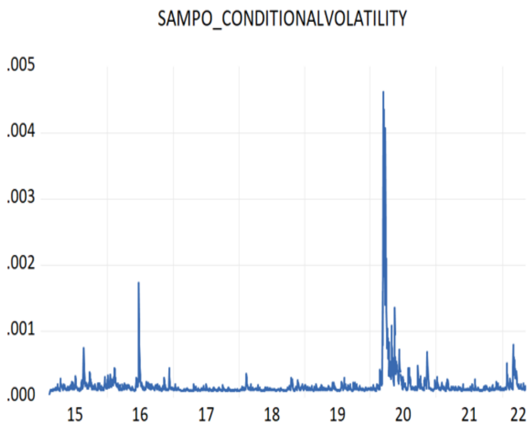
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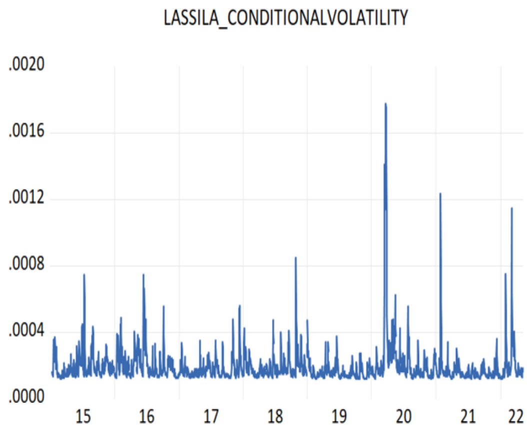
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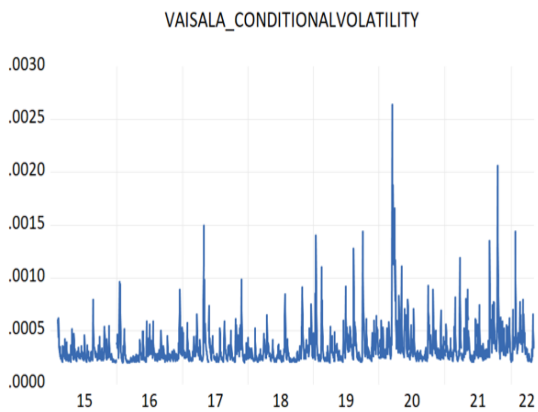
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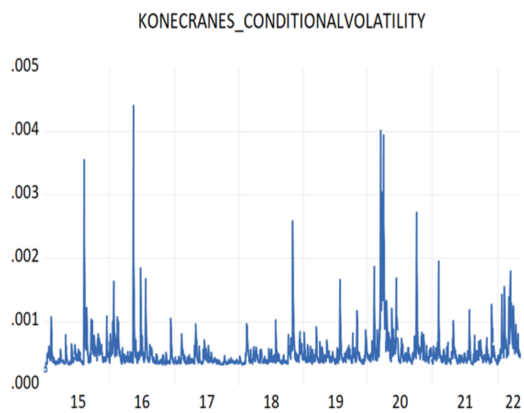
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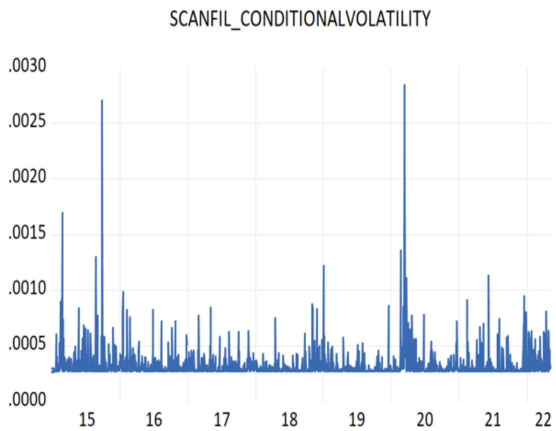
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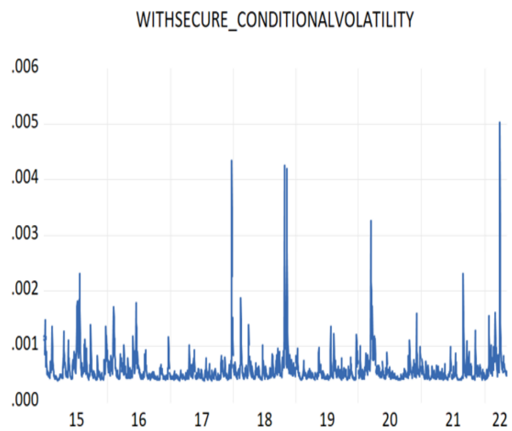
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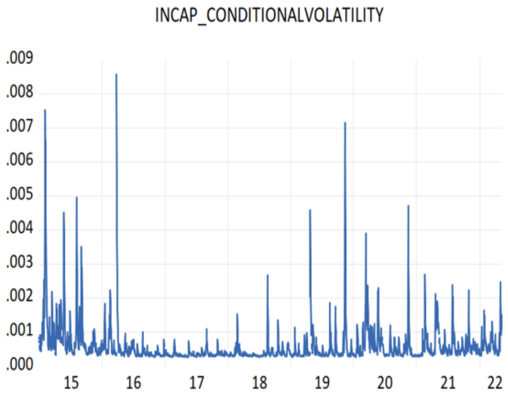
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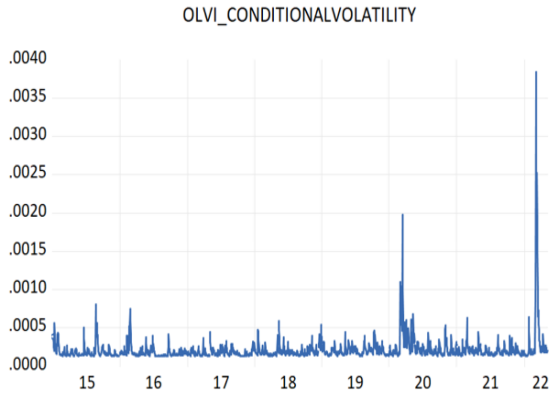
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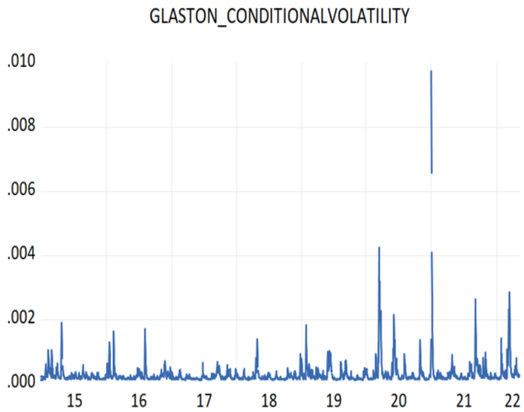
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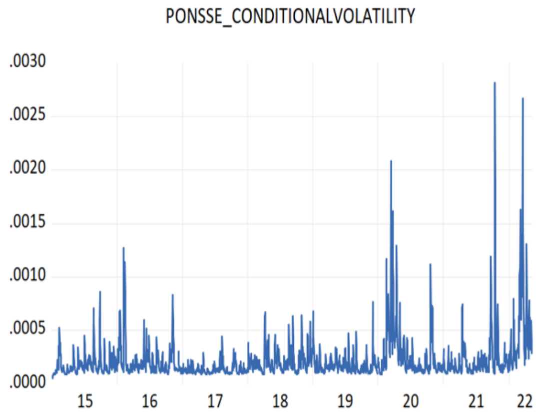
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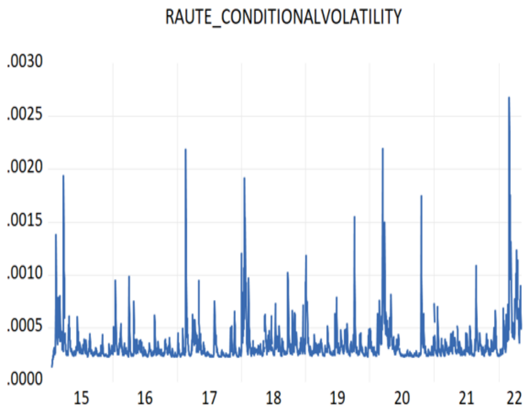
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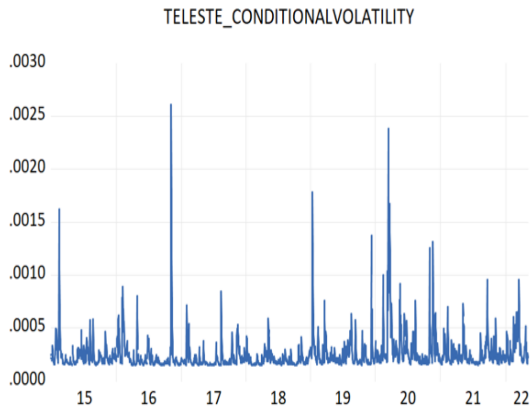
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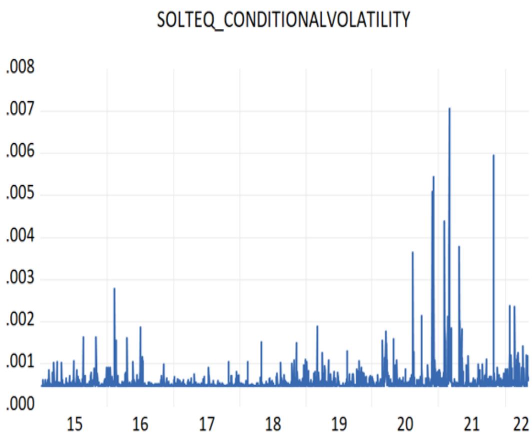
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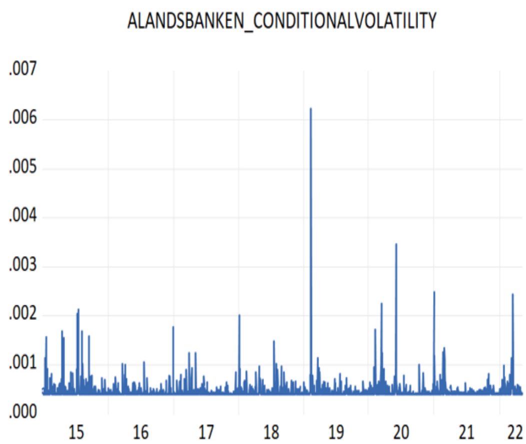
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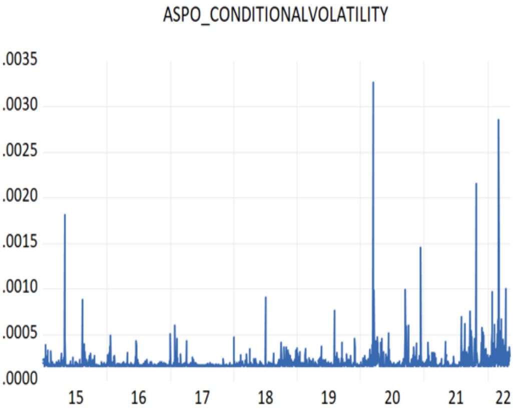
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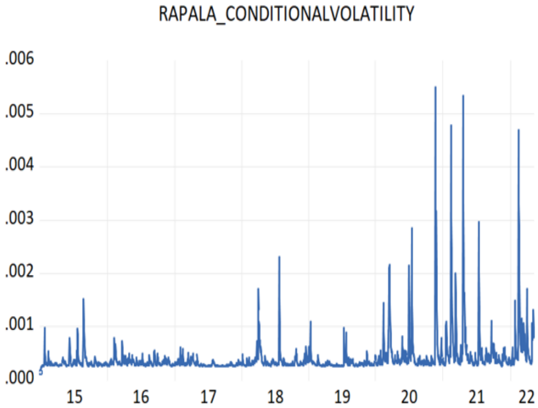
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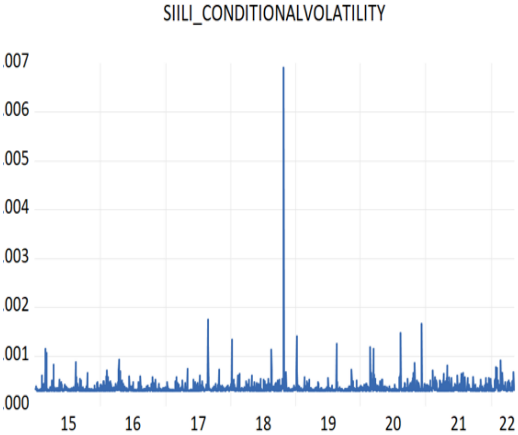
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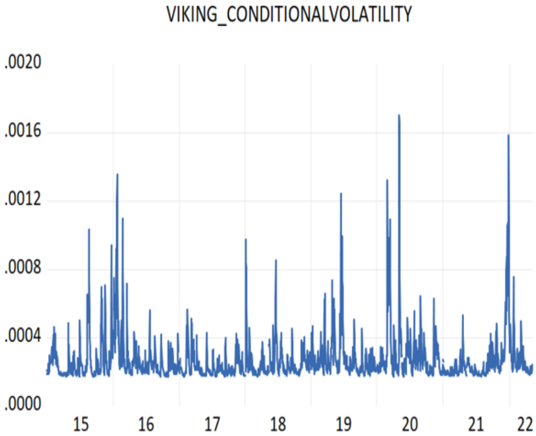
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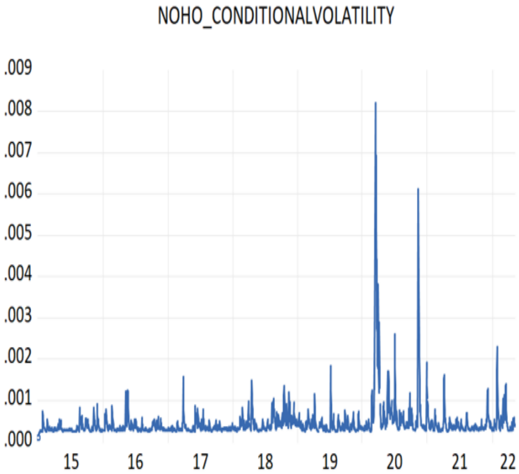
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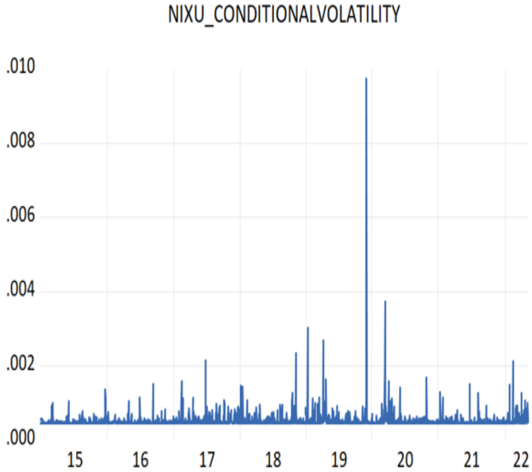
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