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ESG Investing

What is the relationship between ESG, E, S, and G scores and financial performance in the Nordics?

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Abstract

This thesis examines ESG, E, S, and G scored-based portfolios and their financial performance in the Nordic region from 01.01.2006 to 31.12.2021. We collected ESG, E, S, and G scores and financial data from Thomson Reuters Eikon Datastream. The thesis aims to answer the following research question:

What is the relationship between ESG, E, S, and G scores and financial performance in the Nordics?

The Nordic market pool consist of 99 constituents, which we have divided into nine portfolios. For each ESG, E, S, and G screenings, we call the highest-performing portfolio the "High" portfolio and the lowest-performing portfolio the "Low" portfolio. In the analysis, we are performing linear regressions on the High, and Low ESG, E, S, and G screened portfolios to interpret the performance. The analysis consists of three parts:

In Part 1, we analyse Average Allocated High and Low ESG, E, S, and G portfolios. These portfolios are allocated based on the constituents' average ESG, E, S, and G scores and are value-weighted based on the market capitalization in the whole period.

In Part 2, we analyse Yearly Allocated High and Low ESG, E, S, and G portfolios. These portfolios are allocated once every year based on their ESG, E, S, and G scores in the prior year and value-weighted based on the market capitalization in the occurring year.

In Part 3, we build on the findings in Part 1 by adding a sixth factor to the Fama and French (2015) five-factor model. The new risk factor is called "GMB" and is constructed based on the ESG, E, S, and G scores.

We use three performance measures: the average excess return, the Sharpe Ratio, and the alpha.

In Part 1, we find that the High and Low S screened portfolios have the highest and lowest Sharpe ratios, respectively. Further, we find that the Low ESG, E, S, and G portfolios generated significant abnormally low average excess returns, suggesting a positive relationship, cf. our research question.

In Part 2, we find evidence of an abnormally high return in the S screened portfolio. The significant alpha and the polarized Sharpe ratios found in Part 1 and Part 2 provide supportive evidence of the positive relationship between S score and financial performance.

In part 3, the six-factor model finds that six out of eight portfolios had significant exposures to the new risk factor. In five out of eight portfolios, the alpha detected in Part 1 was reduced or diminished. Hence, we argue that the variation in returns can be explained by the portfolio's ESG, E, S, and G scores and that the Low ESG, E, S, and G portfolios yield abnormally low excess returns.

Acknowledgements

This master thesis marks the completion of our two-year master's degree in the program MSc Finance and Investments at Copenhagen Business School. The thesis takes a quantitative approach to examine the impact of ESG, E, S, and G scores on financial performance in the Nordic region. Our motivation to write about this topic is to use the quantitative skillset we have built through our studies to acquire future-oriented insights on sustainability. We want to extend our gratitude to our supervisor Marcel Fischer, who has offered his continuous support and shared exceptional knowledge throughout the process.

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1 Introduction

1.1 Problem Indication and Motivation

There has been a significant shift in the corporate environment in the past decades. The emphasis on ESG has increased due to the various challenges that threaten the Earth and its population. Governments cannot meet these challenges alone and therefore depend on corporations to take responsibility and act on the global challenges we face. Scholars now argue that integrating ESG into the overall strategy is necessary to uphold competitive advantages (Porter & Kramer, 2007). The integration of Environmental, Social, and Governance (ESG) in investment decisions will hereafter be referred to as ESG investing.

ESG scores have changed how investors can evaluate companies' ESG performance beyond their financial profile. ESG scores provide a more precise overview of companies' operations and, therefore, be valuable in investment decisions, creating a new view on the firm's future profitability. There is a fragmented knowledge of the actual impact of ESG on financial performance, and the results vary across geographies, timeframes, and methodologies used (Friede, Busch, & Bassen, 2015). Friede et al., (2015) found a positive relationship between ESG and financial performance in an aggregated study of more than 2200 studies between 1970 and 2016. Scholars argue that this is because companies that consider stakeholder interests and the community around them, and the companies' financial situation will be more profitable over time (Larsen, 2016). Other scholars find that investing based on ESG criteria constrains the traditional risk-return tradeoff and that the reduced diversification will leave the investor with a sub-optimal investment position (Rudd, 1981). However, the magnitude of investment flow shows that many believe in the business case of ESG investing.

ESG investing in the Nordic market is a compelling business case to study due to the strong presence of ESG integration in the area. The Nordic countries Denmark, Norway, Sweden, and Finland are ESG-leaders with a long track record of promoting sustainable development nationally and internationally and consistently ranking among the top ten highest performing on various ESG indexes. For instance, Denmark, Finland, Norway, and Sweden are among the top 10 countries that successfully met the United Nations Sustainable Development Goals (UN SDG) (Refinitiv, 2020). Furthermore, their markets hold some of the largest companies in the world, which makes the countries influential in the global markets (Lekvall et al., 2014). Due to the high level of transparency and market efficiency in the Nordic countries, we have a good foundation to work with.

While there is extensive research on the American and European markets, other regions are underrepresented in literature. For that reason, this thesis is motivated to gain insights for investors in the Nordic area. We want to determine if an investor using ESG, E, S, and G scores in their investment decisions achieves financial returns. Thus, we want to research the relationship between ESG, E, S, and G scores and financial performance in the Nordics.

We begin our thesis with an introduction to ESG investing in Chapter 2. Chapter 3 will present existing literature on ESG, E, S, and G investing globally and in the Nordic countries. Chapter 4 will present relevant theory and introduce the existing model we will be working with throughout the thesis. Chapter 5 will describe the data collection and data preparation process. Chapter 6 presents the findings from our analysis discussed in Chapter 7. Chapters 8 to 10 conclude our thesis with a description of the main implications of our analysis, a discussion of how the findings and analysis live up to three quality criteria, and lastly, how the findings are applicable in a broader perspective.

We divide the analysis in Chapter 6 into three parts. In Part 1, we find that the High and Low S screened portfolios have the highest and lowest Sharpe ratios of the eight portfolios we analyse. The High and Low ESG screened portfolios have the second highest and lowest Sharpe ratios. Furthermore, we find a negative alpha in all the low portfolios. Parts 2 and 3 further assess the findings in Part 1. In Part 2, we find evidence of a very high Sharpe ratio for the High S screened portfolio, and the lowest Sharpe ratio for the Low S screened portfolio. The polarized Sharpe ratios in the S screened portfolios are supported by a positive and significant alpha in the High S screened portfolio. In Part 3, we attempt to explain the negative alphas found in Part 1 by adding a sixth "GMB" factor to the five-factor model. The regression analysis with the six-factor model found that six out of eight portfolios had highly significant exposure to the GMB-factor. In five out of the eight portfolios, the alpha was reduced or diminished, indicating that the sixth factor helps explain the abnormally low returns in the Low ESG, E, S, and G portfolios in Part 1. The main implications of the findings are that there is a positive relationship between the S score and financial performance. We also find that the abnormally low returns in the Low ESG, E, S and G portfolios can be explained by their low ESG, E, S and G scores.

1.2 Research Question

Our research attempts to answer how ESG, E, S, and G scores are related to financial performance. We would like to know how the investor can use ESG and the separate pillars in their investment decisions, and hence we are analyzing High and Low ESG, E, S, and G score-based portfolios in the present thesis. Thus, we have the following research question we would like to answer:

What is the relationship between ESG, E, S, and G scores and financial performance in Nordics?

To answer this question, we will also provide insights into the following five sub-questions:

1. What is ESG Investing, and how is it growing in relevance for investors?
2. How does financial performance get measured?
3. How do High ESG, E, S, and G score portfolios perform compared to Low ESG, E, S, and G score portfolios? How do the findings compare to the Nordic market?
4. How does the financial performance differ using Average Allocated ESG, E, S, and G portfolios and Yearly Allocated ESG, E, S, and G portfolios?
5. Can a six-factor model with an additional ESG, E, S, and G factor explain more variation in portfolio returns relative to the Fama and French (2015) five-factor model?

Based on the problem statement and sub-questions, we have set up the following hypotheses:

- H1: There is a positive relationship between ESG scores and financial performance in the Nordics
- H2: There is a positive relationship between E scores and financial performance in the Nordics
- H3: There is a positive relationship between S scores and financial performance in the Nordics
- H4: There is a positive relationship between G scores and financial performance in the Nordics
- H5: The variation in ESG, E, S, and G portfolio returns is explained by their ESG, E, S, and G scores, respectively

1.3 Delimitations

We want to determine whether it is a positive relationship between the portfolios' ESG, E, S, or G scores and financial performance. Our research will compare the performance of a High and Low ESG, E, S, and G scoring portfolio to the chosen market. We call the E, S, and G in ESG pillars for this delimitation.

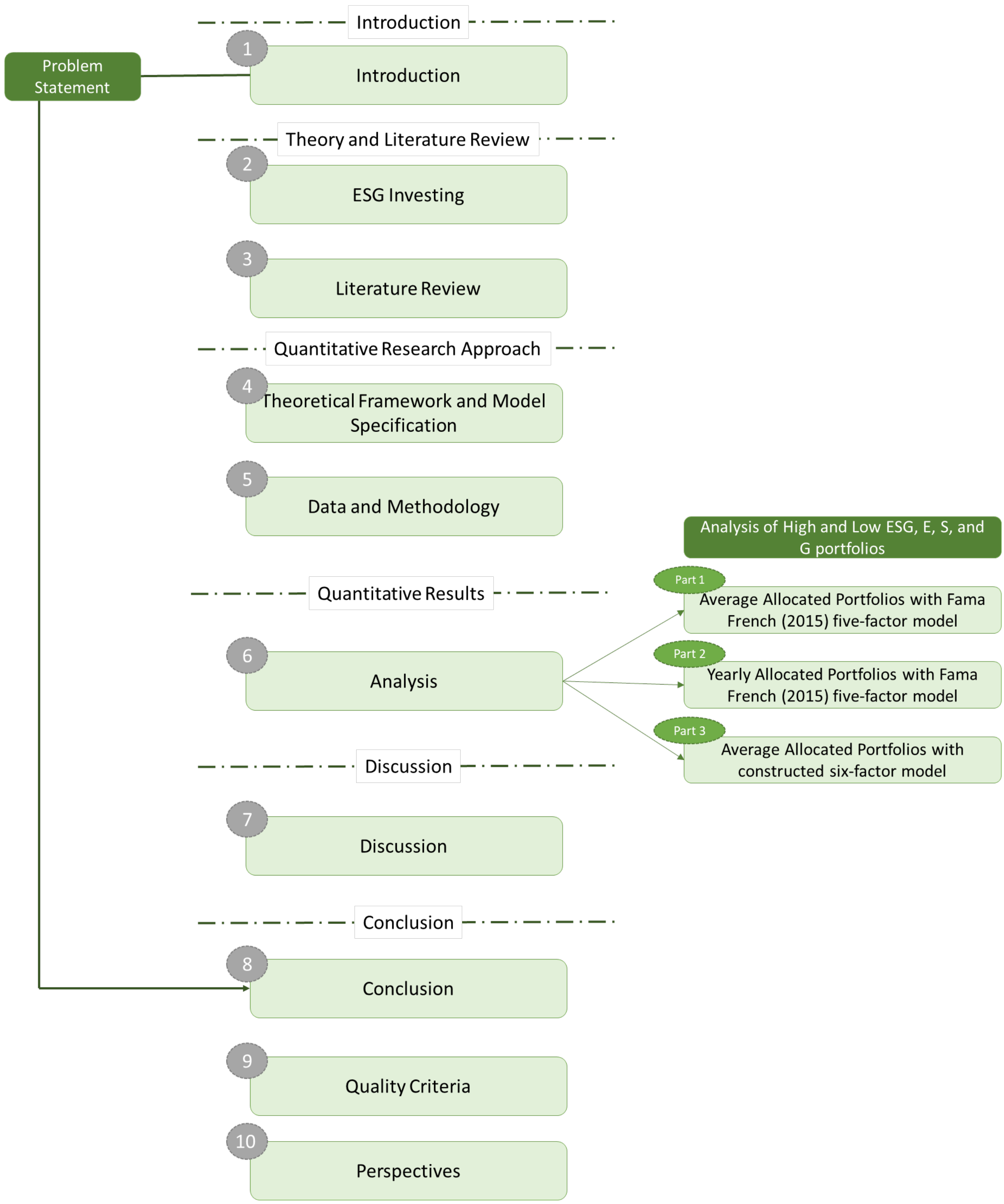
The Nordic region has a high integration of ESG principles, and a higher valuation premium compared to North America and is a top performer in ESG ratings (Leaper, 2017). As a result, we are interested in measuring the impact of ESG momentum on investors' portfolio performance.

To provide the research with a more nuanced view on the matter, we will analyse the behavior of High and Low ESG, E, S, and G score-based portfolios. Our research will separate the pillars to provide information on their performance.

1.4 Structure of the Paper

The thesis is structured in accordance to Figure 1, to answer the research question. The thesis consists of ten chapters and is targeted towards the reader with some knowledge of corporate finance.

Figure 1: *Structure of the study*



Source: own construction

Chapter 2, *ESG investing* discusses the historical development and current market for ESG investing. Furthermore, relevant definitions and terms will be addressed.

Chapter 3, *Literature Review* introduces existing literature on the relationship between ESG, E, S, and G and financial performance.

Chapter 4, *Theoretical Framework and Model Specification* will provide the reader with descriptive presentation of the relevant theories and framework that will be used in the analysis.

Chapter 5, *Data and Methodology* describes our data collection process and data preparation for the analysis in chapter 6.

Chapter 6, *Analysis* presents the results from our Part 1-3 analysis.

Chapter 7, *Discussion* discusses the findings regarding the research question and hypotheses.

Chapter 8, *Conclusion*, presents our main implications and concludes our research by answering the research question.

Chapter 9, *Quality Criteria* evaluates the validity, reliability, and sufficiency in relation to the data collection and analysis.

Chapter 10, *Perspectives* discusses how the findings can be applied from a different point of view.

2 ESG Investing

2.1 Overview of ESG Investing

Increased transparency and ESG rating agencies providing critical analysis of firms' ESG performance led us to wonder if all investors should include ESG in their investment decisions. We structure the present chapter in the following way: First, we learn about the history behind ESG investment. Secondly, we will reflect on the terminology related to ESG investments. Then we will discuss investors' motives for including ESG in investment decisions. After that we will describe the Nordic market for ESG investing. Lastly, we will present various ESG investment strategies for the investors.

2.1.1 History of ESG Investment

ESG investing has been around for centuries but has held different characteristics throughout its lifetime. The oldest ESG screening methods go back to biblical times when ethical guidelines impacted the investment universe through religious or ideological beliefs (Renneboog, Ter Horst, & Zhang, 2008). Investors were responsible for upholding certain ethics and morals in the trading space. Practitioners in Judaism were taught to use money ethically, and in medieval times there were restrictions on loans and investments. John Wesley

(1703-1791) stated in his sermon "The Use of Money" that people should not participate in sinful trade or profit from the exploitation of others (ibid.).

Additionally, modern investors are more focused on personal ethics and social convictions (Renneboog et al., 2008). Religious or value-based investors are still present in the financial markets. They will typically exclude industries or companies that do not align with their beliefs, such as gambling, alcohol, pornography, and tobacco (ibid.). Such industries frequently go under the abbreviation "sin-stocks," and excluding sin-stocks from the portfolio is a "negative screening strategy," an investment strategy still applied today. We will further elaborate on the negative screening strategy in section 2.2.1. With the increased attention towards ESG-investing, many investors integrate ESG into their investment decisions based on pro-active screening and shareholder engagement (Scholtens & Sievänen, 2011).

Since the 1980s, environmental, social, and governance (ESG) issues have led to the development of responsible investments. In 1983 the World Commission on Environment and Development was asked by the United Nations to formulate a "Global Agenda for Change," which addressed the significant challenge to the world community (Brundtland, 1987). The task from United Nations led the World Commission on Environment and Development to assemble "Our Common Future," a plan for change led by Gro Harlem Brundtland, then Prime Minister of Norway. The plan came in response to a widespread feeling of frustration and inadequacy in the international community about the lack of addressing the vital global issues and effectively dealing with them. The report addressed the rising climate crisis, a need for a green economy, and a plan to mitigate poverty (ibid.). By 1994, the United Nations initiated the Framework Convention on Climate Change (The UN FCCC-a, n.d.). The UNFCCC is working towards a low carbon and more circular economy and society. Its primary purpose is to prevent dangerous human interference with the climate system. Today 197 countries have ratified the Convention as "Parties" to the Convention. In 2015 the Paris agreement was established as a legally binding international treaty on Climate Change between parties that shared a common objective to limit global warming to below 2 degrees Celsius, preferably 1.5 degrees Celsius, compared to pre-industrial levels (The UN FCCC-a, n.d.; The UN FCCC-b, n.d.).

By the 2000s, responsible investments had become a significant strategic challenge for companies (Moura-Leite & Padgett, 2011). In 2006, the United Nations launched the Principles of Responsible Investment (PRI), which aimed to create a global sustainable financial system (UNPRI, 2021). The UNPRI dedicates itself to promoting ESG responsibility among investors, and they aim to shift the investor sentiment to integrate ESG practices. The UNPRI is the most extensive global voluntary corporate sustainability initiative today. They rely on voluntary engagement from investors or members, called signatories. Signatories are responsible for $100 trillion in assets worldwide and include some of the largest investors worldwide (UNPRI, 2020). In 2016 they reported that the awareness of ESG investing has increased, but implementation will require a paradigm change and that the financial sector is difficult to redirect (Steward Redqueen B.V., 2016). They also noted that ESG investing is not a mainstream investment strategy yet and is still in its developing stages (ibid.).

After the financial crisis in 2007, there was more significant regulatory pressure on the companies, particularly the prominent players in the financial markets. The ethical and moral controversies put them under scrutiny, and there was an increased demand for transparency from the stakeholders (Nagy et al., 2016). Furthermore, the financial crisis led investors to pay more attention to democracy and responsibility in the markets and more transparency and accountability of market participants (Scholtens & Sievänen, 2011).

There was also a change in sentiment in individual consumers, which helped build momentum around ESG Investing. The momentum was seen by the increase in demand for greener products and services. For instance, research finds that consumers are willing to pay a premium for products and services that align with their values (Miremadi et al., 2012).

Business Roundtable periodically hosts the CEOs of the world's largest companies (US Business Roundtable, 2019). Since 1978 they have issued the Principles of Corporate Governance, which has historically endorsed shareholder primacy principles– corporations exist primarily to serve shareholders. The last meeting in 2019 signaled a change in the zeitgeist, as they outlined a modern standard for corporate responsibility, strongly affirming their commitment to a broad range of stakeholders. The US Business Roundtable strongly affirmed businesses' commitment to the broader range of stakeholders (ibid.).

"By taking a broader, more complete view of corporate purpose, boards can focus on creating long-term value, better serving everyone – investors, employees, communities, suppliers, and customers" – Bill McNabb, former CEO of Vanguard (ibid.)

With the emerging zeitgeist regarding corporate responsibility and sustainability, ESG Investing has experienced a meteoric increase. By 2020, the ESG Investing reached 35 trillion USD in the five major markets: Europe, the US, Canada, Australia, and Japan (GSI Alliance, 2021). The total ESG investments have increased by 15% from 2020 to 2018 and 60% from 2016 to 2020. In Europe, sustainable investment assets under management make up 42% of total assets under management (ibid).

The increased interest in sustainability and incorporating ethics and morals into investment theory led investors to wonder how it would affect the shareholder value. There is not a one-sided opinion on the financial consequences of ESG Investments, and studies find varying results, mainly depending on the geographical area of research, the source for ESG data, and screening processes (Friede et al., 2015). Freeman (1984) argued that meeting the needs of all stakeholders would also benefit the shareholders.

2.1.2 ESG Definition and Terminology

ESG is an acronym for Environmental, Social, and Governance. MSCI (2018) defines ESG as considering environmental, social, and managerial aspects to complement financial concerns in the investment decision process.

Words such as socially responsible investing (SRI), responsible investing (RI), and corporate social responsibility (CSR) all regard corporate responsibility. Although responsible investing has taken form in different shapes and sizes, as presented in the previous chapter, ESG is a relatively new term. The report "Who Cares Wins" first used ESG as a term in 2004 (World Bank Group, 2004). However, ESG differs from the rest because it assumes a measurable financial relevance (Døskeland & Pedersen, 2021). Furthermore, ESG has become a more established and widespread term in literature as scholars and investors are using ESG-ratings and ESG data. Companies that perform high on ESG by improving their social and environmental impact should generate long-term sustainable value (Larsen, 2016). Larsen (2019) argues that investing in ESG should lead to long-term profitability and that the companies' ESG scores will impact the financial returns in the long term.

The E is the environmental dimension and accounts for how companies respond to climate changes, how much waste they leave behind, and how efficiently they utilize their energy (Robeco-a, n.d.). Investors and other stakeholders are increasingly concerned with the environmental impacts of companies' regular activities and are pressuring corporations to mitigate the negative effects on the environment. Initiatives by organizations such as the Task Force on Climate-related Financial Disclosures (TCFD) are incentivizing companies to report climate-related financial disclosures (KPMG, 2020). Consequently, business managers are increasingly integrating environmentally friendly policies and operational activities in their business models and reporting climate-related financial disclosures (KPMG, 2020).

The S is the social dimension related to employees in companies and the local community (Robeco-b, n.d.). Hereunder, this dimension will look at how they employ the fundamental human rights, the safety and health in the workplace, general working conditions in the entire value chain, child labor, and relations with local communities. Good execution of the social dimension can lead to a prominent level of acceptance from the local community and governing authorities, making it easier to get access, approvals, and licenses necessary to harvest growth and operate a business (ibid.).

The G is the governance dimension and relates to the managerial aspects (Robeco-c, n.d.). All companies have a set of rules or principles that clarify rights, areas of responsibility, and expectations for the company's board of directors and general management. Strong governance policies can be used as a management tool and strengthen the organization and its long-term strategy as it shows transparency to stakeholders and ensures that everyone is working towards a collective goal (ibid.).

2.1.3 Investor Motives

Global challenges potentially threatening companies include natural disasters resulting from global warming, security threats related to privacy and data, growing population, and regulatory pressures (MSCI, 2018). Therefore, it is crucial to reevaluate traditional investment decision processes to adapt to the new complexity in the investment world (ibid.).

It can be a tricky challenge to explain the investors' motives because there can be many explanations for why they consider ESG in their investment decisions. Investors can be motivated by regulatory constraints, personal or ethical values, or securing a potentially superior risk-return tradeoff. Many investors will allocate capital towards developing a more sustainable society, but the flow of capital towards ESG investing indicates that it is more than a feel-good exercise. We will explain investors' motives by categorizing them into three dimensions (MSCI, 2018). This way, we can better understand the reasoning behind why investors include ESG, E, S, and G scores in their investment decisions. The three dimensions of investor motives are the following:

- Integration
- Personal values
- Positive impact

The first investor motive is the integration dimension. Many argue that ESG integration will lead to long-term sustainable financial performance and mitigate the exposure risk (MSCI, 2018). ESG integration is to use ESG metrics in financial decisions to improve financial performance and get a superior risk-return tradeoff. Many investors believe that efficient ESG investing holds a considerable value proposition and that investing in ESG prepares companies for the future of business (Larsen, 2016). Research finds supporting evidence for this theory (Friede et al., 2015). Investors aim to use ESG to identify superior performance through better management or by being less exposed to future threats from regulatory, environmental, demographic, or technological trends (MSCI, 2018). It has become relatively normal for institutional investors to apply such a strategy in their investments, but individual or "retail" investors are catching on to the trend (GSI Alliance, 2021).

The second dimension is personal values (MSCI, 2018). Although most research conducted on ESG investing implies a positive relationship between ESG and financial performance, there is yet to be a consensus among scholars as a substantial number of scholars find a neutral or negative relationship (Friede et al., 2015). With the lack of consensus, many investors must be motivated by factors other than financial wealth, and some investors may even be willing to sacrifice some return. They receive a non-financial utility by having an investment strategy that aligns with their personal and ethical values or religious and ideological beliefs

(Brzeszczyński & McIntosh, 2014; MSCI, 2018; Renneboog et al., 2008). Investors who incorporate personal values in investment decisions will often use a negative screening method to exclude companies or industries from their portfolios, a strategy further described in section 2.2.1. Compared to the ESG integrator, the value-based investor will not account for financial performance but align the investments to their beliefs (ibid.).

The third dimension, positive impact, is a motive to invest in making a difference in the world. The positive impact investor will aim to allocate capital to companies that provide solutions to environmental challenges. In addition to financial returns, the impact of the investments is measured through different frameworks as introduced earlier, namely the United Nations Sustainable Development Goals (UN SDGs) (MSCI, 2018).

2.1.4 ESG Market in the Nordics

The Nordic region includes Norway, Denmark, Sweden, Finland, and Iceland. Still, because Iceland does not qualify for the top ten rankings and has limited available ESG records, we limit our research to those who do. Therefore, we will refer to 'the Nordic region' being Norway, Denmark, Sweden, and Finland. The Nordic countries have pioneered the future of ESG by jointly committing to a more sustainable future. The Nordic countries are home to several of the world's largest companies and institutional investors (Lekvall et al., 2014). A total of sixty Nordic companies qualifies on the Forbes list of the two thousand largest publicly listed companies globally (ibid.). The UN SDGs is one of the most adopted ESG and impact-assessment frameworks (Liang et al., 2022). The UN SDGs build on consensus among global stakeholders concerning 17 goals (ibid.). The four Nordic countries, Norway, Denmark, Sweden, and Finland, hold impressive rankings, all being among the ten highest performing countries globally (Refinitiv, 2020). With support and commitment from high political levels and ESG integration in institutional investors, the world has witnessed a remarkable ESG performance in the four countries in many subsequent years. They have contributed to advancements with an elevated level of accountability, transparency, and a consistent effort at innovation.

The Nordic region has historically held a key role and led the way in developing and integrating ESG Principles through collective working, setting ambitious goals, and having influential market players actively promoting ESG. For instance, the United Nations Environment Programme (UNEP) was founded in response to the Stockholm conference in 1972 (Ivanova, 2007). "Our Common Future" was directed by then prime-minister Gro Harlem Brundtland as a "call for action," which was very early in addressing the global challenges (Brundtland, 1987). In the 1990s, Sweden incorporated environmental and ethical standards into its legislation, one of the first countries to do so (Hammerich & Kesterton, 2018).

Furthermore, many institutional investors in the Nordic region recognize ESG factors as a key component in investment decisions. Norway's Government Pension Fund-Global (GPFG) is the largest sovereign wealth fund worldwide (Statista, 2022). It works to generate long-term sustainable returns and moderate its risk by considering ESG issues and publishing clear expectations to companies they invest (NBIM-a, n.d.). The fund was established after discovering oil in 1967 and became an active investor on the stock exchanges around the world (ibid.). They also hold a publicly available exclusion and observation list (NBIM-c, n.d.). The Danish investors have historically followed in the footsteps of their Nordic peers, and they are closing in on the lead of their Swedish peers by allocating dedicated resources to ESG (Hammerich & Kesterton, 2018). A study based on interviews and quantitative data from 37 institutional investors in the Nordic countries shows that ESG has become a norm in the Nordic asset management industry, with Sweden and Denmark at the forefront of development (NN Investment Partners, 2019).

Scholtens & Sievänen (2011) studied the composition and size of SRI in the four Nordic countries, Norway, Sweden, Denmark, and Finland. Due to limited SRI data, they performed the analysis with a case study. The research aims to determine if differences in characteristics in economics, finance, institutions, and culture lead to varying composition and size of SRI. Their findings imply that the four countries have similar economic, social, and CSR performance. However, there are significant differences in the size and composition of SRI. The authors suggest that determining factors can be economic openness, the size of the pension industry and uncertainty avoidance (ibid.). Comparing the markets for SRI, they find that Norway has by far the largest market in both absolute and relative terms and on a per capita basis (Scholtens & Sievänen, 2011). On the contrary, Finland has the smallest SRI market. Denmark and Sweden are the most open economies regarding the percentage of imports and exports to Gross Domestic Product (GDP). The institutional investors are the largest in Norway. Nonetheless, this is due to the inclusion of the Norwegian Pension Fund (NBIM). Finland has a substantial pension fund. Denmark and Sweden have much smaller pension funds, but Denmark has a more significant banking industry. Finland and Norway score substantially higher on uncertainty avoidance than Denmark and Sweden (ibid).

2.2 Investment Strategies

According to GSI Alliance, the most common sustainable investment strategy is ESG integration, followed by negative screening, corporate engagement and shareholder action, norm-based screening, and sustainability-themed investment. The following chapter will introduce the most widespread ESG investment methods.

2.2.1 Negative screening

The first type of screening strategy is negative screening, an exclusion method. It is a practice where the investor will hold potential investments up against ESG-related criteria and exclude companies or industries from the portfolio that do not uphold a sat standard (Renneboog et al., 2008). Excluded companies might be related to alcohol, tobacco, gambling, defense industries, or companies with poor performance under labor relations or environmental protections (ibid.). The companies excluded from investments due to the negative screening often go under "Sin Stocks" (Fabozzi, Ma, & Oliphant, 2008).

However, in empirical research conducted by Hong & Kacperczyk (2009) findings imply that sin stocks, on average, are neglected by norm-constrained investors and, therefore, may generate excess returns. Fabozzi et al. (2008) found supportive evidence to Hong et al. (2009) findings, when they obtained a sample of sin stocks across 21 countries and included exchange-traded stocks from six alcohol, tobacco, defense, biotech, gaming, and adult services industries. They find that these stocks outperformed the market by 11% annually (Fabozzi et al., 2008). However, newer empirical research has shown that adding two new factors in the Fama & French (2015) five -factor model captures the abnormal returns in the low-scoring ESG stocks. Blitz and Fabozzi (2017) use the Five-Factor model to account for investment and profitability factors. They conclude that the inclusion of the two factors explains the positive abnormal returns on sin stocks.

2.2.2 Positive screening

The second type of screening strategy is positive screening, an inclusion method. When using this method, the investor evaluates stocks based on their performance on an ESG-related criterion. Then, they pick the stocks with the highest performance (Kempf & Osthoff, 2007). The most common standard is based on corporate governance, labor relations, the environment, sustainability of investments, and the stimulation of cultural diversity (Renneboog et al., 2008).

A best-in-class (BIC) method is often associated with a positive screening method (ibid.). The BIC method rates each company within their industry or segment on their ESG-performance. Furthermore, the investors will choose the companies with the best ratings within their industry or segment (ibid.).

2.2.3 ESG integration

The third type of screening strategy is the ESG integration based on both positive and negative screens. Furthermore, it integrates ESG-metrics into traditional financial analysis (Renneboog et al., 2008, p. 1728).

The integrated approach has become increasingly important to investors. The ESG investment sphere has shifted from excluding non-ESG compliant companies to using ESG as an essential part of investment decisions (ibid.). This phenomenon is particularly evident among Nordic investors (Hammerich & Kesterton, 2018). Two critical factors have impacted this shift. Firstly, the expectations and regulations for ESG-compliance have increased. It is, for instance, expected that firms voluntarily comply with initiatives such as the United Nations-supported Principles for Responsible Investment (UN PRI). However, in recent years, investors and asset managers have expressed that they expect firms to do more (ibid.). Secondly, more sophisticated ESG-screening tools enable investors to upgrade their methodologies from the traditional financial analysis (Eurosif, 2016).

ESG has become an essential part of investment decisions with most top tier-1 investors in the Nordic region (Hammerich & Kesterton, 2018). Large funds such as the Norwegian Government Pension Fund use ESG-integration in investment decisions to ensure long-term economic performance and reduce risk (NBIM-b, n.d.).

On the contrary, opponents of the ESG integration method say that the approach reduces downside risk and limits the upside potential. Their rationale is rooted in Markowitz, 1952 portfolio theory about optimal portfolio strategy through diversification. Markowitz argues that a constrained investment strategy is inferior in an efficient market and that it will never pay off for an investor to place restrictions on investments. Using ESG screening to exclude companies is a constrained portfolio that results in a less diversified portfolio, which in theory will lead to a suboptimal investment position. This will be further discussed under section 3.4 Risk and Diversification.

3 Literature Review

We will describe the relationship between ESG, E, S, and G scores and financial performance in positive, negative, and neutral dimensions. The present thesis determines the relationships between the alpha coefficient, **x1**, and the portfolio's performance, **y**.

An alpha coefficient greater than zero signals a positive relationship between High ESG, E, S, and G scores and financial performance, and a negative relationship between Low ESG, E, S, and G scores and financial performance. Further, an alpha below zero indicates a negative relationship between High ESG, E, S, and G scores and financial performance and a positive relationship between Low ESG, E, S, and G scores and financial performance. Lastly, an alpha at zero signifies a neutral relationship.

The present chapter will elaborate on relevant published literature regarding the relationship between ESG, E, S, and G scores and financial performance globally. After that, we will elaborate on the same relationship for the Nordic market. We will discuss the presented literature in combination with our results in discussion, chapter 7.

3.1 The relationship between ESG scores and financial performance

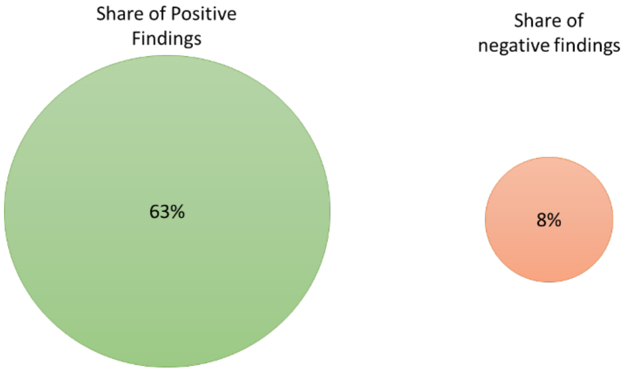
Empirical research finds mixed evidence as to whether there exists a significant positive relationship between ESG scores and financial performance. Over the last few decades, the transparency from corporations to stakeholders has improved, making it easier for investors to evaluate companies' ESG performance. As a result of more available information, investors have a newfound view of individual companies' future profitability (Larsen, 2016).

Between the early 1970s and 2015, over 2200 empirical studies were conducted (Friede et al., 2015). The studies aim to provide supporting evidence to explain the relationship between ESG and financial performance. The studies find mixed evidence, which has led to a fragmented knowledge of the relationship between ESG and financial performance. The mixed evidence occurs because the research question is being tested on various geographies, using different models, screening methods, and timeframes.

In a comprehensive study by Friede et al. (2015), they aggregated the findings from the >2200 unique studies on the topic to overcome the shortcoming of having many different viewpoints. The research was conducted using a voting study and a meta-analysis, resulting in clear evidence supporting ESG investing. Around 90% of studies find a non-negative relationship between ESG and financial performance, and the majority find positive findings (ibid.).

Furthermore, the vote count and the meta-analytic studies comprise nearly independent samples (12.9% overlap), yet they yield comparable results, strengthening the robustness of the results. According to Friede et al., ESG outperformance opportunities are particularly existent in North America, emerging markets, and non-equity asset classes. Furthermore, they argue that investors should orient toward long-term responsible investments. A profound understanding of integrating ESG criteria in investment processes is essential to harvest the full potential of value enhancing ESG scores (ibid.).

Figure 2: *Shows the number of positive and negative findings in a meta-analysis conducted by Friede et al. (2015) on >2200 studies in the period 1970 to 2015.*



Source: Friede et al., (2015) and own construction

Kempf & Osthoff (2007) use negative, positive, and best-in-class screening methods to analyse the relationship between ESG and financial returns between 1992 and 2004. They use ESG data from KLD and the Carhart (1997) four-factor model. They found that the investor can generate an abnormal positive return with a positive or best-in-class trading strategy but not with a negative trading strategy, which is consistent with the implications of (Hoepner, 2010). Their research finds that ESG-information holds valuable insights for the investor and that ESG-strategies are positively associated with stakeholder returns (Kempf & Osthoff, 2007). However, in their report, they raise the question of whether it results from temporary mispricing in the market or if it compensates for an additional risk factor (ibid.).

(Borgers et al., 2013) research provided supporting evidence to answer the question Kempf and Osthoff (2007) left behind. They find that the superior risk-adjusted returns found in High ESG portfolios can be explained by mispricing in the market. Furthermore, they predict that increasing stakeholder information will eliminate this mispricing. Using ESG-data from KLD and the Carhart (1997) four-factor model, they found a positive relationship between the stakeholder-relations index and risk-adjusted returns from 1992 to 2004, which supported Kempf and Osthoff's research from 2007 (ibid.).

However, their findings are highly insignificant from 2004 to 2009 (Borgers et al., 2013; Kempf & Osthoff, 2007). Consequently, they conclude that the stakeholder-relations index predicted risk-adjusted returns up until 2004 due to mispricing from incorrect investor expectations. Borgers' findings suggest that investors are increasingly using ESG score screenings in investment decisions, which has reduced the differences in risk-adjusted returns between high and low-rated ESG portfolios. The investors do not fully understand the intangible value in ESG information, leading to incorrect expectations. Their arguments imply that the market is imperfect, allowing investors' behaviour to impact the market dynamics. Furthermore, they also state that an improved ESG-reporting raises attention toward ESG-investing (Borgers et al., 2013).

3.2 The relationship between E, S, and G scores and financial performance

3.2.1 The relationship between E scores and financial performance

With the E in ESG analysed on a stand-alone basis, there is mixed and even contradictory evidence on whether environmental performance is positively linked to financial performance. The neo-classical argument is that environmental initiative requires significant expenditures and efforts to be executed, which will negatively impact their financial performance (Walley & Whitehead, 1994). This theory is challenged by scholars who believe the cost of environmental initiatives is offset by productivity benefits from innovation and added competitiveness. Other argue that efficient environmental standards can allow companies to improve their resource productivity (Porter & Linde, 1995).

In recent empirical studies, scholars have found evidence for a positive relationship between E scores and financial performance. In a comprehensive study, Liu (2020) uses a multilevel framework to decompose the relationship between E scores and financial performance (Liu, 2020). An overall positive relationship between E scores and financial performance suggests that a proactive environmental strategy is an efficient tool to improve financial performance.

Furthermore, the analysis also uncovers two critical tendencies in the relationship between E scores and financial performance. Firstly, by separating data into companies and industries, Lou (2020) finds that E performance's actual impact on financial performance is heavily dependent on the company characteristics and which industry sector it belongs to. Secondly, he finds a bi-directional causal relationship between E scores and financial performance that implies that companies depend on sufficient financial resources that allow them to integrate environmental policies and initiatives efficiently (ibid.).

3.2.2 The relationship between S scores and financial performance

The S in ESG stands for the social dimension. Allouche and Laroche (2014) conducted a meta-analysis of the reported findings on the relationship between corporate social performance (CSP) and financial performance in the US and UK. Of 82 studies, 75 studies found a positive relationship, and 41 studies found a significantly positive relationship, implying that CSP is strongly related to financial performance on average (Allouche & Laroche, 2005).

Furthermore, Orlitzky (2001) suggested that controlling firm size does not impact the effects of CSP on financial performance. Allouche et al. (2014) found supportive evidence for this theory.

Lastly, Allouche et al. (2014) finds implications of a virtuous cycle between CSP and financial performance, as financial performance as a determinant of CSP found a positive relationship between CSP and financial performance. Hence, companies with more robust financial resources will perform better in CSP.

Edmans (2011) analysed the "100 Best Companies to Work for in America" to their financial performance and found that employee satisfaction is positively related to shareholder returns. The 100 best companies to work for earned an annual four-factor alpha of 2.1% above industry benchmarks between 1983 and 2009.

3.2.3 The relationship between G scores and financial performance

Stanwick and Stanwick (1998) analysed the relationship between G scores and financial performance. Using the ranking of the Best and Worst Board of Directors published in Business Week, they found a positive relationship between corporate governance and financial performance. Furthermore, board independence, board quality, and shareholder accountability had a significant positive impact on financial performance.

3.3 The relationship between ESG, E, S and G scores and financial performance in The Nordics

Lueg and Pesheva (2021) studied the relationship between corporate sustainability in the form of practices and reporting and total shareholder returns in the Nordic countries over eight years between 2007 and 2014. Corporate sustainability is proxied using ESG, E, S, and G scores. They studied 213 firms from the five Nordic countries and their respective ESG, E, S, and G scores with data from Bloomberg terminal. Their findings implied two critical lessons. First, there is a positive relationship between corporate sustainability and total shareholder returns, where good governance practices influence the effects. Friede et al. (2015) found that a positive relationship between corporate sustainability and total shareholder returns is an established understanding in influential capital markets. However, Lueg and Pesheva find the positive relationship to be evident in the smaller companies in smaller Nordic capital markets. Secondly, they found that corporate sustainability has a curvilinear effect on shareholder returns (Lueg and Pesheva, 2021).

3.4 Risk and Diversification

ESG investing may conflict with the modern portfolio theory developed by Markowitz (1952) and (Sharpe, 1966), who finds the optimal investment position based on a risk-return trade-off. This section attempts to discuss whether using ESG, E, S, and G scores in investment decisions will lead to a sub-optimal investment position due to reduced diversification and thus reduced firm-specific risk.

Some research scholars find implications of low unsystematic risk in the high scoring ESG firms. This theory has two explanations. Firstly, empirical research shows that high ESG performing companies have less idiosyncratic risk (Hoepner, 2010). Secondly, high ESG scoring firms have less risk related to litigation and harmful reputational consequences and are better prepared for changes in costs in raw materials or government requirements (Henisz et al., 2019).

Sassen, Hinze, and Hardeck (2016) analyses the relationship between ESG and firm risk in the European stock market from 2002 to 2014. They measure the firm risk by three proxies: systematic, idiosyncratic, and total risk. Their findings suggest a negative relationship between ESG scores and total and idiosyncratic risk. Whereas the social performance has a significant negative effect on all three risk measures, the environmental performance negatively affects the idiosyncratic risk. A relationship between governance factors and firm risk was not detected. The research supports the business case for ESG investments. Chollet and Sandwidi (2018) study support Sassen et al. (2016) that higher social performance reduces risk, but their findings also imply that governance factors are an essential driver.

According to theory, companies are exposed to two types of risks: the unsystematic and the systematic risk. While the unsystematic risk is firm-specific and can be diversified away, the systematic risk is market-specific and affects all firms and thus cannot be diversified away. The investor can diversify their portfolio by spreading the investment across many different assets, reducing the exposure to the firm-specific risk (Barnett & Salomon, 2006). According to the security market line, the market will reward the investor willing to take on more systematic risk, but the systematic risk (Munk - a, 2018). ESG screening will constrain the investors' options, leading to a reduced diversification in the portfolio. The reduced diversification from ESG screening will lead to a sub-optimal portfolio allocation, and it will never be the most optimal position (Rudd, 1981). This theory contradicts investors who believe that using ESG scores in investment decisions will lead to an improved risk-adjusted return.

In response to the argument mentioned above, Hoepner (2010) broke portfolio diversification into three dimensions: the number of selected stocks, the correlation between selected stocks, and the average specific risk.

$$\sigma_P = \sqrt{\sum_{j=1}^{n} w_j^2 \sigma_j^2 + \sum_{j=1}^{n}\sum_{i=1}^{n} w_i w_j \rho_{i,j} \sigma_i \sigma_j} \quad \forall\, \rho_{i,j}\sigma_i\sigma_j \neq \rho_{i,j=i}\sigma_i\sigma_{j=i}$$

According to Hoepner, ESG screening methods reduce diversification due to the first and second dimensions. The screening reduces the number of stocks available and increases the correlation between selected assets. However, Hoepner points toward the third dimension as higher ESG scores tend to have significantly lower specific risk, suggesting that ESG screening may not reduce diversification. The findings motivate investors to use ESG scores to evaluate companies and acquire the offsetting effect from reduced unsystematic risk in the individual stocks.

Using a negative screening would not exhibit the same benefits, as there will not be a change in unsystematic risk in the individual stocks. Overall, the research challenges scholars such as Rudd (1981) and argues that all investors should apply a positive or Best-In-Class strategy to optimize risk management.

The implications made by Hoepner (2010) are supported by Verheyden et al. (2016), who found that ESG score screening leads to an improved risk-adjusted return. According to Verheyden et al. (2016), the specific risk introduced by ESG screening is more than offset by the excess risk-adjusted returns it provides relative to the unscreened universe. They recommend that ESG score screenings are used by all investors, regardless of the investment motives, to optimize risk management and acquire improved risk-return characteristics and diversification.

4 Theoretical Framework and Model Specification

We have chosen the Fama and French (2015) five-factor model for the thesis because it is a relatively new model. Hence, most existing ESG research papers have used the CAPM model, Carhart 4 Factor Model (1997), and Fama & French (1993) three-factor model as analytical models. Thus, we can fill a literature gap using this model. This chapter will introduce the Fama and French (2015) five-factor, its history, and how it has developed over time.

In general, multi-factor models are, as the name implies, models that consist of more than one factor. The sensitivity to the factors explains the variation in returns on individual stocks or portfolios. The factors vary across models, and the tricky part is finding the relevant risk factors (Munk - b, 2015).

In our thesis, we will be using the Fama and French (2015) five-factor model to explain the variation in the High and Low ESG, E, S, and G portfolio performance. Furthermore, we attempt to build on the Fama and French (2015) five-factor model and make a sixth factor that can potentially explain more of the variation in the portfolio's performance using its own constructed ESG, E, S, and G factor.

4.1 CAPM and the Fama and French (1993) three-factor model

The CAPM model, introduced by Sharpe (1964), Lintner (1965), and Treynor (1963), is the original model for finding the equilibrium prices of financial assets. The CAPM model is a one-period model with one factor. According to CAPM, the required rate of return on a security is measured by its exposure to market risk. The model is built on Markowitz's (1952) portfolio selection model which states that the asset price should not be affected by all risk, hence the market risk is beta b_i, the un-diversifiable risk. Resultantly, the variation in returns is explained by the risk-free rate and the return on a market portfolio.

$$E[R_i] = r_f + b_i\left(E[R_m] - r_f\right)$$

The CAPM model is a powerful tool to explain the nature of pricing capital assets and has been a starting point for following models. However, researchers have criticized the CAPM model and its' ability to capture the variation in returns. Two patterns were found to be particularly important in explaining the variation in returns, namely the companies' size and value. This led to the well-known Fama and French (1993) three-factor model.

The size factor includes market capitalization and prices multiplied by the shares outstanding. Further, the value factor includes price ratios such as book-to-market (B/M). Their findings show that companies with a high B/M ratio often outperform those with a low B/M ratio. This observation is known as the "value-effect." Furthermore, they find that small-size companies often outperform large-size companies, known as the "size-effect" (Fama and French, 1993).

$$R_{it} - r_{ft} = a_i + b_i\left(R_{Mt} - r_{ft}\right) + s_i SMB_t + h_i HML_t + e_{it}$$

4.2 The Fama and French (2015) five-factor model

The Fama and French (2015) five-factor model builds on the Fama and French (1993) three-factor model. The five-factor model was introduced in 2015 after several researchers found relationships between average returns and companies' investments and profitability.

Novy-Marx (2013) research found that highly profitable companies outperform less profitable companies. As profitability was found to be strongly related to average returns, this finding led to the profitability factor in the Fama and French (2015) five-factor model. Aharoni et al. (2013) research found a weaker but statistically reliable relationship between investments and average return. These implications led to the study conducted by Fama and French in 2015, where they added profitability and investments to the Fama and French (1993) three-factor model. Following the methodologies of Fama and French (2015) and Hou, Xue, and Zhang (2015), the investment factor corresponds to the annual change in gross property, plant, and equipment plus the annual change in inventories, all divided by the book value of total assets.

$$R_{it}-r_{ft} = a_i + b_i(R_{Mt}-r_{ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{it}$$

Were, R_{it} is the return on a stock or a portfolio in period i for period t, r_{ft} is the risk-free rate, andR_{Mt} is the return on the value-weighted market portfolio. e_{it} is a zero-mean residual. The interpretation behind the zero-intercept hypothesis is that the mean-variance-efficient tangency portfolios combine the risk-free asset, the market portfolio, and the four factors (Fama & French, 2015; Huberman & Kandel, 1987). If the factors capture all variation in returns, the intercept a_i would be zero for all ESG, E, S, and G portfolios.

SMB (Small minus big) is the size premium. It is the average return on a diversified portfolio of small stocks minus the average return on a diversified portfolio of big stocks.

$$SMB = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth)$$

HML (High minus low) is the value premium. It is the difference between the average returns on a diversified portfolio of high and low B/M stocks.

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth)$$

RMW (Robust minus weak) is the profitability premium. It is the difference between the returns on diversified portfolios of stocks with robust and weak profitability.

$$RWA = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak)$$

CMA (Conservative minus aggressive) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which we call conservative and aggressive. Conservative firms have low investment policies, whereas aggressive firms show a higher investment.

$$CMA = \frac{1}{2}(Small\ Conservative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive + Big\ Aggressive)$$

With the profitability and investment factors added to the model, the HML factor is found to be excessive in describing the variation in average returns. According to Fama and French (2015), the other four factors absorb the exposure to HML, particularly the profitability and investments. For the purpose of this thesis, we will keep the Fama and French (2015) five-factor model as it is presented, although the findings imply that the HML factor is excessive.

In this thesis, we would like to see which of the High and Low ESG, E, S, and G portfolios have the highest significant alpha, and we will also examine how they are exposed to the factors in the Fama and French (2015) five-factor model. Examining the portfolios' exposure to the various factors will provide insights into the characteristics of a High and Low scoring ESG, E, S, and G portfolio.

4.3 Performance Measures

4.3.1 Alpha

Michael Jensen introduced the Jensen's Alpha (1968) in 1968, and it is one of the most widespread performance measures. Jensen used the CAPM developed by Sharpe, Lintner, and Treynor (1963), where the alpha determined the excessive returns that the predictive model could not explain.

$$\alpha_p = R_p - \left(r_f + \beta_p\left(R_m - r_f\right)\right)$$

Where R_p is the portfolio return, r_f is the risk-free rate, $\left(R_m - r_f\right)$ is the market risk premium, and β_p is the portfolio's beta which is the exposure to systematic risk.

For a given beta and average market return, Jensen's Alpha returns the difference between the average return of a portfolio and the predicted average return by the CAPM (Bodie, Kane, & Marcus, 2014). In the CAPM where the only factor is the beta, a positive alpha will indicate that the asset has an abnormally high return for the given level of the systematic risk (Bodie et al., 2014; Jensen, 1968).

OLS provides an estimate for t-statistics, which enables us to evaluate the significance of the alpha value. If the model is valid, then economic or market conditions will not influence the alpha. Alpha can then be used to measure the performance of portfolios across different risk levels and periods (Jensen, 1968). The alpha theory applies to multi-factor models, with more explanatory variables or factors than the systematic risk in a one-factor model. The alpha is then the return on the portfolio after checking for the five factors described in section 4.2.

A vital weakness related to Jensen's Alpha is that it assumes a constant beta. A constant beta is unrealistic compared to the market. The beta will consistently change due to buying and selling of assets, which changes the real risk of the asset.

4.3.2 Sharpe Ratio

William F. Sharpe introduced the Sharpe Ratio (1996) and measured the risk-adjusted return. The commonly used performance measure compares the relationship between the excess returns and the riskiness of the portfolio. Here, the riskiness is measured by the standard deviation or volatility of the portfolio (Bodie et al., 2014).

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

The Sharpe ratio is the excess mean divided by the standard deviation. o_P is the portfolio standard deviation. The standard deviation of the portfolio accounts for both systematic and non-systematic risk. It will tell the investor how much return is associated with one extra unit of risk the investor is taking.

The widespread of the measure comes from its simplicity, as it does not require any benchmarking index to compare against. The Sharpe ratio can compare two or more portfolios' risk-adjusted by observing which portfolio provides the highest return to riskiness (Sharpe, 1966).

Scholars have pointed out some weaknesses. For instance, some argue that the performance measure has a bias in estimating standard deviation (Jobson & Korkie, 1981).

5 Data and Methodology

This chapter aims to create an overview of the methodological access used in the thesis by describing the data collection and data preparation process. We have based the methodology on procedures in the existing literature and how we can best approach the research question. We want to depict how we have prepared for the analysis in Chapter 6 in the most transparent way possible.

First, we disclose the methodical considerations, and then the data gathering is reviewed. Lastly, the data process preparation will be explained.

5.1 Methodical Considerations

We base our thesis primarily on quantitative data. Choosing quantitative data helps us better investigate, understand, and answer our research question: what the relationship between ESG, E, S, and G scores and financial performance in the Nordics are. The qualitative method is a basis that allows us to attack, measure, and test the data. A consideration that motivated us to choose a quantitative approach is that a qualitative approach would not provide us with sufficient evidence to answer our research question.

Furthermore, we aim to build the thesis from a critical point of view, as we have an assumption that the constituent's ESG, E, S, and G scores influence their stock performance. Based on a theory that all aspects of ESG scores positively correlate with stock performance in the Nordics, five hypotheses are formulated and presented in section 1.2. We base the hypotheses on our expectations for the investigation outcome, executed in chapter 6.

The hypotheses aim to provide supportive evidence to improve the validity in our conclusion. Furthermore, we believe that the hypotheses will be valuable to strengthen and deepen the discussion that leads up to our conclusion. The hypotheses are either supported by evidence or rejected by evidence based on the findings in the quantitative analysis. However, this approach is based on "pure observation". Critical rationalism does not believe in the existence of pure observation as we constantly have an "idea" of what we want to investigate. Hence, it is essential to emphasize that the authors aim to apply critical rationalism when attending to the research question, and “pure observation” for the constructed hypotheses.

A deductive method is applied in our thesis to generate knowledge to better understand and interpret our quantitative results. Further, the deductive method stems from a non-empirical point of view to substantiate the individual case, i.e., the relationship between ESG, E, S, and G scores and stock performance in the Nordics.

Most of the research within the area applies CAPM, the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, or Carhart's (1997) four-factor model to investigate their hypotheses around ESG, E, S, and G scores and financial performance. Thus, there is a consensus around applying factor models to performance measurements. Hence, we are applying the deductive approach to the present thesis.

We apply both stock and ESG, E, S, and G data from Refinitiv Eikon. We are using Refinitiv as it offers one of the most comprehensive ESG databases in the industry (Refinitiv, n.d.). Based on the ESG, E, S, and G data and the stock data, we construct value-weighted portfolios, where the portfolio's excess return is then tested and analysed.

5.2 Data Gathering

5.2.1 Constituent Identification

The thesis focuses on constituents in the Nordic region, as mentioned in the delimitation. The Nordic region consists of Denmark, Norway, Sweden, Finland, and Iceland, in addition to the Faroe Islands, Greenland, and Åland, autonomous territories connected to the Nordic region. We are choosing the Nordic region as previous research suggests the Nordic region is pioneering in the future of ESG. Thus, it would be interesting to investigate the relationship between different aspects of ESG and Nordic stock performance. Moreover, previous research has been mostly done on the US market or Europe. Hence, we hope to fill a literature cap regarding ESG and financial performance in investigating the Nordic region.

Although we are using four countries in our analysis, we recognize that there are more than four countries that make up the Nordic region. However, Iceland, Faroe Islands, Greenland, and Åland are omitted in the analysis as these countries and territories do not qualify for the top 10 in country based ESG or SDG rankings or lack sufficient empirical data. Therefore, the Nordic countries are in this thesis refer to the four countries Denmark, Norway, Sweden, and Finland. We do not see this limitation in the research question as a disadvantage as the four remaining Nordic countries are large and influential and therefore assumed to be of interest to the investor. Furthermore, the number of constituents and data points from the four countries have been sufficient in providing empirical information to perform our analysis.

We are attending to companies that have previously or are, at the present date, included in any of the following stock exchanges: The Denmark Stock Market Exchange (OMX Copenhagen), The Oslo Børs Stock Exchange (OSEBX), The Stockholm Stock Exchange (OMX) and The Helsinki Stock Exchange (OMXH).

5.2.2 Bias

This thesis limits the research to the four Nordic countries described in 5.2.1. Furthermore, we are limited in our research as we depend on having constituents with sufficient ESG data from 2005 to 2020 and historical stock data from 2006 to 2021. 99 constituents fulfill these requirements, which creates a limited selection of the stocks registered on the respective stock exchanges in the four countries. Common denominators could influence the constituents to get ESG scores in 2005. For instance, companies could be incentives by industry-specific advantages or having sufficient financial resources to invest in ESG scores. Because of this limitation in our study, we could have a selection bias in our constituents, where we overrepresent industries or larger companies.

Furthermore, an increasing number of constituents on the Nordic stock exchanges have ESG scores, so our research can focus on those companies that were early in taking on ESG score evaluation. Alternatively, the constituents can have been limited in their available ESG data to disclose, causing a lack of necessary information to provide an ESG score. However, with these limitations, we accept our chosen dataset. We will analyse Chapter 6 based on the assumption that the dataset is representable and valid for our research. We will further discuss the validity of our findings with the conclusion in chapter 9.

Survivorship bias can occur when one only considers the companies that exist over the entire period (Stock & Watson, 2020). Survivorship bias can lead to an overestimation of performance. We have accounted for both active and inactive companies in our analysis. However, we found that all the companies that we have analysed have been active throughout the period, and therefore this survivorship bias was not an issue we met.

We have chosen to investigate from 01.01.2006 to 31.12.2021. Based on the available empirical data and historical stock information in the period, we include 99 constituents in our analysis. The constituents represent the four countries, with 20 constituents from Denmark, 18 from Norway, 41 from Sweden, and 20 from Finland. The 99 constituents are referred to as our market and will contribute to defining the relationship between the constituents' ESG, E, S, and G scores and financial performance. We provide an overview of the constituent's name, country, and industry in the appendix, annex 1.

5.2.3 Stock Data Gathering

To construct our portfolios, we use constituents listed in one of the four Nordic stock exchanges from 01.01.2006 to 31.12.2021. We use historical stock data as the primary source of data when determining the performance of our portfolios. The source we are using for this thesis is Refinitiv Eikon. Bloomberg Terminal and Refinitiv Eikon are the two most widespread platforms for financial information. Thus, we assess these two databases as equally representative and evaluate Refinitiv Eikon as a good and trustworthy source. As we extract our ESG data from the Refinitiv Eikon database, we also collect the historical stock data from the same source to be consistent in choice of platform, so our data points are utmost comparable.

We are using historical stock data to evaluate the constituent's financial performance. Firstly, we have extracted daily adjusted prices from Refinitiv Eikon from 01.01.2006 to 31.12.2021. Refinitiv has adjusted the daily prices for dividend payments. We calculate the daily prices into monthly returns for our analysis to match the Fama and French (2015) methodology. Secondly, the monthly market capitalization is extracted from Refinitiv Eikon for every constituent in the leading Nordic indices. We are using the same source for the ESG data, the monthly returns, and the monthly market capitalization to underpin that the data is comparable.

Furthermore, we have chosen the period 01.01.2006 to 31.12.2021 for several reasons. Our most important rationale for the chosen period is that a longer time frame is better to have reliable findings in the regression analysis because we will have more data points. As already described, we are limited in the research as we require that the constituents have ESG scores for the entire period. Refinitiv first started issuing ESG performance data in 2002, and there has been an increase in constituents with ESG performance data ever since (Refinitiv, n.d.). The trade-off between more comprehensive historical stock data and more constituents led us to choose 15 years between 2006 and 2020 with 99 constituents. We found that this dataset was the most suitable for the analysis. Moreover, we have assessed that insufficient ESG performance data dates to 2002, and thus we would not have enough constituents to construct our portfolios.

We are assuming that a diversified portfolio requires at least ten stocks (Elearnmarkets, 2021). We have constructed nine portfolios with 11 constituents in each portfolio to ensure that the portfolios are sufficiently diversified. We will be working with the highest and lowest-performing portfolios of the nine portfolios, namely the "High" and "Low" portfolios. Then we determine the High and Low portfolios for ESG, E, S, and G screened portfolios. We aim to analyse and compare the High and Low performing portfolios in ESG, E, S, and G categories. We end our period on 31.12.2021 as the last published ESG, E, S, and G score is from 2020.

5.2.4 ESG, E, S, and G Scores Data Gathering

Accurate and representative ESG, E, S, and G score data is crucial for answering the research question on how the ESG, E, S, and G scores are related to the constituent's financial performance. Refinitiv Asset4 offers one of the most comprehensive ESG databases in their industry. They have more than 350 research analysts who collect ESG data and manually assess constituents' performance based on more than 650 ESG (Refinitiv, n.d.). Thus, we are determined to use ESG, E, S, and G scores from Refinitiv Asset4 in our thesis. We evaluate that these scores are highly accurate and representative of our constituents' real ESG, E, S, and G performance.

The Refinitiv ESG scores evaluate companies based on an overall score based on self-reported information in the environmental, social, and corporate governance pillars (Refinitiv, 2022). To understand and interpret what the ESG score and each of the pillars contain, we provide Refinitiv's definitions on each of the pillars.

The environmental pillar measures a constituent's impact on living and non-living natural systems. This pillar includes the air, land, water, and complete ecosystems. Furthermore, it reflects best management practices to avoid environmental risks and capitalize on environmental opportunities to generate long-term shareholder value (ibid.).

The social pillar measures a constituent's capacity to generate trust and loyalty with its workforce, customers, and society. These measurements rely on best management practices. Further, the pillar score reflects the constituent's reputation and the health of its license to operate, which are critical factors in determining its ability to generate long-term shareholder value (ibid.).

Last, the corporate governance pillar measures a constituent's systems and processes, ensuring that its board members and executives act in the best interests of its long-term shareholders. Moreover, it reflects a constituent's capacity, through its use of best management practices, to direct and control its rights and responsibilities by creating incentives and checks and balances to generate long-term shareholder value (ibid.).

Asset4 updates its ESG-data every other week, mainly because of the constituent's different accounting years, and consequently uploads its annual reports at different times (Thomson Reuters Eikon, 2018). In Parts 1 and 3 of our analysis, we construct the "Average Allocated portfolios" based on the constituents' average ESG, E, S, and G scores over the analysis period. However, we will also take advantage of the yearly issued ESG scores in Part 2 of our analysis. We construct the "Yearly Allocated portfolios" allocated based on the constituents' yearly ESG, E, S, and G scores. We will provide a more detailed description of the portfolio construction in section 5.3.1.

5.2.5 Factor Data Gathering

We use the Fama and French (2015) five-factor model as our analytical model. To conduct the analysis, we will collect secondary factor data. This chapter describes where we collected the data and why we used this source.

Applying the Fama and French (2015) five-factor model in our thesis is not to test the model itself but to use it as an analytical quality model to determine significant abnormal returns and explain the variation in the portfolio excess returns by its' five factors. Resultantly, we collected the five factors from a secondary data source.

Vi chose the same method as (Blitz & Fabozzi, 2017), (Borgers et al., 2013), (Hoepner, 2010), and (Kempf & Osthoff, 2007). They use Kenneth French's Data Library[1] to collect four explanatory variables: SMB, HML, RMW, and CMA. The five explanatory variables are assessed as secondary data as we have not constructed them but used them in our analysis. However, we consider them reliable as Kenneth French Data Library is well known and used for several research papers (Fama & French, 1992, 1993, 1996, 2015).

There are three methods that are applied when constructing the factors for the multi-factor model:

1. A 2x2 sorting method whereas all factors are divided after the NYSE median

2. A 2x3 sorting method where the size factor is divided by the NYSE median and B/M, OP, and Inv. are divided into three groups according to the NYSE's classification; top 30%, middle 40%, and the 30% lowest.

[1] Kenneth R. French - Data Library (dartmouth.edu)

3. A 2x2x2x2 sorting method divides the actuaries according to the NYSE media into two size groups, two B/M groups, two OP groups, and two Inv. groups.

Furthermore, Fama and French (2015) conclude that the 2x3 sorting method gives reliable results as the 2x2 and 2x2x2x2 sorting methods. Therefore, our explanatory variables are based on data formed from the 2x3 sorting. Further, information on the composition of the factors can be found in the appendix, annex 3.

5.2.6 Market Factor and Risk-free Rate

Our complete constituents consist of 99 constituents with available ESG data from 01.01.2005 to 31.12.2020 and historical stock data from 01.01.2006 to 31.12.2021. The 99 constituents make up the market. Resultantly, one may refer to both the market and the benchmark interchangeably.

We are constructing the market factor in the following way:

$$Market\ Factor = Rm - rf,$$

Where Rm is the market return and rf the 1-month risk-free rate.

Furthermore, we use the 1-month Kenneth French risk-free rate collected from Kenneth French Data Library[2] as a proxy for the risk-free rate. We are using the Kenneth French 1-month risk-free rate as we want to remain persistent in using data sources. Alternatively, we evaluated the option to construct a risk-free rate based on a 1-month T-bill for all the Nordic countries represented in the present thesis from 01.01.2006 to 31.12.2020 and calculated an average rate. However, we were limited in this approach as a 1-month T-bill for the Nordic countries is not available as a primary data source. Thus, we conclude that Kenneth French's risk-free rate is a better option.

In part 3 analysis, we have constructed a new factor included in the chosen analytical model to see if this ESG, E, S, and G factor has some explanatory power in the variation in the ESG, E, S, and G portfolio's excess returns. This way, we can better understand and analyse our hypothesis whether the variation in ESG, E, S, and G portfolio excess returns can be explained by their ESG, E, S, and G scores, respectively. Throughout the thesis, we will try to accept or reject all our five hypotheses presented for this research and accordingly conclude on our research question. The ESG, E, S, and G factors construction follows the Fama and French (1993, 2015) methodology that we will elaborate on in chapter 6, section 6.9.1.

[2] Kenneth R. French - Description of Fama/French Factors (dartmouth.edu)

5.2.7 Criticism of Rating Agencies

ESG Integration is still in its developing stages. There is a central challenge related to its implementation, as there is an urgent need for greater precision and consensus for efficient utilization of ESG data in investment decisions. The challenge is that ESG scores come from different ESG data providers who are inconsistent in their methods of evaluating ESG performance, which results in a lack of consensus in the market.

The market for rating agencies has emerged in a market that demands transparency and corporate accountability measures. One of the primary purposes of rating agencies is to provide ESG ratings to investors who would like to incorporate ESG measures in their investment strategy. Without a common standard to measure corporate performance in ESG, E, S, and G, rating agencies provide ESG evaluations that vary in practice and methodology (Deloitte, 2019). The variation in methodologies makes it difficult for the investor to compare the constituents' ESG, E, S, and G performance.

(Halbritter & Dorfleitner, 2015) Investigated the variation in ESG scores given by different rating agencies and found a substantial difference in the performance of High and Low portfolios alpha dependent on the rating agency an investor chooses to incorporate in their investment strategies. As a result, investors demand more precision and transparency to integrate ESG in investment decisions (Nelson & Bell, 2021). Accordingly, we have chosen to use one of the most widespread and trusted agencies and be consistent with the use of our data providers. We depend on Refinitiv Asset4 ESG data for every analysis to compare the results. Asset4s ESG data is solely based on public information to construct their scores (CBS, n.d.).

5.3 Data Processing

5.3.1 Portfolio Creation

As mentioned in section 5.2.4, we have yearly ESG, E, S, and G score data available from Refinitiv Asset 4. To prepare for our analysis in Chapter 6, we construct Average and Yearly Allocated portfolios. We sort the Average and Yearly Allocated portfolios from highest to lowest performing in the categories ESG, E, S, and G based on their scores in respective. This section will provide a detailed description of how we construct the portfolios for our analysis.

In our market pool, we have a total of 99 constituents. We divide the pool of 99 constituents into nine portfolios with 11 constituents each. A general rule for a well-diversified portfolio is to have more than ten constituents (Elearnmarkets, 2021). In our thesis, all the portfolios are value-weighted, meaning the market capitalization will determine the portfolio weight in each constituent. The market capitalization that determines the weight of each constituent is the average market capitalization over the period. We use the value-weighted approach in our portfolio construction because we use the Kenneth French Data Library factors. As the Kenneth French Data Library factors are value-weighted, using the same approach will make our data compatible with the factors.

We focus on the highest and lowest-performing portfolios in each ESG, E, S, and G category throughout our analysis. The highest performing ESG, E, S, and G portfolios are named the "High" portfolio, and the lowest-performing ESG, E, S, and G portfolios are named the "Low" portfolios. We will describe how we allocate the constituents to the High and Low portfolios.

Our analysis consists of three parts, parts 1 to 3. In Part 1 and Part 3, we will use the Average Allocated portfolios, and in Part 2, we will use the Yearly Allocated portfolios.

The Average Allocated portfolios are static, and therefore they are based on the constituents' average ESG, E, S, and G over the whole period. Furthermore, the market capitalization is equal to the constituent's average market capitalization over the whole period. These portfolios get allocated once; hence there is no portfolio rebalancing throughout the analysis.

The Yearly Allocated portfolios are dynamic and rebalanced once every year. We use the constituents' ESG, E, S, and G scores in the prior year to determine the portfolio's combined ESG, E, S, and G scores for the following year. Furthermore, the portfolio's weight in each constituent is dependent on the constituent's average market capitalization in that same year.

By using two types of portfolio allocation processes, we will have better explanatory power to provide a conclusion to the research question. We provide a detailed description of the allocation processes in sections 5.3.2 to 5.3.3.

The two following sections explain how we construct the Average and Yearly Allocated High and Low ESG, E, S, and G portfolios.

5.3.2 Portfolio Creation: Average Allocated High and Low ESG, E, S, and G portfolios

The portfolio creation process will describe the Average Allocated High and Low ESG portfolios, but the same process is applied to the Average Allocated High and Low E, S, and G portfolios.

First, the 99 constituents are sorted based on their average ESG score. We find their average ESG score by taking the average yearly ESG score they have received over the 15 years. We assume the ESG score is recorded on 31.12 of each year; hence our period dates 31.12.2005 to 31.12.2020. Then, we sort the constituents from 1 to 99 based on their ESG score. The 99 constituents are divided into nine portfolios with

11 constituents in each. The High ESG portfolio has the highest ESG score, and the Low portfolio is the portfolio with the lowest ESG score.

The weight of each constituent is determined based on the constituents' market capitalization. To find the average market capitalization, we take the average market capitalization of each constituent for 15 years.

$$Weight_{Constituent,Average\ Allocated\ Portfolio} = \frac{Constituent's\ Average\ Market\ Capitalization}{Portfolio's\ Average\ Total\ Market\ Capitalization}$$

Once we have allocated the Average Allocated High and Low ESG portfolio, we do not reallocate the portfolio for the remainder of the analysis. In other words, the portfolios have fixed constituents for the entire period we are analyzing.

We will be using the Average Allocated portfolio in Part 1 and Part 3 analyses. In Part 1, we will analyse the portfolio's descriptive statistics and conduct a regression analysis using the Fama and French (2015) five-factor model. In Part 3, we will conduct regression analysis using a constructed six-factor model that we will introduce and explain in the Part 3 analysis. We aim to construct a model that can explain more of the variation in returns than the Fama and French (2015) five-factor model can.

5.3.3 Portfolio Creation: Yearly Allocated High and Low ESG, E, S, and G portfolios

The progress of the portfolio creation will be described for the Yearly Allocated High and Low ESG portfolios and applies to the Yearly Allocated High and Low E, S, and G portfolios.

The High and Low ESG portfolios are constructed based on constituents' ESG scores in the prior year. The 11 constituents with the highest ESG score in 2019 will make up the High ESG portfolio in 2020. We use this approach because the ESG score will be public knowledge when issued at the end of the year. Therefore, we assume that the ESG score in one year will affect the performance in the following year.

We reallocate the portfolios every year, so the High and Low ESG portfolios will have different constituents based on which constituents scored the highest and lowest in the year prior.

As we rebalance the High and Low ESG portfolios every year for 15 years, we end up with 30 different portfolios based on the ESG score. We analyse the Yearly Allocated High and Low ESG, E, S, and G portfolios in chapter 6, part 2.

The portfolios are value-weighted, so each constituent's average yearly market capitalization will decide how considerable weight it will have in the portfolio. We use the 12-month average of the monthly market capitalizations dated on the first day of the month. The following formula is applied to find the individual constituent's weight each year:

$$Weight_{Constituent,Yearly\ Allocated} = \frac{Constituent's\ Yearly\ AverageMarket\ Capitalization}{Portfolio\ Yearly\ Average\ Market\ Capitalization}$$

We use the value-weighted portfolios from the beginning of the period because we would like to match the market capitalization with the historical stock data, which starts at the beginning of the month.

In Part 2, we will analyse the descriptive statistics of the Yearly Allocated High and Low portfolios and then conduct regression analysis using the Fama and French (2015) five-factor model. We use yearly allocation in the Part 2 analysis as we believe that it will add perspective and value to our thesis that will help us discuss and draw conclusions to our research question. Furthermore, it is an approach previously applied by trusted scholars, such as Kemp & Osthoff (2007) and Halbritter & Dorfleitner (2015).

5.3.4 Portfolios returns

In our analysis, we will be using historical stock data as a proxy for financial performance. Therefore, we will be using monthly stock returns, cf. section 5.2.3. The monthly data provides a close distance between the data points; thus, we believe it is a sufficient basis for the analysis.

As described in 5.2.3, we have extracted daily prices for the 99 constituents. Then, we apply the following formula to find the discrete daily return for every constituent:

$$R_{constituent} = \frac{Price_1 - Price_0}{Price_0}$$

Where $R_{constituent}$ is the discrete daily return, $Price_1$ is the adjusted closing price today, $Price_0$ is the daily adjusted closing price yesterday.

We are applying discrete stock returns to aggregate the returns across the constituents. Conversely, this aggregation would not be possible with logarithmic returns.

As Fama and French (2015) apply a one-month time horizon, we recalculate the discrete daily returns to discrete monthly returns. We recalculate the discrete daily returns to monthly returns by finding the average daily return for a given month, then applying the following formula.

$$R_{monthly} = (1 + R_{constituent})^{Number\ of\ trading\ days\ in\ the\ respective\ month} - 1$$

The number of trading days depends on the month. The typical trading days in each month are 21 days. However, we calculate each month's trading days to get a more precise estimate for the portfolios.

We find the monthly return on the Average Allocated portfolio by applying the following formula.

$$R_{Average\ portfolio} = Weight_{Average\ Allocated} * R_{monthly}$$

Where $Weight_{Average\ Allocated}$ is defined as the portfolio weights, and $R_{monthly}$ is defined as the average monthly stock return.

The Yearly Allocated portfolio's monthly return on the value-weighted portfolios is calculated the following way:

$$R_{Yearly\ portfolio} = Weight_{Yearly\ Allocated} * R_{monthly}$$

Where $Weight_{Yearly\ Allocated}$ is defined as the portfolio yearly weights, and $R_{monthly}$ is defined as the average monthly stock return.

A few constituents have missing data points in the stock return data. However, these constituents have an ESG score, and thus they get included in the market pool. The missing data points receive a return of 0% as we conclude this value represents the data points the best. In terms of reliability, the missing data is not substantial and is therefore assumed not significantly to impact the results in the analysis.

We are using the portfolio's excess return in the regression analysis, and hence we must contract the risk-free rate from the portfolio return. We use the following formula to find the Average Allocated and Yearly Allocated portfolio's excess returns:

$$R_{Average\ Allocated\ Excess} = R_{Average\ Allocated} - Rf$$

$$R_{Yearly\ Allocated\ Excess} = R_{Yearly\ Allocated} - Rf$$

5.4 Data Testing

The Fama and French (2015) five-factor regression will be executed in Excel using the OLS regression.

For analysis of Chapter 6, Part 1, and Part 3, we will use the following equation:

$$R_{Average\ Allocated\ Excess} - Rf = \alpha_p + \beta_p(Rm - Rf) + s_p * SMB_t + h_p * HML_t + r_p * RMW_t + c_p * CMA_t + e_{p,t}$$

In the analysis in Chapter 6, Part 2, we will use the following equation:

$$R_{Yearly\ Allocated\ Excess} - Rf = \alpha_p + \beta_p(Rm - Rf) + s_p * SMB_t + h_p * HML_t + r_p * RMW_t + c_p * CMA_t + e_{p,t}$$

Where **α**, **β**, **s**, **h**, **r,** and **c** are coefficients from the OLS estimation, and **e** is the residual between the return and the estimated return. The OLS method minimizes the sum of squared residuals between observed and expected values. Thus, we use OLS regressions to estimate the portfolio's performance.

However, OLS multiple regressions are built upon several assumptions, called "Least Square Assumptions," and these assumptions are:

- Linearity – The model has linear parameters
- Zero conditional mean error – The residual has an expected mean of zero
- No heteroscedasticity – The variance for the residuals is constant over time for all variables
- Large outliers are unlikely – Multiple regression models are sensitive against significant outliers
- No perfect multicollinearity – The independent variables should not be perfectly correlated
- No serial correlation – No correlation between the residual's lags
- Normality of Errors – Normal Distribution among the residuals

In this analysis, Chapter 6, we are testing whether our Average Allocated, and Yearly Allocated High and Low ESG, E, S, and G portfolio performance is living up to the expectations of these assumptions and thereby making our regressions more robust. Further, we will use Excel and STATA to analyse our regressions and the respective assumptions. Our significance level will be 5% as this is the level most used.

In terms of the first assumption, there must be a linear relationship between **x** and **y**. This assumption is best tested using Excels line fit plots. We are using this line fit plot to determine a connection between the dependent variable, **y**, and each of the independent variables, **x**.

The following assumption is the zero conditional mean error, one of the critical conditions for the regression coefficients to be unbiased. The residual needs to be unsystematic and consist of random values to meet the assumption; this can be tested based on a plot of the residuals versus the fitted values (Frost, 2018). We are looking at where the residuals are placed and if the trend line is zero. STATA is used to create these residual plots, and Excel is used to find the average of the residuals. If the average value of the residuals is zero, the assumption is met (ibid.).

For the no heteroscedasticity to be met, we check whether the variance of the residuals is constant for all observations (Woolridge, 2018). Here, we are using the residuals vs. fitted plots. If the variance of the residuals is constant, we will see that the residuals do not decrease or increase over time in line with the "fitted values." Moreover, we perform a Breusch-Pagan test in STATA to extract the p-value test statistic. The null hypothesis of the test is constant variance among the residuals. P-values less than the significance level of 5%, we reject the null hypothesis and conclude the variance is non-constant, and heteroscedasticity is thus present in the data. This rejection indicates that the standard errors of the regression are unreliable (ibid.).

If the assumption is not met, we will recalculate the standard errors to correct for heteroscedasticity. Robust standard errors are more robust to the problem of heteroscedasticity and thus provide a more accurate measure of the true standard error of a regression coefficient (Woolridge, 2018). Robust standard errors correct for both heteroscedasticity and autocorrelation. Without autocorrelation in the residuals, it is only necessary to correct for heteroscedasticity (ibid.).

A residual vs. leverage plot is being created to estimate whether there are significant outliers in the data. This plot is one of the most useful diagnostic graphs, which shows the leverage against the normalized residuals squared. This plot helps us identify the most extreme points and the respective leverage levels. The points in the right corner of the residual vs. leverage plot indicate high leverage and might influence the regression results (Statology, 2019). A general rule of thumb is that an outlier is any point with a Cook's distance over 4/n, where n is the total number of data points (ibid.). Cooks Distance can help us identify potential outliers and, thus, whether these outliers influence the regression results (ibid.). Any outliers identified will be assessed either removed, replaced, or kept. The outliers are either removed from the data set, replaced with the mean, or kept but carefully noted when interpreting the results.

Perfect multicollinearity occurs when at least two predictor variables have an exact linear relationship (Stock & Watson, 2020). Furthermore, perfect multicollinearity makes it challenging to estimate OLS estimations, and thus it should be low correlations between the explanatory variables to ensure that the coefficient estimates are precise (ibid.). We estimate these correlations in Excel.

Next, we estimate the Variance Inflation Factor, henceforth VIF, in STATA to investigate the correlations even more closely. The VIF value starts at one and has no upper limit (Woolridge, 2018). If the VIF value is one, there is no multicollinearity. A VIF value over ten is critical, indicating that multicollinearity is a problem among the independent variables (ibid.).

Autocorrelation measures the relationship of the observations between the different points in time. Thus, we look for a pattern over the time series through lags. One lag defines the correlation between the residuals between time t and t-k (Woolridge, 2018). If autocorrelation occurs, there is bias in the parameter's residuals, which have immense value for our statistical significance (ibid.). We use a Breusch-Godfrey test (BG-test) performed in STATA to test for autocorrelation in the residuals. Another method is to use a Durbin-Watson D-test to detect whether there is autocorrelation in the residuals. The Durbin Watson test assumes that the residuals are normally distributed, whereas the BG-test is less sensitive to this assumption (ibid.). We conclude by using the BG-test in our analysis, as this allows us to test for serial correlation through several lags. The null hypothesis is that there is no serial correlation. If the p-value is less than 5%, we will reject the hypothesis, and there is a serial correlation between the residuals in the model (ibid.). We can use robust standard errors to correct this serial correlation, the same method we use for correcting heteroscedasticity.

The OLS methodology does not require the residuals to distribute normally to produce estimates that are non-biased (Frost, 2018). This distribution is through a classical assumption within linear models and thus should be met to use OLS residuals and the respective statistics. Hence, there is necessary to detect normally distributed residuals to perform statistical hypothesis tests (ibid.). We test the normality using normal distribution plots extracted from STATA. If the residuals follow a straight line, our residuals are normally distributed.

When we have met all the assumptions, we can begin to test our regressions. This thesis tests whether the Fama and French (2015) five-factor model can explain our Average and Yearly Allocated High and Low constructed excess portfolio return in terms of significant alphas. Further, we are testing whether our portfolios are significantly exposed to the model's quality and risk factors and our constructed ESG, E, S, and G factors. The latter, however, is only considered in the second part of the analysis.

We are testing null hypotheses that positive relationships exist between financial performance in the Nordic and ESG, E, S, and G scores, respectively. For our testing, we use t-statistics, more precisely p-values, to determine whether to find evidence supporting to accept or reject our null hypotheses. The acceptance or rejection of these null hypotheses will help us detect and determine any trends in our portfolios and thus help answer the present thesis research question. To sum up, the relevant null hypotheses we want to test in our analysis are:

- H1: There is a positive relationship between ESG scores and financial performance in the Nordics.
- H2: There is a positive relationship between E scores and financial performance in the Nordics.
- H3: There is a positive relationship between S scores and financial performance in the Nordics.
- H4: There is a positive relationship between G scores and financial performance in the Nordics.
- H5: The variation in ESG, E, S, and G portfolio performance can be explained by their ESG, E, S, and G scores, respectively.

6 Analysis

6.1 Introduction

Our analysis tests the two different portfolio methodologies, described in sections 5.3.1 to 5.3.3, to answer our research question about the relationship between ESG, E, S, and G scores and financial performance in the Nordics. Additionally, the analysis examines whether the variation in ESG, E, S, and G portfolio performance is explained by their ESG, E, S, and G scores, respectively. The testing includes multiple linear regressions using our chosen regression model introduced by Fama and French (2015) on the excess returns of all the constructed High and Low ESG, E, S and G portfolios. Using linear regression predicts the value of the portfolio excess return based on the quality factors in the Fama and French (2015) five-factor model.

First, we present the portfolio specifications to analyse and interpret the results in the best feasible way. Portfolio specifications are, after that, divided into sub-sections: sector classification and market capitalization. Further, we use the global industry classification (GICS) to overview the portfolio's exposure to the different sectors. Then we present the market capitalization to check whether exposure to the "small-size-effect" mentioned in the theoretical framework, section 6.2.2, is observed.

Our market consists of 99 Nordic companies that we can provide ESG, E, S, and G scores from 2005 to 2020 and historical stock data from 2006 to end of 2021. We have constructed nine portfolios with 11 constituents in each portfolio, as mentioned in the methodology sections 5.3.1 to 5.3.3.

We classify High and Low ESG, E, S, and G portfolios. The respective portfolios signal the 11 highest and 11 lowest scoring ESG, E, S, and G constituents. This classification is done for the Average Allocated portfolios in Part 1 and 3, and the Yearly Allocated portfolios in Part 2, which are our two portfolio construction methodologies described in section 5.3.1 to 5.3.3. This way, we can analyse how the High ESG, E, S, and G scoring portfolios perform compared to the Low ESG, E, S, and G scoring portfolios and conclude whether we can accept or reject any of our hypotheses for this paper.

The analysis is divided into three parts: Average Allocated High and Low ESG, E, S, and G portfolios, Yearly Allocated High and Low ESG, E, S, and G portfolios, and Average Allocated High and Low ESG, E, S, and G portfolios with the new ESG, E, S, and G factors. The respective parts will contribute to attacking our research questions from three different angles. The structure of the individual parts is the following:

First, the OLS assumptions are presented to check the validity of the regressions. Adjustments to the regressions are made if any assumptions are validated.

Second, relevant descriptive statistics are displayed for the High and Low ESG, E, S, and G portfolios' excess return characteristics. This way, we can identify the mean, measure the risk-adjusted return with performance measures such as the Sharpe ratio, and address risk in terms of standard deviation.

Third, we perform the regression analysis on the High and Low ESG, E, S, and G portfolios and identify the significant abnormal returns, volatility, quality-, and risk factors.

Last, a summary is created to address the results and previously stated facts relevant to our research question about the relationship between ESG, E, S, and G scores and financial performance in the Nordics. Additionally, the analysis examines whether the variation in ESG, E, S, and G portfolio performance is explained by their ESG, E, S, and G scores, respectively.

6.2 Portfolio Specifications

6.2.1 Sector Classification

This section describes how our market is exposed to the different industries in the Global Industry Classification Standard (GICS). S&P Dow Jones and MSCI developed GICS to provide an efficient investment tool to capture industry sectors' breadth, depth, and evolution (MSCI, N.D). There are 11 sectors in the GICS, which are displayed below.

This classification will be used throughout chapter 6 when analyzing the High and Low ESG, E, S, and G portfolios.

Table 1: *Total number of constituents classified in each GICS-sector*

Total Stocks in Each Industry in Our Portfolio	Constituents	% of Market Pool
Industrials	23	23.2%
Consumer Staples	6	6.1%
Healthcare	10	10.1%
Consumer Discretionary	9	9.1%
Financials	15	15.2%
Real Estate	3	3.0%
Information Technology	3	3.0%
Communication Services	7	7.1%
Energy	11	11.1%
Utilities	1	1.0%
Materials	11	11.1%
Total	**99**	**100%**

Our market is primarily exposed to the Industrials GICS sector with 23.2%. Further, the Financial, Energy, Materials, and Healthcare GICS sectors have above 10% exposure in our portfolios, a large position compared to Utilities, Real Estate, and Information Technology with 3% or less exposure.

All four Nordic countries have historically been dependent on the Industrials, Materials, and Energy sectors due to their vast natural resources and by taking advantage of global trade. Norway's primary sector has historically derived from Energy and Materials with companies such as Norsk Hydro ASA and Yara International. Further, Sweden is a significant producer of Materials, Consumer Staples, and Consumer Discretionary with companies such as Volvo and Husqvarna. Finland's main industrial branches are within the Communication Services and Industrials with companies such as Nokia Oyj and Kone Oyj. Denmark has historically been well-positioned in Energy and Healthcare with large companies such as Ørsted and Novo Nordisk (Nordics, 2019).

6.2.2 Market Capitalization in the average allocated portfolio

This chapter looks at the distribution of companies with high market capitalizations in the High and Low ESG, E, S, and G portfolios. We use Average Allocated High and Low ESG, E, S, and G portfolios, which are described in sections 5.3.1 to 5.3.3.

Table 2: *Number of Constituents with Market Cap Above Average*

	ESG portfolios	E portfolios	S portfolios	G portfolios
High Portfolio	7	5	9	5
Low Portfolio	0	1	0	0
Total Constituents with Market Cap > Average	27	27	27	27

The average market cap is found to be DKK 65.275.035.967. There are 27 of 99 companies with an above-average market cap in the market pool. However, this does not change for the different ESG, E, S, and G screening processes, as all market caps are the same when using the High and Low Average Allocated portfolios.

In the Average Allocated High ESG Portfolio, seven companies have an average market cap above the market pool's average market cap. This observation indicates there are many large companies in the High ESG Portfolio. The S portfolios have the most significant exposure to large companies, with nine companies above average size. The Average Allocated Low ESG portfolios have zero companies with above-average market caps. The Low portfolios consistently have none to one smaller constituent than average companies for all ESG, E, S, and G portfolios. This observation shows that the Low ESG portfolios have many small companies.

Our constructed portfolios are value-weighted, and thus, a constituent with very many or no large companies will have a more diversified position, as the weights in each stock will be more evenly distributed. A more diversified position will lead to more stable returns and less volatility (Munk, 2015, page 97). Notably, the large-cap constituents in the "lower" scored portfolios receive a more significant weight as fewer large-cap constituents are in the portfolios. Hence, these constituents have a considerable influence on portfolio performance. For instance, Investor AB is the large-cap constituent in the Average Allocated Low E portfolio and received a weight of 47,1% of the total portfolio.

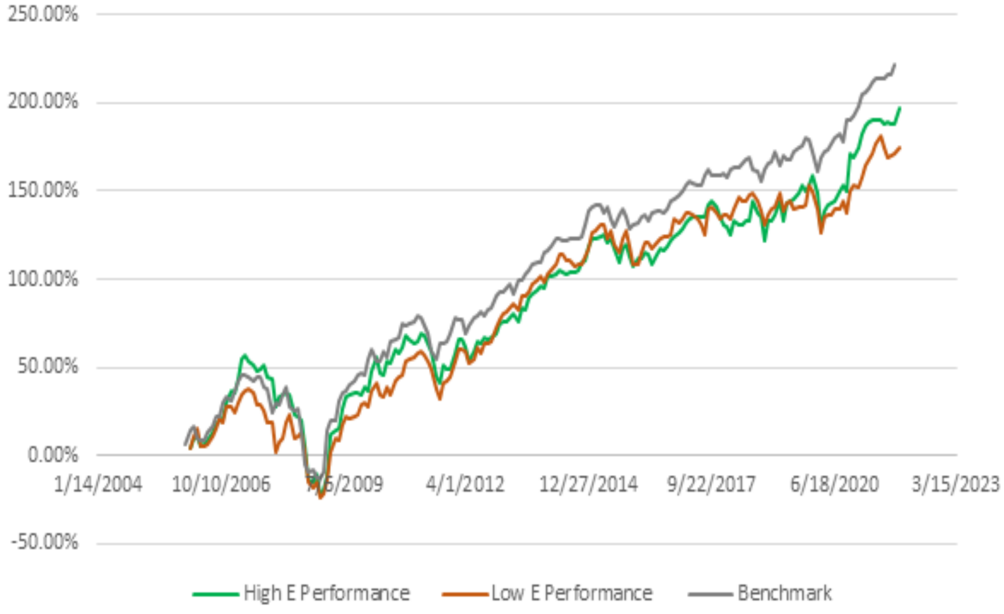
The high number of large companies in the Average Allocated High ESG, E, S, and G portfolios can be explained by the relationship between market cap and ESG scores found by Drempetic, Klein & Zwergel (2019). The results indicate that ESG scores are biased towards large-cap constituents, as they have more resources to invest in reporting tools and thus can disclose more ESG data. Furthermore, large-cap constituents are under more significant pressure from society and stakeholders to disclose more public information to maintain legitimacy. Larger companies have more influence on the market, and therefore the pressure to act according to ESG standards is higher than for small companies.

The small size of the companies in the Low ESG, E, S, and G Portfolios may be relevant in our analysis due to the small-size effect described in section 6.2.2. Small-sized companies are expected to outperform large-sized companies. Therefore, the Low ESG, E, S, and G portfolios may perform better because of the small-size effect (Fama, French, 1993). This observation is particularly apparent in our analysis as we have 11 stocks in each portfolio, making one significant weighting substantial.

Graph 1 to 4 displays the Average Allocated High and Low ESG, E, S, and G portfolio performance, against the benchmark throughout the whole period from 01.01.2006 to 31.12.2021. The graphs show that the High S screened portfolio outperforms the market while the High and Low ESG, E, G, and Low S underperform the market. Further, the performance of the Average Allocated High ESG, E, S, and G against the benchmark, and the Low ESG, E, S, and G against the benchmark are found in the appendix, annex 2.

Graph 1 – *Average Allocated High and Low ESG Performance*

Graph 2 *– Average Allocated High and Low E Performance*



Graph 3 – *Average Allocated High and Low S Performance*

Graph 4 *– Average Allocated High and Low G Performance*

PART 1 – AVERAGE ALLOCATED HIGH AND LOW ESG, E, S, AND G PORTFOLIOS

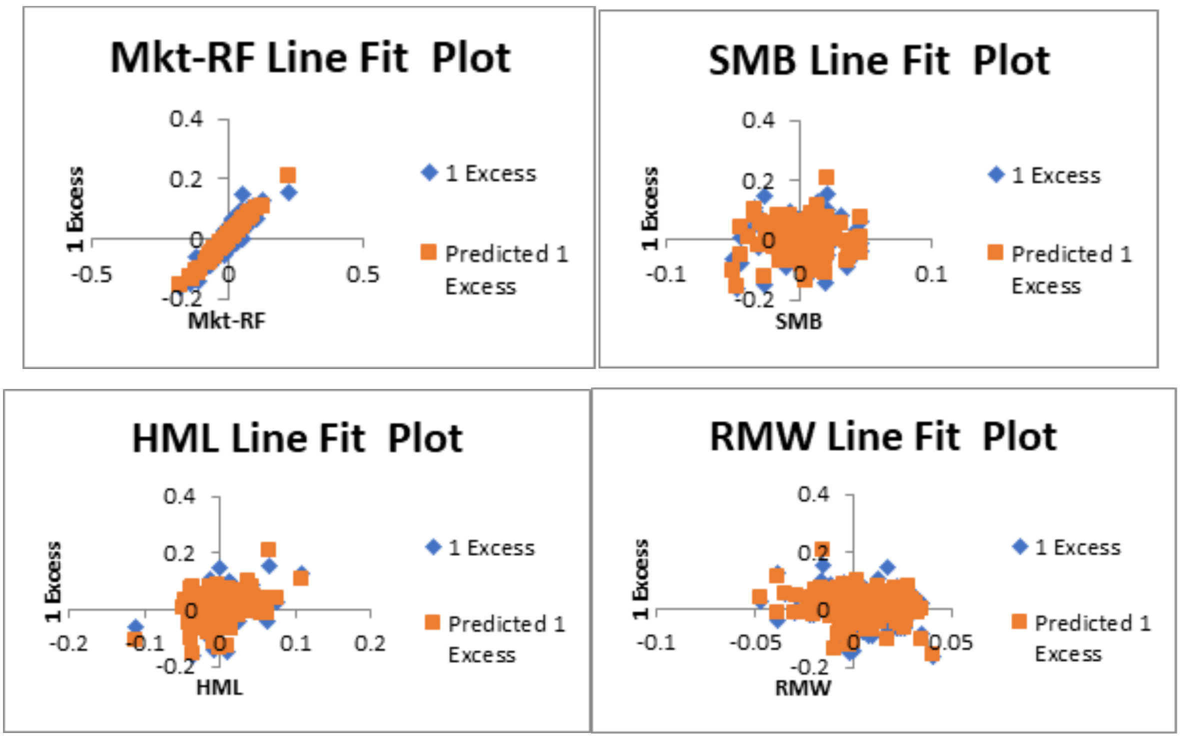
6.3 Test of Assumptions for Average Allocated High and Low ESG, E, S, and G Portfolios

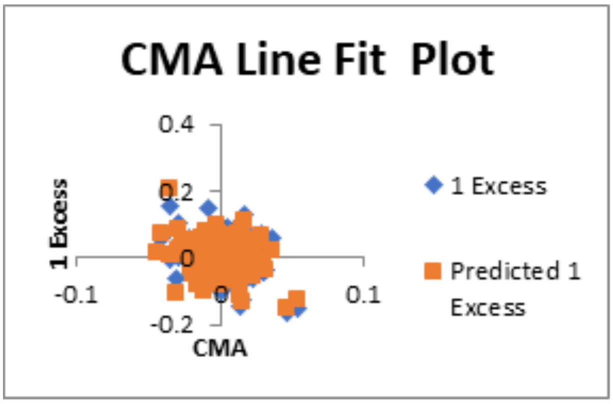
This section will check whether the OLS assumptions are met for the Average Allocated High and Low constructed portfolios. However, we will examine and present these assumptions on the Average Allocated High ESG portfolio. The assumptions for the Average High E, S, and G and the Average Low ESG, E, S, and G portfolio are found in appendix, annex 4. Annex 4 will include regressions, associated plots, and statistics for the remaining portfolios in part 1.

Tests of these assumptions are essential for the validity of the results produced by the Fama and French (2015) five-factor model.

6.3.1 Assumption 1: Linearity

Figure 3: *Line Fit Plot for Average Allocated High ESG Portfolio*



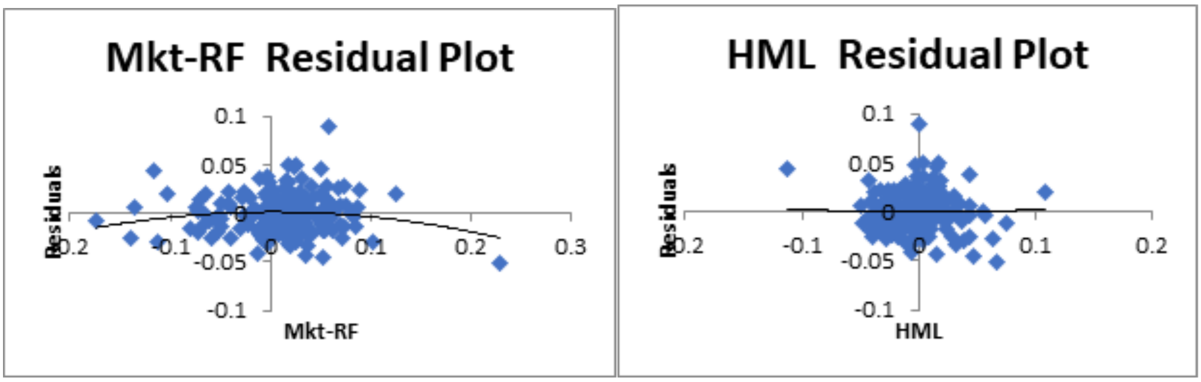


The line fit plots above are from the Average Allocated High ESG portfolio, which shows the relationship between the High ESG portfolio's excess return and the regression model predicted excess return. Mkt-RF Line fit plot shows a perfect increasing linear relationship between the High ESG portfolio excess return and the average market premium. Furthermore, the other factors do not have the same linear relationship, but one can see that the dependent variable is dependent on the independent variables. For that reason, the assumption of linearity is met for a High ESG Portfolio.

The line fit plots for all the other portfolios are found in the appendix, annex 4. They show the same perfect increasing linear relationship between the portfolio's excess return and the market premium. Moreover, the other factors indicate the same linear relationship, and hence the first OLS assumption is met for all portfolios in the present thesis.

6.3.2 Assumption 2: Zero Conditional Mean Error

Figure 4: *Residuals vs. Fitted values for Average Allocated High ESG portfolio*



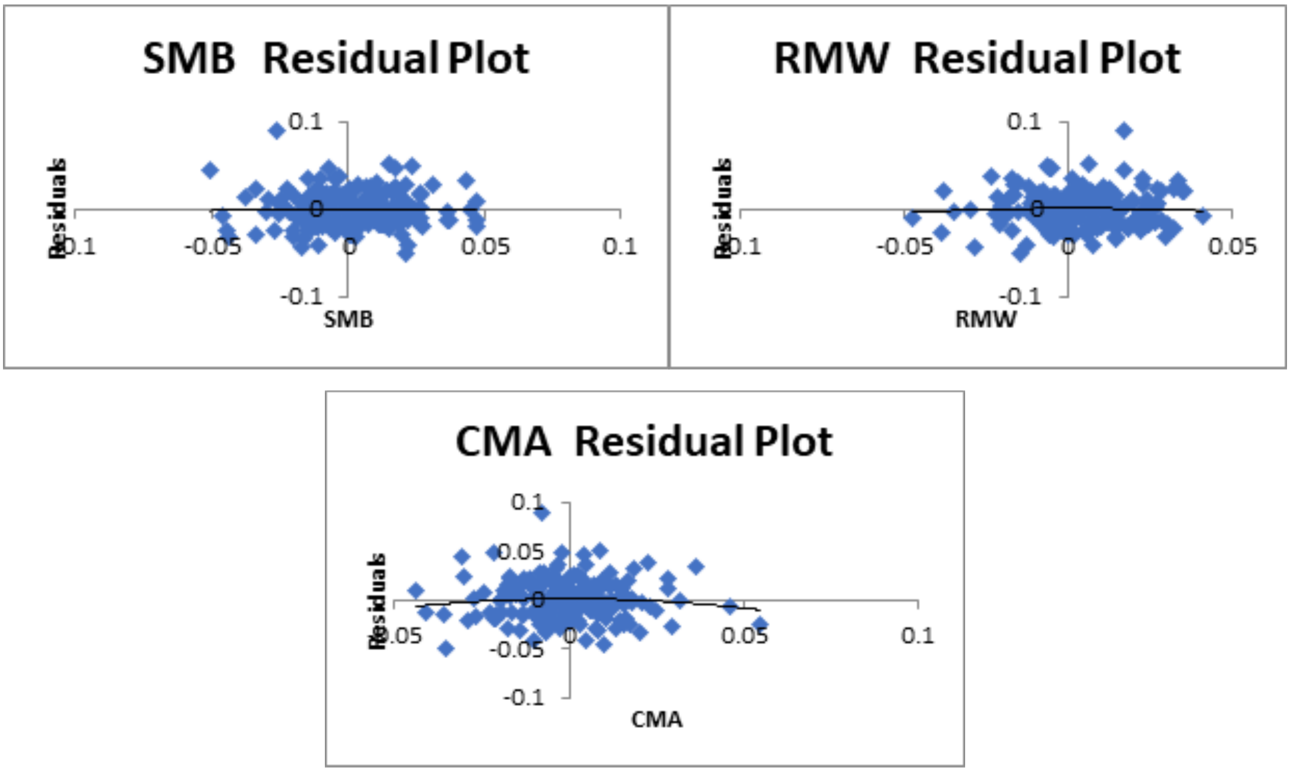


Figure 4 shows the residuals versus the fitted values for the High ESG portfolio. A black trend-line is applied, which lies around zero at every factor. This trend-line indicates that the assumption is being met for this portfolio. However, we will be checking the average of the residuals to be sure that the coefficients are not biased.

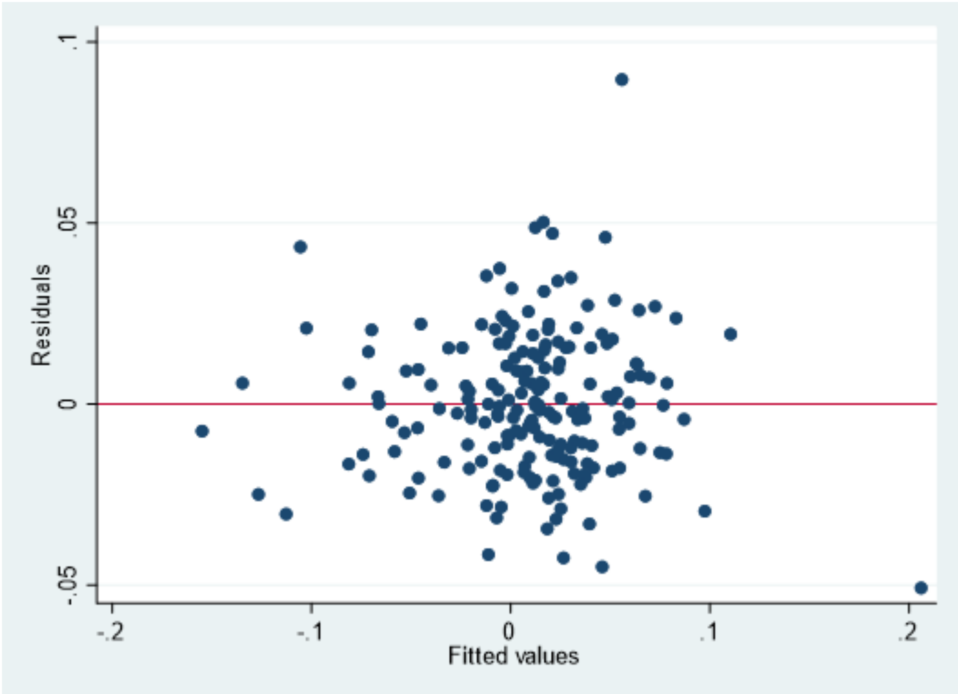
Table 3: *Mean of residuals for Average Allocated High ESG portfolio*

	Mean residuals
High ESG portfolio	9,39642E-19

The average of the residuals is zero. Consequently, assumption two is met for the High ESG portfolio. Further, we conclude that the assumption of zero conditional means is met as the trend-line is zero and the mean of the residuals is zero for all the remaining portfolios in part 1, cf. appendix, annex 4.

6.3.3 Assumption 3: No heteroscedasticity

Figure 5: *Residual vs. fitted plot for the Average Allocated High ESG portfolio*



Heteroscedasticity reduces the precision of the estimates in the OLS regression (Woolridge, 2018). Thus, we expect to spot heteroscedasticity through a great spread of the observations. Therefore, an increase in either one of the directions is expected. In the plot displayed, we might have heteroscedasticity. Hence, we perform regression with our Fama and French (2015) five-factor model and then the BP-test in STATA to detect whether heteroscedasticity is present in the observations.

Figure 5: *Breusch-Pagan Test for Heteroscedasticity for the High ESG portfolio*

	P-value
High ESG Portfolio	0,0131

Figure 5 shows a p-value of 0,0131, meaning we can reject the null hypothesis that the residuals have constant variance and the assumption of no heteroscedastic is not met. Hence, the present standard errors need to be recalculated to robust standard errors. The robust standard errors correct for heteroscedasticity in the residuals. We are running the regression using robust standard errors, which can be used when the assumption of uniformity of variance is violated. The new standard errors, t-values, and p-values can be found in the appendix, annex 4.

All the Average Allocated portfolios where the assumption of uniformity of variance is violated are corrected for using robust errors and are found in appendix, annex 4. The new values are further used in the analysis. Cf. appendix, annex 4, it can be concluded that the assumption of no heteroscedasticity is met for most of the portfolios in our thesis, part 1, and the remaining are corrected.

6.3.4 Assumption 4: Large Outliers are Unlikely

Figure 6: *Residual vs. Leverage Plot for the High ESG Portfolio*

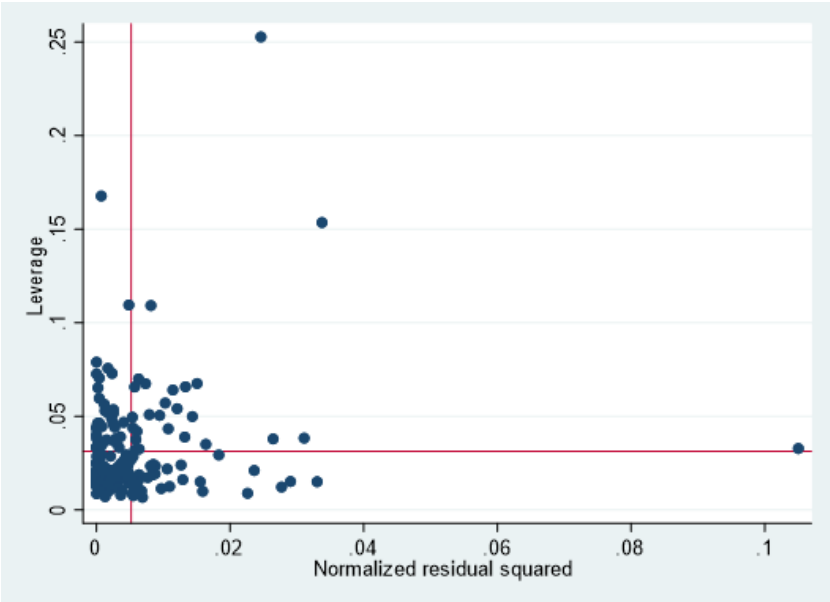


Figure 7: *Bar Chart of Cook's Distance for the returns with values of Cook's Distance that Exceed the Rule-of-Thumb Value for being Considered Large for the High ESG portfolio*

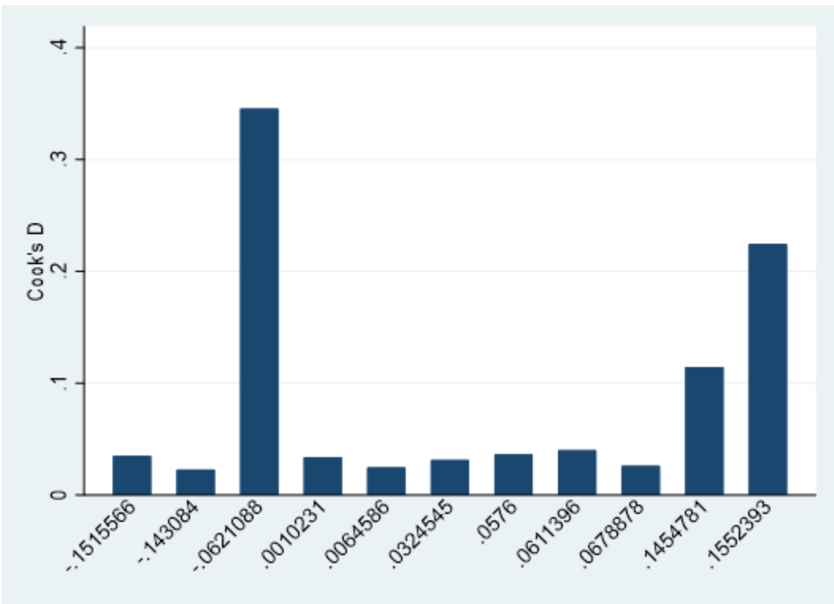


Figure 7 shows a residual versus leverage plot for the high ESG portfolio. Here we can spot that several observations may classify as significant outliers. Further, we use Cook's Distance to determine whether these observations are outside this distance. Cook's distance summarizes how our regression changes when the outlier observation is removed.

The leverage plot for the High ESG portfolio shows potential outliers. Moreover, we have spotted the outliers in a Graph Bar Chart based on Cook's Distance. The residuals vs. leverage plot for the remaining portfolios are found in the appendix, annex 4.

We pay special attention to these outliers in the data set as our multiple linear models are sensitive to these large outliers. However, as it is just a matter of a few observations in the dataset, we do not make any further corrections. Hence, the assumption is viewed as met.

Outliers may influence the residual's normal distribution. The normal distribution of the residuals gets further investigated in section 6.3.7.

6.3.5 Assumption 5: No multicollinearity

Table 6: *Correlation matrix between the factors for the Average Allocated portfolios*

	Beta	SMB	HML	RMW	CMA
Beta	1				
SMB	0,1142	1			
HML	0,3779	0,0113	1		
RMW	-0,2136	-0,0783	-0,7764	1	
CMA	-0,2703	-0,2369	0,4467	-0,3659	1

The table displays the correlations between the factors for the Average Allocated portfolios. Furthermore, all the correlations are low except for the correlation between HML and RWA, with a negative correlation of – 0,77. We are aware that this high correlation is a weakness for our regression. Therefore, we are further investigating the severity of this correlation.

There are several mechanisms to check for the severity of multicollinearity, and among them is to use the variance inflation factor (VIF). VIF equals the ratio of the overall model variance to the variance of a regression model, only including one factor. Furthermore, a high VIF indicates that the independent factor is highly collinear with other factors in the model. We assume that a factor above five is considered a high VIF, and thus the assumption is not met.

Table 7: *Variance Inflation Factor between the Factors for the Average Allocated portfolios*

Variable	VIF
Beta	1,66
SMB	1,10
HML	3,68
RMW	2,61
CMA	1,85
Mean VIF	**2,18**

However, table 7 shows a low VIF value of 2,18 for the Average Allocated portfolios factors, meaning that the assumption of no multicollinearity is met for these portfolios. No further actions are necessary. Further, the correlation matrix for the Yearly Allocated portfolio shows a high negative correlation between HML and RMW. However, the VIF value is below five, and the assumption is met. The tables for the Yearly Allocated portfolios are found in appendix, annex 4.

6.3.6 Assumption 6: No Autocorrelation

Table 8: *Breusch-Godfrey LM test for autocorrelation for the High ESG portfolio*

	P-value
High ESG Portfolio	0,4742

We are performing a BG-test for Autocorrelation for the High ESG portfolio and see that the test has a p-value of 0,4742. Hence, we cannot reject the null hypothesis of 5%, and the assumption is met for this portfolio.

Furthermore, we have performed this BG test on all the Average Allocated portfolios in our analysis part 1. We can conclude that autocorrelation is found in some of the portfolios. To correct this autocorrelation, we rerun the regression using robust standard errors. Robust standard errors are used when the autocorrelation assumption is not met. The BP-tests and robust error regressions for the respective portfolios are found in appendix, annex 4. The new values of standard deviation, t-values, and p-values are used further in chapter 6.

6.3.7 Normality of Errors

Figure 8: *Normal Q-Q Plot for the High ESG Portfolio*

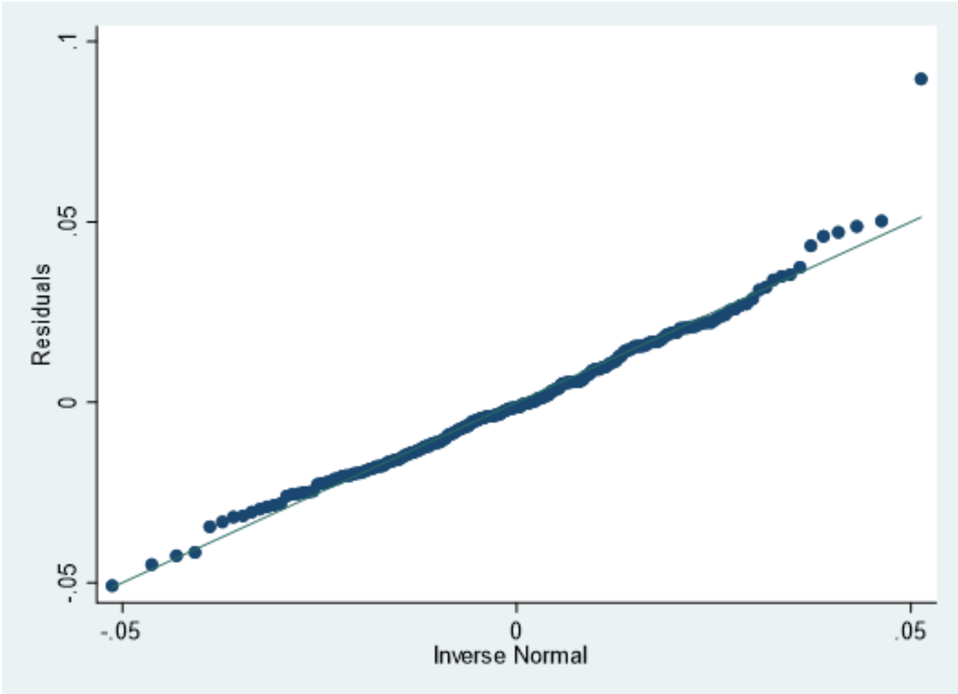


Figure 8 shows a quantile-quantile plot, which is used to assess whether the residuals in a regression model are normally distributed. If the residuals lie on a straight line, then the residuals are normally distributed. The Q-Q plot displays the residuals lying along a straight line except for some data points at the beginning and end of the plot. These data points are our outliers.

Figure 9: *Shapiro-Wilk W Test for normal data for the High ESG portfolio*

	P-value
High ESG Portfolio	0,00705

Further, we perform a Shapiro-Wilk-test to determine whether the residuals follow a normal distribution. We set the null hypothesis that the residuals follow a normal distribution with a significance level of 5%. If the p-value is greater than 5%, we cannot reject the null hypothesis that the residuals are normally distributed, which is desirable. Figure 9 shows a p-value of 0,00705, meaning that we reject the null hypothesis that the residuals are distributed around the mean of null for the High ESG portfolio, and thus the "assumption" is not met. An explanation is that the normal density in the tails is higher for stock returns than in the normal distribution. This higher normal density can give misleading values in the statistical output and thus lead to type ll error. A type ll error is when a hypothesis test fails to reject the null hypothesis that is false because the tests lack statistical power to detect enough evidence for the alternative hypothesis. This situation is identical for all the Average Allocated portfolios. The Q-Q plots and respective Shapiro-Wilk W tests for the other portfolios can be found in appendix, annex 4.

We have assessed the detected outliers in our data set and concluded to keep the model's points as of the few numbers of outliers. However, we are aware of these outliers when interpreting the findings in chapter 6 and 7.

6.4 Descriptive Statistics of Average Allocated Portfolios

The present section presents the descriptive statistics for the High and Low ESG, E, S, and G portfolios. We will use these statistics to understand the portfolio characteristics and link the statistics to the regression analysis. This way, we can better interpret the findings in section 6.5 and thus determine whether we can find a significant relationship between the Average Allocated High and Low ESG, E, S, and G scoring portfolios and stock performance in the Nordics.

6.4.1 Average Allocated Market Portfolio

Table 10:

Table 10 depicts the monthly descriptive statistics of the Average Allocated market portfolio from January 2006 to December 2021.

Descriptive Statistics	Monthly	Yearly
Mean	0,0116	0,1484
Excess Mean	0,0107	0,1362
Standard Deviation	0,0470	0,1628
Sharpe Ratio	0,2273	0,8367
Kurtosis	3,7059	
Skewness	-0,3662	

In the Average Allocated Portfolio, the portfolio is constructed based on the weights found based on the constituents' average market capitalization over the entire period.

6.4.2 Average Allocated High and Low ESG, E, S, and G Portfolios

Table 11:

Table 11 depicts the Mean return (Mean), Excess Mean return, Standard Deviation (Std.), Sharpe Ratio, Kurtosis, and Skewness for portfolios based on the highest ESG, E, S, and G performing constituents in the Average Allocated market pool. The Yearly Mean Return is found by the geometric average amount earned by the portfolio each year over 15 years between 2006 to 2021, through the formula

*$(1+r1) * (1+r2) *...* (1+rn)1n-1$ where n= 15 years.*

ESG	Monthly	Yearly	E	Monthly	Yearly
Mean	0,0099	0,1255	Mean	0,0102	0,1295
Excess Mean	0,0091	0,1148	Excess Mean	0,0094	0,1188
Std.	0,0492	0,1704	Std.	0,0591	0,2047
Sharpe Ratio	0,1844	0,6738	Sharpe Ratio	0,1586	0,5804
Kurtosis	1,4805		Kurtosis	2,4579	
Skewness	-0,4331		Skewness	-0,3020	
S	**Monthly**	**Yearly**	**G**	**Monthly**	**Yearly**
Mean	0,0121	0,1553	Mean	0,0073	0,0912
Excess Mean	0,0112	0,1430	Excess Mean	0,0064	0,0796
Std.	0,0440	0,1524	Std.	0,0504	0,1746
Sharpe Ratio	0,2551	0,9382	Sharpe Ratio	0,1276	0,4557
Kurtosis	0,6965		Kurtosis	1,4651	
Skewness	-0,3113		Skewness	-0,0366	

Table 11 shows monthly and yearly descriptive statistics for the Average Allocated High ESG, E, S, and G portfolios.

The descriptive statistics show that the S screened portfolio has the highest average return. The S portfolio has a higher average yearly return of 0,1553 than the market of 0,1484. The other three portfolios have lower average returns than the market, with the lowest average yearly return in the G screened portfolio of 0,0912. These results imply that the S portfolio outperforms, whereas the ESG, E, and G underperform the market.

According to the capital market line (Munk, 2015), high returns is followed by a high standard deviation.

The ESG, E, and G portfolios have lower yearly returns than the market. Furthermore, they have higher standard deviations compared to the market. Based on the Capital Market Line, this would indicate that the portfolios are less efficient than the market. Meanwhile, the S portfolio's yearly return and standard deviation of 0,1553 and 0,1524 are better than the benchmark of 0,1484 and 0,1628. The greater return and lower standard deviation imply that the S portfolio is more efficient than the benchmark. Because of the high return and low standard deviation, the S portfolio has a highly competitive yearly Sharpe ratio of 0,9382.

In comparison, the market has a Sharpe ratio of 0,8367. As a result, the S screening is a relevant performance measure for investors who want to gain financial returns. However, the other three ESG, E, and G portfolios have a less competitive Sharpe, and the worst position is in the G portfolio with a Sharpe at 0,4557. This value means that the financially motivated investor wants to use S screenings in the investment decisions. Else, the market portfolio yields the second-best risk-adjusted return. Our hypothesis is whether we can find significant positive relationships between High and Low ESG, E, S, and G scored portfolios and financial performance. The High S scoring portfolio signals a financial performance above the benchmark. Thus, this observation implies a positive relationship between the High S and financial performance in the Nordics.

Skewness and kurtosis help determine if indicators meet standard assumptions. Firstly, kurtosis measures whether the data is heavily tailed or not compared to a normal distribution. A lower kurtosis indicates fewer outliers in the data, thus less extraordinarily positive or negative returns. On the other hand, a high kurtosis indicates more outliers, thus more extraordinarily positive or negative returns. The portfolio with the lowest kurtosis is the S portfolio. All four portfolios have lower kurtosis than the market, ranging between 0,6925 and 2,4579, whereas the market has a kurtosis of 3,7059. All five portfolios have very acceptable values, according to Kallner (2018), who states that the kurtosis should optimally lie between -10 and 10. A normal distribution has a kurtosis of 3 (ibid.). Thus, none of the portfolios carry significant risks related to return asymmetry.

Lastly, the skewness measures the symmetry of the returns (Kallner, 2018). An acceptable level of skewness indicates that the portfolio returns are symmetrical. Low skewness indicates that the returns have longer left tails, meaning they frequently have small returns and few significant losses. A low skewness value means that the portfolios' skewness ranges between –0,4431 and –0,0366, which is a very acceptable value, as the skewness should be between -3 and 3 (Kallner, 2018).

Table 12*:*

Table 12 depicts the Mean return (Mean), Excess Mean return, Standard Deviation (Std.), Sharpe Ratio, Kurtosis, and Skewness for portfolios based on the lowest ESG-, E-, S-, and G- performing stocks in the average allocated market pool. Yearly Mean Return is found by the geometric average amount earned by the portfolio over 15 years between 2006 to 2021, through the formula
(1+r1) ∗ (1+r2) ∗…∗ (1+rn) ^n−1 *where n= 15 years.*

ESG	Monthly	Yearly	E	Monthly	Yearly
Mean	0,0037	0,0453	Mean	0,0091	0,1148
Excess Mean	0,0029	0,0354	Excess Mean	0,0082	0,1030
Std.	0,0692	0,2397	Std.	0,0550	0,1905
Sharpe Ratio	0,0415	0,1475	Sharpe Ratio	0,1497	0,5404
Kurtosis	1,6981		Kurtosis	0,8926	
Skewness	-0,2396		Skewness	-0,5422	
S	**Monthly**	**Yearly**	**G**	**Monthly**	**Yearly**
Mean	0,0025	0,0304	Mean	0,0072	0,0899
Excess Mean	0,0016	0,0194	Excess Mean	0,0063	0,0783
Std.	0,0744	0,2577	Std.	0,0640	0,2217
Sharpe Ratio	0,0221	0,0752	Sharpe Ratio	0,0989	0,3531
Kurtosis	1,6489		Kurtosis	1,4636	
Skewness	-0,1610		Skewness	-0,2241	

Table 12 shows monthly and yearly descriptive statistics for the Average Allocated Low ESG, E, S, and G portfolios.

The highest return from the low portfolios is from the E portfolio. However, none of the portfolios perform above the market portfolio, confirming what we expected for the low ESG, E, S, and G scored portfolios. On the contrary, the S portfolio yields the lowest return with a yearly return of 0,0304. This observation is interesting as the High S portfolio performs above the market level of 0,1484 with a yearly return of 0,1553. According to the Capital Market Line, low returns are often followed by a low standard deviation. The low S screened portfolio's yearly standard deviation is 0,2577 compared to the high S screened portfolio of 0,1524 and the market of 0,1628, which implies that the Low S portfolio carries overall risk compared to the High S portfolio. This observation contradicts the Capital Market Line theory from Munk (2015).

The Sharpe ratio is an essential characteristic as it measures the risk-adjusted performance of the portfolios. The highest yearly Sharpe ratio is found in the E portfolio of 0,5404, and the lowest for the S portfolio of 0,7520. Further, the yearly Sharpe ratio of the market is 0,8367, indicating that all the Low ESG, E, S, and G portfolios are performing below the benchmark in terms of risk-adjusted performance.

Our hypothesis is whether we can find significant positive relationships between High and Low ESG, E, S, and G scored portfolios and financial performance. These statistics are interesting as the Low ESG, E, S, and G scoring portfolios signal a financial performance below the benchmark. This observation implies a positive relationship between the Low ESG, E, S, and G and financial performance in the Nordics.

The kurtosis is below the market portfolio for all the low portfolios, indicating less extraordinarily positive or negative returns than the benchmark. On the other hand, the skew is more significant for the low ESG, S, and G portfolios than the market pool, suggesting that these respective portfolios frequently experience small returns and few significant losses.

On the contrary, the E screened portfolio has a skewness above the benchmark, indicating more frequent losses and significant positive returns.

6.5 Regression Analysis of Average Allocated High and Low ESG, E, S, and G Portfolios

This section will overview the regression output for the Average Allocated High and Low ESG, E, S, and G portfolios. Furthermore, the section will present the Fama and French (2015) five-factor model regression for the respective portfolios. The relevant outputs for determining the relationship between the High and Low ESG, E, S, and G portfolios and financial performance are the alpha, beta, SMB, HML, RMW, CMA, and the adjusted R-squared. With these values and respective significance levels, we can find supporting evidence in accepting or rejecting our hypothesis made and consequently conclude whether the ESG, E, S, and G scores positively, neutral, or negatively influence the stock performance in the Nordics.

Table 13:

*Table 13 displays the regression results from the Fama and French (2015 five-factor model. Namely the Alpha, Market Factor Betas (Beta), Small-Minus-Big (SMB), High-Minus-Low (HML), Robust-Minus-Weak (RMW), Conservative-Minus-Aggressive (CMA), which were introduced in chapter 4. It also shows the Adjusted R-Squared, which tells us how much of the model's variation in returns can be explained. We run time-series multiple regressions of each portfolio on the Average Allocated Nordic market. Standard errors are adjusted for heteroscedasticity and autocorrelation using HAC standard errors (Newey & West, 1986). Note that all figures are rounded to the nearest decimals for presentation. The statistical significance is highlighted as follows: *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.*

	Alpha	Mkt-Rf	SMB	HML	RMW	CMA	$Adj.R^2$
ESG Screening							
High	-0,0019	1,0186***	-0,0641	-0,1788	0,0264	0,3185**	0,8348
Low	-0,0093***	1,0558***	0,4380**	0,4373*	0,2126**	-0,1851	0,6440
E Screening							
High	0,0009	0,9801***	-0,1437**	-0,4586***	-0,0770	0,5310***	0,8441
Low	-0,0113***	1,1458***	0,4936***	0,4461**	0,1558	-0,1023	0,6518
S Screening							
High	-0,0019	1,1246***	-0,0063	0,1650	-0,0394	0,2368	0,8383
Low	-0,0037**	1,0710***	-0,0291	0,0048	0,1418	0,0751	0,8131
G Screening							
High	-0,0033	0,8564***	0,0026	0,0991	0,1085	0,1306	0,6489
Low	-0,0086***	1,0328***	0,3282**	0,3339	0,2461	-0,2351	0,6616

6.5.1 Average Allocated High and Low ESG Score Portfolio

The three largest constituents based on market capitalizations included in the High ESG Portfolio are Atlas Copco AB from Sweden, Telefonaktiebolaget LM Ericsson from Sweden, and Equinor ASA from Norway. These three constituents make up a total average market capitalization of DKK 1 019B[3]. Combined, they take up 59% of the portfolio weights, which means that three stocks make up almost 60% of the total portfolio.

On the contrary, the three largest constituents in the Low ESG portfolio are Industrivarden AB from Sweden, Seadrill Ltd from Norway, and Demant A/S from Denmark. They make up for a total market cap of DKK 141B and a total weight of 63%. These observations are essential in understanding what drives the High and Low portfolio performance. Hence, looking at their ESG score performance is essential in determining which relationship ESG scores and financial performance have.

The adjusted R-squared for the High ESG portfolio indicates that the independent variables can explain 0,8348 of the variation in the portfolio excess returns. In comparison, 0,6440 is explained for the Low ESG portfolio. This comparison suggests that our analytical model is better at capturing the High ESG portfolio performance variation by our chosen quality and risk factors. On the other hand, the alpha for the Low portfolio is highly

[3] B = 1.000.000.000

significant, signaling that the variation in the excess return not explained by the model is -0,0093. This alpha value means that the low portfolio has underperformed by -0,0093 compared to the market pool with a certainty of >0,99. Thus, the underperformance indicates a positive relationship between the Low ESG score portfolio and financial performance in the Nordics.

Further, both the High and Low ESG portfolio is slightly riskier than the market, with a beta of 1,0186 and 1,0558 observed at a 1% significance level. The betas for both portfolios are highly significant, resulting from the portfolios being constructed based on the market pool.

The Low portfolios have a significant positive SMB at a 5% level, affirming the knowledge from section 6.2.2 that the High Portfolios have more large-cap constituents and the Low portfolios more small-cap constituents. There is also significant positive exposure to HML, indicating that the Low ESG portfolio has more value than growth companies. An explanation for this is that the constituents in the Low portfolio have low market capitalizations but comparably high B/M value, which results in high positive exposure to the HML factor.

Further, the RMW is positively significant for the Low portfolio, indicating more robust profitability, which is unexpected as the low portfolio significantly consists of more small-cap constituents.

The CMA is positively significant for the High portfolio, suggesting that the portfolio constituents have a conservative investment strategy. None of the other quality factors are significant. Thus, we cannot conclude that these factors have any explanatory power in interpreting the high and low portfolio performances.

Due to the negative and significant alpha in the Low ESG portfolio, the financially motivated investor would prefer to short sell this portfolio to acquire abnormal returns.

6.5.2 Average Allocated High and Low E Score Portfolio

We use an environmental screening to rank the High and Low constituents in the E portfolios based on the constituents E scores. The top three largest constituents for the High E portfolio based on market capitalizations are Volvo AB, Hennes & Mauritz AB, and Skandinaviska Enskilda Banken AB. These three companies have a combined market capitalization of DKK 703B[4] and have 74% of the portfolio weights. All three constituents are from Sweden.

[4] B = 1.000.000.000

The three largest constituents for the Low E portfolio are Investor AB from Sweden, Industrivarden AB from Sweden, and Seadrill Ltd from Norway. They make up for a total market cap of DKK 325B and a total weight of 70%.

These observations are essential as they emphasize which constituents significantly affect the E portfolio performance. Thus, looking at their E score performance is essential in determining which relationship between E scores and financial performance have.

Table 12 shows the multiple regression output for the High and Low E portfolios from January 2006 to December 2021. The alpha for the High portfolio is positive but insignificant, suggesting that we cannot be certain about the positive performance. The Low portfolio, on the other hand, is negative and significant. This negative alpha means the low E screened portfolio performs 0,0113 worse than the benchmark with a significance level of 1%. The underperformance, in turn, confirms our hypothesis that Low E scores result in lower financial performance in the Nordics. Thus, the underperformance indicates a positive relationship between the Low E score portfolio and financial performance in the Nordics.

The beta is significant at a 1% level and is 0,9801 and 1,1458. A beta below 1 would imply that the portfolio is less risky than the market, and a beta above 1 implies that the portfolio is riskier than the market. The beta below 1 confirms our theory that investing in a high E scored portfolio reduces the investor's risk. In contrast, the Low E scored portfolio would have a risk profile above the benchmark.

The SMB factor is significant for both the High and Low portfolios, with opposite signs. Again, the significant negative factor affirms our statement regarding high E scored portfolios having more large-cap constituents in their portfolio than the Low E scored portfolios.

Also, the HML factor is significant for both portfolios with opposite signs, suggesting that the High portfolio has a low book-market value, and the Low portfolio has a high B/M value. The Low ESG portfolio has the same positively significant factor as the Low E portfolio. This interesting observation suggests that the market undervalues the small-cap constituents. Further, the CMA factor exposure is highly positively significant for the High E portfolio, the same significant observation we had for the High ESG portfolio. Again, this affirms our theory that the large-cap constituents do not need an aggressive investment strategy as they are well established with a high market share.

Due to the low beta in the High E portfolio, the risk-averse investor will prefer the High E screening method. The Low E portfolio generates a significant negative alpha, so the financially motivated investor would want to short-sell this portfolio.

6.5.3 Average Allocated High and Low S Score Portfolio

We use a social screening to rank the High and Low constituents in the S portfolios based on the constituents S scores. The top three largest constituents for the High S portfolio based on market capitalizations are Novo Nordisk A/S from Denmark, Telefonaktiebolaget LM Ericsson from Sweden, and Hennes & Mauritz AB from Sweden. These three companies have a combined market capitalization of DKK 1 052B and have 52% of the portfolio weights.

The three largest constituents for the Low S portfolio are Industrivarden AB from Sweden, Jyske Bank A/S from Denmark, and Seadrill Ltd from Norway. They make up for a total market cap of DKK 126B and a total weight of 62%.

Table 12 shows the multiple regression output for the S screened portfolios. The High S portfolio has an insignificant alpha. However, the Low portfolio is negative and significant, meaning the linear regression intercept starts at -0,0037 with a 5% significance level. The High and Low S portfolio has a beta above 1, implying it holds more risk than the market pool, signaling that the investor will be rewarded with 1,1246% and 1,071% return for an upward market movement of 1%, respectively. The R squared for the High, and Low S portfolios are 0,8383 and 0,8131. Despite the R-squared, neither the quality nor risk factors are significant. We cannot explicitly conclude that these factors can explain any variation in the High and Low S portfolio performance.

We find a negative and significant alpha for the Low S portfolio, implying that the investor can gain abnormal returns by short-selling the portfolio. Thus, the underperformance in the Low S score portfolio indicates a positive relationship between S and financial performance in the Nordics, as the Low S score constituents have lower financial performance.

6.5.4 Average Allocated High and Low G Score Portfolio

We use a governance screening to rank the High and Low constituents in the G portfolios based on the constituents G scores. The top three largest constituents for the High G portfolio based on market capitalizations are Equinor ASA from Norway, Telia Company from Sweden, and Telefonaktiebolaget LM Ericsson from Sweden. These three companies have a combined market capitalization of DKK 951 B7 and have 74% of the portfolio weights.

On the contrary, the three largest constituents in the Low G portfolio are Industrivarden AB from Sweden, Seadrill Ltd from Norway, and Demant A/S from Denmark. They make up for a total market cap of DKK 141B8 and a total weight of 58%.

The Low G screened portfolio has a significant alpha of -0,0086, which generates an abnormal low return. The alpha of the High portfolio is negative at -0,0033 but is insignificant. The High portfolio has a lower beta than the Low portfolio of 0,8564 to 1,0328. This low beta indicates that the High portfolio is a safer investment.

The Low portfolio has a positive exposure to the SMB factor, indicating that the Low G portfolio has more small-cap than large-cap constituents. This exposure is in line with our expectations from 6.2. The quality factors are insignificant for both High and Low portfolios, and therefore they do not provide any significant insights to explain the variation in returns for either portfolio.

The negative alpha of -0,0086 in the Low portfolio indicates that the portfolio is underperforming in the market. Further, the five factors cannot explain -0,0086 of the excess negative returns in the model. This observation could indicate that the negative return can be due to the Low portfolio's negative G performance. Thus, the underperformance indicates a positive relationship between the Low G score portfolio and financial performance in the Nordics. If this is true, low G scores correlate with low financial performance, and a short position in the portfolio could be financially rewarding for the investor. This opportunity will be further examined in the Part 3 analysis.

6.5.5 Summary of the regression analysis of the Average Allocated High and Low ESG, E, S, and G Portfolio

Section 6.5 aims to provide supportive evidence to accept or reject our hypothesis of whether there is a positive relationship between ESG, E, S, and G and financial performance in the Nordic. Observing the High ESG, E, S, and G screened portfolios finds insignificant alphas for the respective portfolios. Therefore, we cannot determine if they generate abnormal returns that the five risk factors model does not explain. However, we have negative and significant alphas for the Low ESG, E, and S screened portfolios. This observation is interesting as this suggests the ESG, E, and S portfolios perform 0,0093, 0,0113, and 0,0037 worse than the benchmark in the respective order. These findings imply that low ESG, E, and S scores are related to lower financial performance. Hence, we find a positive relationship between Low ESG, E, and S scores and financial performance in the Nordics. The investor can take advantage of these findings by short-selling the Low ESG, E, and S portfolios.

The additional factors can help explain the variation in the portfolio's returns. The SMB factor is negatively significant for the high E portfolio, signaling that the high environmental scoring constituents have a significant market share. On the contrary, the SMB factor is negatively significant for the low ESG and E portfolios, suggesting that these low-scoring portfolios have more small-cap than large-cap constituents. Further, The HML factor is positively significant for the Low ESG, E, and G portfolios. The respective portfolios are high in B/M value and hence undervalued by the investors. Lastly, the CMA is positively significant for High ESG and E portfolios, which indicates a more conservative investment method. This observation can be based on high ESG, and E scoring constituents have a significant market share and an established position in the market and thus may not need to invest largely.

Based on the presented observations, we can accept H1, H2, and H3 that there is a positive relationship between ESG, E, and S scores and financial performance in The Nordics. The results indicate that the constituent's low ESG, E, and S scores lower financial performance. Thus, a short position in the Low ESG, E, and S portfolio could be financially rewarding for the investor.

Graph 5 – *Yearly Allocated High and Low ESG Performance*

Graph 6 – *Yearly Allocated High and Low E Performance*

Graph 7 – *Yearly Allocated High and Low S Performance*

Graph 8 – *Yearly Allocated High and Low G Performance*

PART 2 – YEARLY ALLOCATED HIGH AND LOW ESG, E, S AND G PORTFOLIOS

6.6 Test of assumptions for Yearly Allocated High and Low ESG, E, S, and G portfolios

This section will check whether the OLS assumptions are met for the Yearly Allocated High and Low ESG, E, S, and G portfolios. A table is created to present an overview of the portfolio's different assumptions, test fulfillment, and necessary corrections. The High and Low ESG, E, S, and G portfolio regressions, associated plots, and statistics are found in appendix, annex 5.

Table 14:

Overview of all the OLS assumptions, test fulfillment of the Yearly Allocated High and Low ESG, E, S, and G portfolios, test used for correction, and the numbers of outliers.

Assumption	Test	Fulfilled	Not fulfilled	Test for correction
Linearity	Linearity plots	All portfolios		
Zero Conditional mean error	Residual vs. fitted plots	All portfolios		
No heteroscedasticity (Less than 5% -> not fulfilled)	Breusch - Pagan	ESG, Low E, High G	High E, S, Low G	Heteroscedasticity robustness standard error test
Large Outliers (Careful note)	Cook's Distance	All portfolios		
No multicollinearity	VIF-test	All portfolios		
No Autocorrelation (Less than 5% -> not fulfilled)	Breusch-Godfrey LM	ESG, E, S, low G	High G	Heteroscedasticity robustness standard error test
Normality of Errors (Less than 5% -> not fulfilled)	Shapiro Wilk + QQ-plots		All portfolios	

6.6.1 Assumption 1: Linearity

A line fit plot shows the relationship between the five factors or explanatory variables, x, used in the regression model, and the excess portfolio return, the dependent variable, y. We use these plots to determine whether the linearity assumption is met.

Mkt-Rf Line Fit Plots in appendix, annex 5, display a perfect linear relationship between all the portfolio excess returns and the market premium. The other plots do not show the same perfect linear relationship. However, one can see a trend that the portfolio's excess return moves in the same direction as the other factors. Thus, the linearity assumption is appraised to be met for all the Yearly Allocated High and Low ESG, E, S, and G portfolios.

6.6.2 Assumption 2: Zero Conditional Mean Error

The second assumption determines whether the zero conditional mean error is met. This assumption is one of the key assumptions for the coefficients in regression to be unbiased. Zero conditional determines when the residual on average is zero. Having positive and negative residuals will cancel each other out on average and thus helps us precisely estimate the excess portfolio return dependent variable, **y**. The trendline in the scatterplots lies at approximately zero for all the factors in the regression model. The scatterplots for the High and Low ESG, E, S, and G portfolios are found in the appendix, annex 5.

Moreover, the tables in the appendix, annex 5 show the average of the residuals to be zero. Thus, we conclude that the assumption of zero conditional means is met as the trendline is zero and the mean of the residuals is zero for all the High and Low ESG, E, S, and G portfolios in part 2, cf. appendix, annex 5.

6.6.3 Assumption 3: No heteroscedasticity

The variance of the residuals should be constant for all observations, i.e., the variance does not change for each observation. We will use Breusch–Pagan test for heteroscedasticity to determine whether there is heteroscedasticity presence in the data.

The figures in appendix, annex 5 show that some of the portfolio's residuals are spread around zero, and thus we might have heteroscedasticity in the data. These are portfolios High E, High and Low S, and Low G as seen in table 13. Consequently, we are running the regression for all the portfolios in STATA and preform a Breusch-Pagan test, hereafter BP-test, to check whether the data have constant variance.

The BP-test for all the portfolios shows p-values above and below a 5% significance. Further, we cannot reject that portfolio High and Low ESG, Low E, and High G have constant variance and that the respective dataset has the preferred condition of homoscedasticity. Therefore, we do meet the assumption of no heteroscedasticity for these portfolios. However, portfolios High E, High and Low S, and Low G are below 5%, and we reject the hypothesis of constant variance, meaning that the respective dataset has not the preferred condition of homoscedasticity. Therefore, we do not meet the assumption of no heteroscedasticity for these portfolios

All the portfolios where the assumption of variance uniformity is violated are corrected for using robust errors. These portfolios are mentioned in table 13. The new regressions can be found in the appendix, annex 5, and the new values are further used in the analysis. Cf. table 13 and annex 5, it can be concluded that the assumption of no heteroscedasticity is met for all the portfolios in our thesis part 2.

6.6.4 Assumption 4: Large Outliers are Unlikely

Figures in the appendix, annex 5 show a residual versus leverage plot for the all the estimated High and Low ESG, E, S, and G portfolios. Here we can spot that several observations may be classified as significant outliers. Further, we use Cook's Distance to determine whether these observations are outside this distance. Cook's distance summarizes how our regression changes when the outlier observation is removed.

The graph bars in the appendix, annex 5 display all the observations considered above the general rule of thumb for Cook's Distance and may be classified as potential large outliers in the dataset.

We pay special attention to these outliers in the data set, and our multiple linear models are sensitive to these large outliers. However, as it is just a matter of a few observations in the dataset, we do not make any further corrections. The assumption for the High and Low E, S, and G portfolios are viewed as met. Outliers may have an influence on the residual's normal distribution. The normal distribution of the residuals gets further investigated in the assumption regarding normal distribution.

6.6.5 Assumptions 5: No multicollinearity

The assumption regarding no perfect multicollinearity is met if there are low correlations between every one of the five factors in the model. A correlation of 0,8 or greater is assumed as a high correlation such that the effects of the independents on the outcome variable cannot be separated (Stock & Watson, 2020).

This means that one factor can be perfectly predicted by one of the other factors. Assumption 5 in the appendix, annex 5 shows a correlation between HML and RMW factor. Therefore, we perform a VIF test on the factors in the regression model.

A VIF above five indicates that one independent factor is highly collinear with other factors in the model.

The tables in the appendix, annex 5 show a low VIF factor for all the factors in the model, meaning that the assumption of no multicollinearity is met, and no further actions are necessary.

6.6.6 Assumption 6: No Autocorrelation

The last assumption is autocorrelation, a test to detect the randomness in a time series. Furthermore, this assumption is tested by creating a variable that has only one unit gap among the whole data set. Next, we are time series setting this variable and performing a Breusch-Godfrey Serial Correlation test on all the portfolios.

The null hypothesis has no serial correlation. Thus, with a p-value below a 5% significance level, we can reject the null hypothesis, and there is a serial correlation in the data points. On the contrary, with a p-value above a 5% significance level, we cannot reject the null hypothesis, and there is no serial correlation in the data set. Table 13 displays that portfolio High and Low ESG, E, S, and Low G have a significance level above 5%, and thus the assumption is met for the respective portfolios. On the contrary, the p-value the High G is below a significance level of 5%, and hence we can reject the null hypothesis of no serial correlation, and thus the assumption is not met for this respective portfolio.

To correct autocorrelation, we run the regression using robust standard errors on portfolio the Low G portfolio which can be used when the assumption of autocorrelation is not met. The BP-tests and robust error regressions for the respective portfolios are found in the appendix, annex 5. Moreover, the new values of standard deviation, t-values and p-values are used further in the analysis part 2 for the portfolios with autocorrelation.

6.6.7 Normality of Errors

The normality of errors claims that the error term is normally distributed. If the residuals are not normally distributed, then the standard errors of OLS estimates would not be reliable. This means that the confidence intervals would be too wide or narrow.

Further, a Shapiro-Wilk-test determines whether the residuals follow a normal distribution. We set the null hypothesis that the residuals follow a normal distribution with a significance level of 5%. If the p-value is greater than 5%, we cannot reject the null hypothesis that the residuals are normally distributed, which is desirable.

We have performed the Shapiro-Wilk-test for all the portfolios, and all show a p-value below 5%, meaning that we can reject the null hypothesis that the residuals are distributed around the mean of null for the respective portfolios, and thus the "assumption" is not met.

An explanation for this why this assumption is not met is that that the normal density in the tails is higher for stock returns than in the normal distribution. This can give misleading values in the statistical output, thus leading to type ll error. This situation is identical for all the portfolios analysed in part 2. The Q-Q plots and Shapiro-Wilk W Test can be found in the appendix, annex 5.

6.7 Descriptive Statistics of Yearly Allocated portfolios

The present section presents the descriptive statistics for the Yearly Allocated High and Low ESG, E, S, and G portfolios. We will use these statistics to understand the portfolio characteristics and link the statistics to the regression analysis. This way, we can better interpret the findings in section 6.8 and thus determine whether we can find a significant relationship between the Yearly Allocated High and Low ESG, E, S, and G scoring portfolios and stock performance in the Nordics.

Compared to the Average Allocated Portfolios, the Yearly Allocated Portfolio is reallocated every year. The reallocation depends on the ESG, E, S, and G scores in the prior year. Further, the High and Low portfolios are value-weighted and depend on the yearly market capitalizations in that year.

6.7.1 Yearly Allocated Market portfolio

Table 15: *Descriptive Statistics of the Yearly Allocated Market Portfolio*

Descriptive Statistics	Monthly	Yearly
Mean	0,0099	0,1255
Excess Mean	0,0091	0,1148
Standard Deviation	0,0458	0,1587
Sharpe Ratio	0,1976	0,7238
Kurtosis	3,3410	
Skewness	-0,8051	

Table 15 shows the monthly and yearly descriptive statistics of the Yearly Allocated Market portfolio from January 2006 to December 2021. The Yearly Allocated market portfolio is constructed based on the weights found based on the market pool's yearly market capitalization each year over the entire period.

6.7.2 Yearly Allocated High and Low ESG, E, S, and G portfolios

Table 16:

Table 16 depicts the Mean return (Mean), Standard Deviation, and Sharpe Ratio for portfolios based on the highest (High Portfolios) and lowest (Low Portfolios) ESG, E, S, and G performing stocks in the Yearly Allocated market pool. Yearly Mean Return is found by the formula's geometric average amount earned by the portfolio over 15 years between 2006 and 2021. (1+r1) ∗(1+r2) ∗…∗(1+rn) 1n−11+r1∗1+r2∗…∗1+rn1n−1 where n= 15 years.

	High Portfolios			Low Portfolios		
	Mean	Standard Deviation	Sharpe Ratio	Mean	Standard Deviation	Sharpe Ratio
ESG						
Monthly	0,0128	0,0523	0,2273	0,0152	0,0589	0,2431
Yearly	0,1649	0,1812	0,8419	0,1984	0,2040	0,9104
E						
Monthly	0,0126	0,0530	0,2222	0,0160	0,0581	0,2613
Yearly	0,1621	0,1836	0,8233	0,2098	0,2013	0,9860
S						
Monthly	0,0139	0,0507	0,2569	0,0112	0,0650	0,1597
Yearly	0,1802	0,1756	0,9546	0,1430	0,2252	0,5871
G						
Monthly	0,0106	0,0572	0,1706	0,0136	0,0580	0,2191
Yearly	0,1349	0,1981	0,6266	0,1760	0,2009	0,8138

Table 16 shows the High ESG, E, S, and G portfolios, generating higher average returns than the market. The highest return is found for the High S portfolio. This observation is consistent with the findings in the Average Allocated Portfolios, where the S also yielded the highest returns and thus signal that investing in an S screened portfolio is outperforming the market. On the other hand, the Low ESG, E, S, and G portfolios have a higher average return than the market, and the highest return is observed in the Low E portfolio. The S screened portfolio has the highest return in the High portfolio and, on the contrary, the lowest return in the Low portfolio, which might indicate a positive relationship between financial returns and the S scores. This relationship will be further analysed in our regression analysis in the present part and Part 3.

According to the Capital Market Line, the higher average return will be followed by a higher standard deviation. This statement is true in the High Portfolios, where the ESG, E, and G screenings generate a higher standard deviation than the market. Furthermore, the Yearly Allocated market portfolio has many more constituents than the High portfolio, resulting in a lower standard deviation, cf. diversification (Munk, 2015, p97). However, the Low S Portfolio has a higher standard deviation but a lower return, contradicting the CML.

The highest Sharpe ratio is found in the Low Portfolio that is screened based on E, with a yearly Sharpe ratio of 0,9850. The Sharpe ratio follows this in the High Portfolio that is screened based on S, with a yearly Sharpe ratio of 0,9546

6.8 Regression Analysis of Yearly Allocated High and Low ESG, E, S, and G portfolios

Table 17:

*Table 17 displays the regression results from the Fama and French (2015) five-factor model. These factors are the Alpha, Market Factor, Betas (Beta), Small-Minus-Big (SMB), High-Minus-Low (HML), Robust-Minus-Weak (RMW), Conservative-Minus-Aggressive (CMA), which were introduced in chapter 4. It also shows the Adjusted R-Squared, which shows how much of the model's variation in returns can be explained. We run time-series regressions of each portfolio on the benchmark. Standard errors are adjusted for heteroscedasticity and autocorrelation using HAC standard errors (Newey & West, 1986). The difference is showing the results in the Low portfolio minus the High portfolio. Note that all figures are rounded to the nearest decimals for presentation. The statistical significance is highlighted as follows: *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.*

	Alpha	Beta	SMB	HML	RMW	CMA	$Adj. R^2$
ESG							
High	0,0020	1,0179***	-0,0976	0,1869	0,3325**	0,1828	0,7882
Low	0,0048	0,9697***	0,1981	0,4601***	0,2189	-0,5048**	0,7491
E							
High	0,0023	0,9776***	0,0680	0,3770***	0,3391**	0,1064	0,7896
Low	0,0050	1,0714***	-0,1183	0,1495	0,1268	-0,4856***	0,8044
S							
High	0,0041**	1,0486***	-0,2204**	-0,4098***	-0,1302	0,4766***	0,7222
Low	0,0012	0,9349***	0,3242**	0,8591***	0,3186	-0,6298***	0,7082
G							
High	0,0016	0,8957***	-0,0493	0,8516***	0,3862**	-0,2487	0,7697
Low	0,0022	1,0516***	0,0926	0,0888	0,1399	-0,4452**	0,7757

6.8.2 Yearly Allocated High and Low ESG Score Portfolio

With the Yearly Allocated portfolio, the High ESG screening generated an insignificant but positive alpha of 0,0020 and a beta of 1,0179. Thus, we cannot be sure that ESG screening generates abnormal returns, and our analysis finds implications of it being riskier than the market. Comparing the High portfolio to the Low, the Low portfolio has a higher but insignificant alpha at 0,0048 and a lower and significant beta at 0,9697. Therefore, we do not find supporting evidence for H1. The financially motivated investor does not seem to benefit from going long in the High ESG screened portfolio nor shorting the Low ESG screened portfolio.

With the ESG screening, the Low portfolio has significant and positive exposure to the HML, indicating that the portfolio consists of more value companies. Previous analysis of the respective portfolios revealed that the Low portfolio had few to no companies with a market cap above Average in the market pool. Furthermore, the High portfolio has significantly positive exposure to the quality factor RMW, which indicate that the portfolio has profitable companies. The Low portfolio has a negative exposure to the quality factor CMA at a 5% significance level, indicating that they are more aggressive in their investment strategy.

Our analysis implies that the variation in returns in the High and Low ESG screened portfolios are better explained by their systematic risk and exposure to the HML and two quality factors, RMW and CMA.

6.8.3 Yearly Allocated High and Low E Score Portfolio

The High E portfolio has a positive and insignificant alpha, which is higher than the insignificant alpha in the Low E portfolio. In section 6.5, we found a highly significant negative alpha for the Low E screened portfolio. However, although not significant, the High E portfolio generates a higher positive alpha than the Low E portfolio. If significant, the higher alpha would imply that the High E screened portfolio outperforms the market and the Low E portfolio.

Furthermore, the High E portfolio beta is significantly lower than 1. In contrast, the Low E portfolio is higher than one, implying that the High E portfolio has less systematic risk than the Low E portfolio and the market. These findings support the findings in section 6.5, where the High E portfolio was found to have a lower systematic risk than the market and Low E portfolio. Therefore, investors can uphold a less risky position by investing based on E scores.

Further, the High E screened portfolio has significant positive exposure to the HML factor, indicating that it has more value companies than growth companies. Furthermore, the High portfolio has significant positive exposure to RMW, one of the quality factors of the Fama and French (2015) five-factor model and indicates that the portfolio has profitable companies. The Low portfolio has significant and negative exposure to CMA, indicating that they are more aggressive in their investment strategies, which could also explain the higher beta.

The High and Low E screened portfolios do not generate significant abnormal returns. However, the High E portfolio is exposed to less market risk than the Low E portfolio in both the Average and Yearly Allocated portfolios indicating that it might be a safer option.

6.8.4 Yearly Allocated High and Low S Score Portfolio

The High portfolio generates a significant positive alpha of 0,0041 in the S screening. This alpha implies that the financially motivated investor can use S screening to acquire abnormal returns above the benchmark and thus suggests evidence against accepting the hypothesis, H3. In section 6.5, we used Average Allocated portfolios and found that the Low S portfolios alpha was negative and significant. Now, the Low S portfolio has an insignificant alpha of 0,0012. Consequently, we cannot be confident that there is a positive relationship between the S score and financial performance and accepting H3.

The beta for the High S portfolio is significant at 1,0486. Since the beta is above 1, we find the High S portfolio to carry slightly more risk than the market and the Low S portfolio with a beta of 0,9349. A higher beta in the S portfolio was also found in section 6.5.

Further, the High S screening portfolio generates significant negative exposure to the SMB factor, while the Low S screening portfolio has significant positive exposure. This exposure indicates that large-cap constituents dominate the High S portfolio, and small-cap constituents dominate the Low portfolios. In section 6.2.2, we found similar observations for the Average Allocated portfolios. This finding indicates that the large-cap constituents dominate the High ESG, E, S, and G portfolios. We also find that the High portfolio has significant negative exposure to the HML factor, indicating that the portfolio has the most growth constituents.

The opposite can be said about the Low S screening portfolio, where the HML factor has a positive exposure, indicating that the portfolio has more value constituents. The High portfolio has significant and positive exposure to the CMA factor, indicating that the constituents in the portfolio are more conservative in their investments. Oppositely, the Low S portfolio has significant and negative exposure, indicating that they have more aggressive investment strategies. The S screened portfolio does not have significant exposure to the RMW factor.

The findings imply that the High S portfolio generates an abnormal return that the Fama and French (2015) five-factor model cannot explain. Furthermore, the High S portfolio is riskier than the overall market and the Low S portfolio.

6.8.5 Yearly Allocated High and Low G Score Portfolio

The High G screened portfolio generates a positive but insignificant alpha of 0,0016. This alpha is lower than the insignificant alpha of 0,0022 in the Low G screened portfolio.

Noteworthy, the High G portfolio was found to have a higher beta in section 6.5. However, in the Yearly Allocated portfolios, the High G portfolio beta is 0,8957, lower than the Low G portfolio with a beta of 1,0516.

In the G screened portfolios, the High portfolio has significant and positive exposure to the HML, indicating that the portfolio has more value stocks. Comparatively, the Low portfolio has significant negative exposure to CMA, indicating more aggressive in their investment strategies. This significant exposure has been repeatedly observed for all the High and low ESG, E, S, and G screening methods in the present analysis.

The G screening generates insignificant alphas for both the High and Low portfolios based on the findings, we do not find supporting evidence to H4. Further, the High G screened portfolio has less market risk in the Yearly allocated portfolios than the Average Allocated portfolios.

6.8.6 Summary of the regression analysis of the Yearly Allocated High and Low ESG, E, S, and G Portfolio

The regression analysis for the ESG portfolio is found to have a beta above the market, indicating that it is riskier than the market, and findings also show that it is riskier than the Low ESG portfolio. Further, the Yearly Allocated portfolios regression finds the most exciting implications for the E and S screened portfolios. The High E screened portfolio generates a lower beta compared to the market and the Low E portfolio. We did not find implications of higher returns for the E screened investor, but the investor who prefers lower risk would like to use E screening.

Further, the S screening investor generates a positive and significant alpha, indicating that it generates a return that the five factors cannot explain in the model. This significant alpha provides significant evidence for accepting H3 that there is a positive relationship between S scores and financial performance. However, we do not find supporting evidence for either of the other hypotheses provided in section 1.2. In Part 3 of our analysis, we will attempt to answer if this can be explained by constructing a new model with an incorporated ESG, E, S, and G factor.

The regression analysis shows that the High ESG portfolio has a beta above the market, indicating it is riskier than the market. The findings also indicate that it is riskier than the Low ESG portfolio. Further, the Yearly Allocated portfolios regression finds the most exciting implications for the E and S screened portfolios. The High E screened portfolio generates a lower beta compared to the market and the Low E portfolio. We did not find implications of higher returns for the E screened investor, but the investor who prefers lower risk would like to use E screening.

Further, the S screening investor generates a positive and significant alpha, indicating that it generates a return that the five factors cannot explain in the model. This significant alpha provides significant evidence for accepting H3 that there is a positive relationship between S scores and financial performance. However, we do not find supporting evidence for either of the other hypotheses provided in section 1.2. In Part 3 of our analysis, we will attempt to answer if this can be explained by constructing a new model with an incorporated ESG, E, S, and G factor.

PART 3 – AVERAGE ALLOCATED HIGH AND LOW ESG, E, S, AND G PORTFOLIOS WITH NEW ESG, E, S, AND G FACTOR

6.9 Introducing the Six-Factor Model

In parts 1 and 2, we have used two different portfolio construction methodologies to see whether any of the two portfolio constructions give significant abnormal returns, thus finding supporting evidence for our first three hypotheses and answering the thesis problem statement. In part 3, we introduce a new analytical model to see whether we can capture more of the variation in the excess returns. Then, try to find supporting evidence for our fourth hypothesis, whether our new model with an additional ESG, E, S and G factor explains more variation in portfolio excess return than a Fama and French (2015) five-factor model. This way, we can better analyze whether the constituents' ESG, E, S, and G scores influence their financial performance and what relationship ESG, E, S, and G scores and financial performance in Nordics have.

Our ESG, E, S, and G factor is called GMB, which stands for "Good minus Bad" ESG, E, S, and G score. To construct the GMB factor, we have used a similar approach as Fama and French's construction of B/M, OP, and INV factors (Fama & French, 2015). We use the data set from part 1 for this analysis in part 3. The data set is the Average Allocated High and Low ESG, E, S, and G portfolios.

This approach relies on constructing two portfolios using the 30th and 70th percentile of the market pool and then using median average market capitalization to determine the big and small portfolios. After that, the Fama and French (2015) five-factor approach then uses the average return on the High minus Low portfolio.

6.9.1 Construction of the New ESG, E, S, and G Factor

We start by sorting all the 99 constituents in the market pool based on their ESG, E, S, and G scores. After that, we standardized the ESG, E, S, and G scores based on the median. We chose the 30th and 70th percentile for breakpoints in constructing our Average Allocated High and Low ESG, E, S, and G portfolios.

To determine the Big and Small portfolios, we found the median of the average market capitalization for all the 99 portfolios. The Top 30 above the median is classified as "Big High ESG," and the Top 30 below the median is classified as "Small High ESG." Further, the Bottom 30 above the median is classified as "Big Low

ESG," and the Bottom 30 below the median is classified as "Small Low ESG." We have 19 "Big" and 11 "Small" stocks in the High ESG score portfolio, while we have 10 "Big" stocks and 20 "Small" stocks in the Low ESG scored portfolio. The same approach and classification are applied to the E, S, and G score-based portfolios.

Further, GMB is the average performance on the two High ESG scored portfolios minus the average performance on the two Low ESG scored portfolios. Moreover, GMB has been constructed the same way for E, S, and G score-based portfolios.

$$GMB_{ESG} = \frac{1}{2} * (Small\ High\ ESG + Big\ High\ ESG) - \frac{1}{2} * (Small\ Low\ ESG + Big\ Low\ ESG)$$

GMB factor for the Average Allocated ESG constructed portfolios

$$GMB_{E} = \frac{1}{2} * (Small\ High\ E + Big\ High\ E) - \frac{1}{2} * (Small\ Low\ E + Big\ Low\ E)$$

GMB factor for the Average Allocated E constructed portfolios

$$GMB_{S} = \frac{1}{2} * (Small\ High\ S + Big\ High\ S) - \frac{1}{2} * (Small\ Low\ S + Big\ Low\ S)$$

GMB factor for the Average Allocated S constructed portfolios

$$GMB_{G} = \frac{1}{2} * (Small\ High\ G + Big\ High\ G) - \frac{1}{2} * (Small\ Low\ G + Big\ Low\ G)$$

GMB factor for the Average Allocated G constructed portfolios

6.10 Test of Assumptions for Average Allocated Portfolios with New ESG, E, S, and G Factor

This section will check whether the OLS assumptions for our regressions are met concerning our new analytical model, the six-factor model. A table is created to present an overview of the portfolio's different assumptions, test fulfillment, and necessary corrections. The Average Allocated High and Low ESG, E, S, and G portfolio with a new ESG, E, S, and G factor regressions, associated plots, and statistics are found in the appendix, annex 6.

Furthermore, tests of these assumptions are essential for the validity of the results produced by the six-factor model.

Table *18*:

Overview of all the OLS assumptions, test fulfillment of the Average Allocated High and Low ESG, E, S, and G portfolios with new ESG, E, S, and G factor, test used for correction, and the numbers of outliers.

Assumption	Test	Fulfilled	Not fulfilled	Test for correction
Linearity	Linearity plots	All portfolios		
Zero Conditional mean error	Residual vs. fitted plots	All portfolios		
No heteroscedasticity (Less than 5% -> not fulfilled)	Breusch - Pagan	High E, High S, Low G	ESG, Low E, Low S, High G	Heteroscedasticity robustness standard error test
Large Outliers (Careful note)	Cook's Distance	All portfolios		
No multicollinearity	VIF-test	All portfolios		
No Autocorrelation (Less than 5% -> not fulfilled)	Breusch-Godfrey LM	ESG, E, S, Low G	High G	Heteroscedasticity robustness standard error test
Normality of Errors (Less than 5% -> not fulfilled)	Shapiro Wilk + QQ-plots	High E, High S	ESG, Low E, Low S, G	

6.10.1 Assumptions 1: Linearity

The plots in appendix, annex 6 show the relationship between all the factors in the six-factor model and the excess return for our High and Low ESG, E, S, and G portfolios. Further, the Mkt-Rf Line Fit Plots in appendix, annex 6, display perfect linear relationships between the portfolio excess returns and the market premiums. The other plots do not show the same perfect linear relationship. However, one can see a trend that the portfolio's excess return moves in the same direction as the other factors. Thus, the linearity assumption is appraised to be met for all the Average Allocated High and Low ESG, E, S, and G portfolios with a new ESG, E, S, and G factor.

6.10.2 Assumptions 2: Zero Conditional Mean Error

The figures in appendix, annex 6 determine whether the zero conditional mean error assumption is met. The black trendline is observed around zero on all the explanatory variables. Further, the tables in appendix, annex 6, determine that the mean of the residuals for the High and Low ESG, E, S, and G portfolios is zero. Hence, it can be concluded that the assumption is also met for the portfolios, as the trend lines are observed around zero, and the independent variable residuals average is zero.

6.10.3 Assumptions 3: No heteroscedasticity

The figures in appendix, annex 6 show that some of the portfolio's residuals are spread around zero, and thus we might have heteroscedasticity in the data. These are portfolios High and Low ESG, Low E, Low S, and High G as seen in table 18. Consequently, we are running the regression for all the portfolios in STATA and preform a Breusch-Pagan test, hereafter BP-test, to check whether the data have constant variance.

The BP-test for the portfolios shows p-values above and below 5% significance. Further, we cannot reject that portfolio High E, High S, and Low G have constant variance and the respective dataset has the preferred condition of homoscedasticity. However, portfolios High and Low ESG, Low E, Low S, and High G are below 5%, and we reject the hypothesis of constant variance, meaning that the respective dataset has not the preferred condition of homoscedasticity. Therefore, we do not meet the assumption of no heteroscedasticity for these portfolios.

All the portfolios where the assumption of variance uniformity is violated are corrected for using robust errors. These portfolios are mentioned in table 18. The new regressions can be found in the appendix, annex 6, and the new values are further used in the analysis. Cf. Table 18 and annex 6 show that the assumption of no heteroscedasticity is met for all the portfolios in our thesis part 3.

6.10.4 Assumptions 4: Large Outliers are Unlikely

The graph bars in appendix, annex 6 display all the observations considered above the general rule of thumb for Cook's Distance and may be classified as potential significant outliers in the dataset.

The assumption for the Average Allocated High and Low E, S, and G portfolios with a new ESG, E, S, and G factor is viewed as met. We pay special attention to these outliers in the data set, and our multiple linear models are sensitive to these significant outliers. However, as it is just a matter of a few observations in the dataset, we do not make any further corrections.

6.10.5 Assumptions 5: No multicollinearity

The assumption regarding no perfect multicollinearity is met if there are low correlations between the six factors.

As shown in the matrix in appendix, annex 6, the correlation between the six factors for the Average Allocated portfolios is low except for the correlation between HML and RWA. The respective have a negative correlation of –0,77. Further, our new GMB factor has a low correlation to the other factors in the Fama and French (2015) five-factor model.

We use the VIF value to check the severity of multicollinearity among the six factors. The mean VIF for our six factors is 2,02, thus below five. Hence, we can conclude the assumption of no multicollinearity is met.

6.10.6 Assumptions 6: No Autocorrelation

Table 18 shows that portfolios High and Low ESG, E, S, and Low G have significance levels above 5%, and thus the assumption is met for the respective portfolios. On the contrary, the p-values for portfolios the High G is below the significant level of 5%. Hence, we can reject the null hypothesis of no serial correlation, and thus the assumption is not met for the respective portfolios.

We rerun the regression using robust standard errors on the High G portfolio to correct autocorrelation. The BP-tests and robust error regressions for the respective portfolios are in the appendix, annex 6. Moreover, the new values of standard deviation, t-values, and p-values are used further in the analysis part 3 for the portfolios with autocorrelation.

6.10.7 Normality of Errors

We have performed the Shapiro-Wilk-test for all the portfolios, and the ESG, Low E, Low S and G show a p-value below 5%, meaning that we can reject the null hypothesis that the residuals are distributed around the mean of null for the respective portfolios. Thus the "assumption" is not met.

An explanation for this why this assumption is not met is that the normal density in the tails is higher for stock returns than in the normal distribution. This high density in the tails can give misleading values in the statistical output, thus leading to type ll error. This situation is identical for all the portfolios analysed in part 3. The Q-Q plots and Shapiro-Wilk W Test can be found in the appendix, annex 6.

6.11 Descriptive Statistics of Average Allocated portfolios with New ESG, E, S, and G factor

Descriptive statistics describe the characteristics of the portfolio's performance, cf. section 6.1. As we analyze the same portfolios as in part 1, we have identical portfolios performance as in part 1. Thus, the descriptive statistics from sections 6.4.1 and 6.4.2 can be used for this present part. The key takeaways from the statistics in part 1, section 6.4 is the following:

For the High ESG, E, S, and G portfolios, the Social-screened portfolio return is the highest and the only portfolio performing above the benchmark. Moreover, the standard deviation of the respective portfolio is lower than the market portfolio, resulting in a competitive Sharpe ratio for an investor using S-screening in their investment strategy. Further, the skewness and kurtosis for all portfolios lie within the acceptable range, according to Kallner (2018), suggesting that none of the portfolios carry significant risks related to return asymmetry.

On the other hand, the E screened portfolio has the highest return for the Low ESG, E, S, and G portfolios. However, none of the four portfolios perform above the benchmark. The S screened portfolio yields the lowest return, which is interesting as the High S screened portfolio performs the highest and above the benchmark. The standard deviation is above the benchmark, and accordingly, the Sharpe ratio is lower for all the low portfolios.

Our hypothesis is whether we can find significant positive relationships between High and Low ESG, E, S, and G scored portfolios and financial performance. These statistics imply that the Low ESG, E, S, and G scoring portfolios have a risk-adjusted performance below the benchmark. This observation implies a positive relationship between the Low ESG, E, S, and G and financial performance in the Nordics.

6.12 Regression Analysis of Average Allocated High and Low ESG, E, S, and G Portfolios with new ESG, E, S, and G factor

Table *19*:

*Table 19 displays the regression results from the six-factor model. These are the Alpha, Market Factor Betas (Beta), Small-Minus-Big (SMB), High-Minus-Low (HML), Robust-Minus-Weak (RMW), Conservative-Minus-Aggressive (CMA), and Good-Minus-Bad (GMB). It also shows the Adjusted R-Squared, which shows how much of the model's variation in returns can be explained. We run time-series multiple regressions of each portfolio on the Average Allocated Nordic market. Standard errors are adjusted for heteroscedasticity and autocorrelation using HAC standard errors (Newey & West, 1986). Note that all figures are rounded to the nearest decimals for presentation. The statistical significance is highlighted as follows: *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.*

	Alpha	Beta	SMB	HML	RMW	CMA	GMB	$Adj. R^2$
ESG								
High	-0,0020	1,0239***	-0,0442	-0,1748	0,0300	0,3062**	0,0598	0,8304
Low	-0,0070**	0,9837***	0,1691	0,3839*	0,1642	-0,0192	-0,8082***	0,7250
E								
High	0,0002	0,9732***	-0,0559	-0,3778***	-0,0806	0,4561***	0,1951***	0,8616
Low	-0,0084***	1,1758***	0,1146	0,0975	0,1712	0,2210	-0,8423***	0,7697
S								
High	-0,0019	1,1253***	-0,0035	0,1655	-0,0389	0,2350	0,0085	0,8374
Low	-0,0026	1,0361***	-0,1594*	-0,0211	0,1183	0,1555	-0,3916***	0,8430
G								
High	-0,0032	0,8847***	0,0972	-0,0320	0,1170	0,0952	0,6320***	0,7466
Low	-0,0086***	1,0058***	0,2377	0,4594**	0,2380	-0,2011	-0,6053***	0,7137

We conduct the same analysis on the identical dataset as in Part 1, section 6.5. The difference between Part 1 and Part 3 analysis is that we add the sixth GMB factor to the model. The intention of displaying the above regression output is to learn if the six-factor model with an additional ESG, E, S, and G factor explains more variation in portfolio excess return than the Fama and French (2015) five-factor model in Part 1 section 6.5 did. In addition, we further analyze the relationship between ESG, E, S, and G scores and financial performance in The Nordics and try to conclude on the problem statement in section 1.2.

6.12.1 Average Allocated High and Low ESG Score Portfolio with New ESG Factor

In the Average Allocated ESG portfolio, the added GMB factor is constructed based on the ESG score.

The GMB factor for the High portfolio is insignificant. However, the alpha is negative and significant for the Low portfolio at a 5% level. This negative significance implies that constituents' ESG scores can explain the variation in the Low portfolio returns, which supports hypothesis H5.

Furthermore, the High portfolio alpha is more positive than the Low alpha at -0,0020 and -0,0070. Furthermore, the Low portfolio's alpha is now less negative than in Part 1, section 6.5, where the alpha was -0,0093 for the Low ESG portfolio. This observation indicates that the new six-factor model explains 0,0023 more of the alpha for the Low ESG portfolio than the Fama and French (2015) five-factor model. Further, this alpha increase may be explained by the significant GMB factor of -0,8082, which would support our hypothesis H1 of a positive relationship between ESG score and financial performance. We, therefore, find supporting evidence accepting H1.

The High portfolios' significant and positive exposure to CMA is unchanged from Part 1. However, the significant and positive exposure to RMW and the significant and positive exposure to SMB in the Low portfolio has diminished after adding the GMB factor to the model. This diminishing could indicate that the GMB is better at explaining the variation in returns that were earlier thought to be explained by SMB and RMW.

Furthermore, we find that the GMB factor is negatively significant, implying that our six-factor model can help explain the variation in excess returns in the Low portfolio. Thus, we find supporting evidence for accepting H5. The Low portfolio still has a significant excess return of -0,0070 that we cannot explain.

6.12.2 Average Allocated High and Low E Score Portfolio with New E Factor

The added GMB factor is constructed based on the E score in the Average Allocated E portfolio.

The High and Low E portfolios have highly significant exposures to the GMB factor with 0,1951 and -0,8423, respectively. The GMB factor is positive in the High portfolio and negative in the Low portfolio, indicating high and low performance in E, respectively. This observation implies that a six-factor model can be supportive in explaining the variation of the High and Low portfolios' returns.

In Part 1, section 6.5, the alpha in the High portfolio was insignificant and positive at 0,0009, while we now find it insignificant at 0,0002. Although insignificant, findings still imply that the alpha is closer to zero with the new factor. If significant, this would have been an implication that the six-factor model is better at explaining the variation in returns as the alpha is closer to zero. The GMB factor would explain the positive alpha in Part 1, meaning that the high E score yields abnormally high financial returns. The alpha in the Low E portfolio has gone from -0,0113 to -0,0084. This decrease implies that the six-factor model is helpful to explain some of the alpha. We evaluate as supporting evidence to accept H5.

With the new factor, the beta is slightly lower in the High portfolio and slightly higher in the Low portfolio than in our findings in Part 1. These findings mean that when adjusting for the new risk factor GMB based on E, the beta went from 0,9801 to 0,9732 in the High portfolio and 1,1458 to 1,1758 in the Low portfolio. This observation supports our rationale about the beta in the High, and Low E screened portfolios from Part 1, section 6.5. We stated that the High portfolio was more resilient and could be viewed as a safer investment than the market and the Low portfolio.

Based on the evidence, we accept that the GMB factor can explain some variations in the positive insignificant alpha in the High portfolio. Further, we accept that the GMB factor can explain some variations in the negative alpha in the Low portfolio. Thus, the evidence suggests a positive relationship between the excess returns for the E and abnormal financial returns. Consequently, we argue for accepting H2 and H5.

6.12.3 Average Allocated High and Low S Score Portfolio with New S Factor

The added GMB factor is constructed based on the S score in the Average Allocated High and Low S portfolio.

The GMB factor for the High portfolio is insignificant but highly significant in the Low portfolio. The Low portfolio has exposure to the GMB factor of -0,3916, indicating that the negative excess return that the model in Part 1, section 6.5 did not explain can be explained by the exposure to the risk factor GMB. Or implicitly, the negative S score in the Low S portfolio. This finding is supportive of hypothesis H5.

The alpha in the High portfolio is insignificant and unchanged from Part 1, section 6.5. The Low portfolio's alpha was significant at a 5% level at -0,0037 and is now insignificant at -0,0026. The significant alpha is diminished, which implies that the six-factor model can explain the excess return that the five-factor was unable to. These findings support hypothesis H3, implying that the Low S portfolio yields low returns because of its low S score. In addition, the findings in this present section support H5 that the six-factor model with an additional S factor can explain more of the variation in the low S portfolio excess return relative to a Fama and French (2015) five-factor model.

6.12.4 Average Allocated High and Low G Score Portfolio with New G Factor

The added GMB factor is constructed based on the G-score in the Average Allocated G-portfolio.

The sixth factor GMB is significant in both the High and Low portfolios at the 1% level, providing supporting evidence that the GMB factor can explain the variation in returns in the G portfolio, our hypothesis H5.

Furthermore, the negative alphas found in Part 1, section 6.5 are unchanged, which indicates that the new six-factor model could not explain the negative alphas found in the five-factor model. This finding is unsupportive of our hypothesis H4. As a result, we do not know if the negative abnormal return in the Low portfolio results from its G performance or other factors.

As a result, our findings provide supporting evidence that a GMB factor based on G can help explain the variation in the returns in the G portfolio. Thus, we accept H5. However, we do not find evidence of a positive relationship between G and financial performance. We, therefore, reject the H4 hypothesis.

6.12.5 Summary of the regression analysis of the Average Allocated High and Low ESG, E, S, and G Portfolio with new ESG, E, S, and G factor

The findings show that the GMB factor was significant at a 1% significance level and negative in all the four Low portfolios, ESG, E, S, and G, which successfully explained more of the variation in the returns. The same was true for the High E and G portfolios, which had significant and positive exposure to GMB. Since the GMB factor was significant at a 1% level in all the respective portfolios, we suggest that this is sufficient evidence to support H5 and therefore accept it.

In Part 1, section 6.5, we found evidence that the Low ESG, E, and S portfolios had significant and negative alphas indicating that the portfolios yielded abnormal negative returns. This section aimed to explain this negative alpha using a sixth factor, the GMB factor based on ESG, E, S, and G scores. Our analysis findings provided significant evidence that the GMB factor reduced or diminished the alpha in the Low ESG, E, and S portfolios. Further, significant evidence supports that the GMB factor reduced the alpha in the High E and G portfolios. These findings support a positive relationship between ESG, E, and S scores and financial performance, which makes us accept our H1, H2, and H3 hypothesis.

7 Discussion

Chapter 7 will present the main findings of our analysis and discuss the key takeaways with the literature review presented in Chapter 3.

We structure the discussion in the following way: Firstly, the results from Chapter 6, Part 1, will be discussed. Then, a discussion of Part 2 will follow, and lastly, we will interpret the results from part 3. We will discuss all parts with the relevant statements and hypotheses mentioned throughout the paper.

Table *20*:

Summary of Estimated Alphas and exposure to GMB factor from Part 1-3 analysis. Statistically significant? (Stat. sig?) Indicates whether the value is significantly different from zero at the 1%, 5% or 10% level.

	PART 1: AVERAGE ALLOCATED, FAMA FRENCH (2015) FIVE-FACTOR MODEL		PART 2: YEARLY ALLOCATED, FAMA FRENCH (2015) FIVE-FACTOR MODEL		PART 3: AVERAGE ALLCOATED, CONSTRUCTED SIX- FACTOR MODEL			
	Alpha	Stat. sig?	Alpha	Stat. sig?	Alpha	Stat. sig?	GMB	Stat. sig?
ESG Screening								
High	-0,0020	✗	0,0020	✗	-0,0020	✗	0,0598	✗
Low	-0,0093	✓	0,0048	✗	-0,0070	✓	-0,8082	✓
E Screening								
High	0,0009	✗	0,0023	✗	0,0002	✗	01951	✗
Low	-0,0113	✓	0,0050	✗	-0,0080	✗	-0,8423	✓
S Screening								
High	-0,0020	✗	0,0041	✓	-0,0020	✗	0,0085	✓
Low	-0,0037	✓	0,0012	✗	-0,0026	✓	-0,3916	✓
G Screening								
High	-0,0030	✗	0,0016	✗	-0,0030	✗	0,6320	✓
Low	-0,0086	✓	0,0022	✗	-0,0086	✓	-0,6053	✓

7.1 Average Allocated High and Low ESG, E, S, and G portfolios

This section discusses the main findings from the Fama and French (2015) five-factor regression analysis on the Average Allocated High and Low ESG, E, S, and G portfolios from part 1.

The analysis found a positive and insignificant alpha in the High E portfolio. Further, we find negative and insignificant alphas for the High ESG, S, and G portfolios. We find no significant implications of a positive abnormal return in any high portfolios. Therefore, we cannot determine the relationship between the High ESG, E, S, or G scores and financial performance. These results contradict the findings of Verheyden, Eccles, Feiner, and Partners (2016). They found that the specific risk introduced by ESG screening is more than offset by the excess risk-adjusted return.

We found a negative and significant alpha for the Low ESG, E, S, and G screened portfolios. These results indicate that all the Low ESG, E, S, and G scoring portfolios consistently underperform the market. Thus, we find statistical evidence to accept the H1, H2, H3, and H4 hypotheses. Furthermore, these findings support evidence of a positive relationship between the Low ESG, E, S, or G scores and financial performance. In Part 3, we attempted to explain this underperformance using the sixth factor. This attempt would align with Larsen

(2019), who states that the ESG scores will impact the long-term financial returns. Due to the negative and significant alpha in the Low ESG, E, S, and G portfolios, the financially motivated investor would prefer to short sell this portfolio to acquire abnormal returns.

7.2 Yearly Allocated High and Low ESG, E, S, and G portfolios

This section discusses the main findings from the Fama and French (2015) five-factor regression analysis on the Yearly Allocated ESG, E, S, and G portfolios in part 2.

We find a positive and significant alpha in the High S portfolio in analysis part 2. This finding implies that a High S portfolio generates an abnormal return that the Fama and French (2015) five-factor model cannot explain. This observation is in line with the results of Allouche and Laroche (2014), who found that corporate social responsibility is strongly related to financial performance on average. Furthermore, we find positive and insignificant alphas in the High ESG, E, and G portfolios. These findings support our theory that High ESG, E, S, and G performance outperforms the market. Furthermore, this observation is supportive of Friede et al. (2015), who find that approximately 90% of studies find a non-negative relationship between ESG and financial performance. However, the alpha for the High ESG, E, and G portfolios is not significant. Hence, we cannot conclude that a positive relationship exists between ESG, E, and S scores and financial performance.

The Low portfolio generates insignificant and positive alphas for all four ESG, E, S, and G portfolios. These results align with Lueg et al. (2021). They found a curvilinear relationship between corporate social responsibility and financial performance.

The analysis provides evidence that the S screened portfolio yields a significant positive alpha in the High portfolio. This result implies that the S portfolio generates an abnormal return that the five factors cannot explain. Thus, this outperformance can be explained by its high S score, which is supportive of a long investment strategy in the High S portfolio. Our findings also support that the High ESG, E, and G portfolios generate a positive alpha, which indicates that the investor may be rewarded for going long in these portfolios. However, these findings are not statistically significant. As a result, our findings provide statistical evidence to support H3, but not H1, H2, and H4.

7.3 Average Allocated High and Low ESG, E, S, and G portfolios with New ESG, E, S, and G Factor

This section discusses the main findings from the six-factor regression analysis on the Average Allocated ESG, E, S, and G portfolios in Part 3. The six-factor model builds on the Fama and French (2015) five-factor model by adding the GMB factor. The GMB factor is constructed based on ESG, E, S, and G scores and is used respectively on the ESG, E, S, and G screened portfolios.

The analysis finds that the GMB factor is significant at a 1% level in the High E and G portfolios and Low ESG, E, S, and G portfolios. As the GMB factor can successfully explain the variation in returns in six of the eight portfolios, we argue that this is supportive evidence for accepting hypothesis H5. The null hypothesis is whether the variation in ESG, E, S, and G portfolio excess return can be explained by their ESG, E, S, and G scores.

The six-factor regression analysis builds on the findings in Part 1, section 6.5, as both studies are conducted on the Average Allocated Portfolio. When adding a sixth factor, the alphas in the High and Low ESG and E portfolios are reduced.

Further, the Low ESG, E, and G portfolios are significant in Part 1 and Part 3. However, the significant alpha in the Low S portfolio from the Part 1 analysis is no longer significant in the Part 3 analysis.

This observation indicates that adding the sixth factor can significantly explain some positive alphas in the High E and G portfolios and Low ESG, E, and S portfolios found in Part 1. These findings imply that the high E and G scores may explain the positive excess return in the High E and G portfolios. Furthermore, the negative excess return in the Low ESG and E, and S portfolios may be explained by their low ESG, E, and S scores. These are solid supportive arguments for accepting our hypotheses H1, H2, and H3.

Although there is weak evidence that a long-short strategy will provide the investor with abnormal returns, there are strong indications that a short strategy on the Low ESG, E, and S portfolio can be a profitable investment strategy. To conclude the Part 1 and Part 3 analysis viewed in combination, we find supporting evidence to the hypotheses H1, H2, H3, and H5.

8 Conclusion

This thesis has contributed to the academic debate on the relationship between ESG, E, S, and G scores and financial performance. We have examined this relationship for the Nordic countries, in the period from 2006 to end of 2021. In our analysis, ESG scores and financial data have been collected from Thomson Reuters Eikon Datastream. The analysis has aimed to answer the following research question:

What is the relationship between ESG, E, S, and G scores and financial performance in the Nordics?

This study has analyzed if the investor can gain abnormal returns from integrating ESG, E, S, and G scores in the investment decisions, by going long in the High or going short in the Low portfolios. The analysis was conducted by constructing two portfolios for each ESG, E, S, and G screening methods. The High portfolios consist of the highest-scoring constituents in each category. The Low portfolio consists of the lowest scoring constituents in each category. Hence, the portfolio construction process has been based on the ESG, E, S, and G scores.

Our analysis was divided into three parts. In Part 1 and Part 2, we used the Fama and French (2015), five-factor model to investigate our hypotheses. The difference between Part 1 and Part 2 is that the Part 1 portfolios are allocated based on the constituents' average ESG, E, S, and G scores and the average market capitalization. In the Yearly Allocated portfolios, the portfolios are allocated once every year. The reallocation is based on the constituents' ESG score in the prior year and the market capitalization in the present year. In Part 3 of our analysis, we build on the Fama and French (2015) five-factor model by adding a factor that we call “Good minus Bad” (GMB). The GMB is a sixth factor constructed and tested based on the ESG, E, S, and G categories. In Part 3 of our analysis, we still use the same Average Allocated portfolio as in Part 1.

Although we do not find a clear tendency that the High portfolios outperform the market, we find a tendency that the Low portfolios underperform the market in Part 1. This statement is based on the negative alphas in the ESG, E, S, and G screened Average Allocated portfolios. The most severe underperformance is found in the Low E screened portfolio. The low-scoring ESG, E, S, and G portfolios underperform the market. Resultantly, we presume a positive relationship between ESG, E, S, and G scores and financial performance, and that low ESG, E, S and G scores results in a lower financial performance in the Nordics.

This Part 1 analysis provided weak, insignificant, but supportive evidence of outperformance in the High ESG, E, S and G portfolios. When using the Yearly Allocated portfolios in Part 2, the significant negative alpha diminishes in the Low ESG, E, S and G portfolios. However, a positive alpha is detected in the High portfolios, where the alpha is significant in the High S screened Yearly Allocated portfolio. The significant and positive alpha in the High portfolio indicates that the investor will benefit from investing in a High S portfolio. Thus, we presume a positive relationship between S and financial performance, and that a high S score results in a higher financial performance in the Nordics. Evidence also imply that the investor may benefit from investing in the High ESG, E, and G portfolios, but this analysis cannot determine this.

In Part 3, we build on the Fama and French (2015) five-factor model and add the sixth-factor GMB. The GMB factor was significant at a 1% level in six out of eight portfolios. By adding the GMB factor based on the ESG, E, S, and G scores, we aimed to explain the alphas found in Part 1. The alpha in Part 1 is the excess return that the five-factor model did not explain. The Part 3 analysis find that the alpha is reduced or diminished in the High and Low ESG and E portfolios and the Low S and High G portfolios. The diminished or reduced alpha indicates that the alphas found in Part 1 can explain the portfolio's exposure to the sixth factor, hence their ESG, E, S, or G score. We evaluate that this evidence strongly indicates a positive relationship between ESG, E, S, and G scores and the financial performance in the Nordic countries because the excess returns can be explained by their ESG, E, S and G scores.

In the Yearly Allocated portfolios, we found evidence of outperformance of the market in the High S portfolio, indicating that the investor may yield abnormal financial returns by going long in a High S portfolio. Furthermore, we find a significant negative alpha in the Low Average Allocated ESG, E, S, and G portfolios, where the alpha fully or partially diminished in the ESG, E, and S portfolios with the six-factor model. The results indicates that the investor can yield abnormal financial returns by short-selling the Low ESG, E, and S portfolios as there is a positive relationship between ESG, E, S, and G scores and financial performance in the Nordics.

9 Quality Criteria

A high validity means that there is a connection between the measuring instrument and the purpose of which it is being used (Carmines & Zeller, 1979). We have chosen Refinitiv Eikon, Asset 4 to gather data for historical stock performance, market capitalization, and ESG scores. Our reason for choosing this source for data is that they are large and reputable databases specializing in financial data and ESG reporting. There is yet to be one common framework for reporting ESG performance, which leads to a lack of consensus among ESG score distributors. Therefore, we believe that the size and widespread of Refinitiv Eikon leads to a high validity in the ESG data. On the other side, our analysis is dependent on all constituents to have ESG data from 2005 to 2020 and historical stock data from 2006 to 2021. We have 99 constituents in the Nordic region that fulfill these requirements. The 99 constituents are only a selection of constituents listed on the Nordic stock exchanges, and therefore the findings may not be representable for the entire market. The limited number of constituents may cause selection bias in the dataset. There might be characteristics that dominate the pool of constituents. For instance, some industries may have incentives or available resources to invest in ESG scores. This bias would prevent us from finding implications that apply to the entire market.

Reliability will tell us if the analysis findings will be the same if the analysis is conducted multiple times (Carmines & Zeller, 1979). The reliability evaluates if there are random mistakes or systematic errors in the dataset. The historical stock data is from Refinitiv Eikon, Asset4, one of the most widespread data distributors globally. Therefore, we assume that our data is reliable without systematic errors for this research. Since we are using the same distributor for the ESG scores and historical stock data, we find that the results are comparable. However, the results from various studies on the same topic will depend on the timeframe, data distributors, and framework. Therefore, it can be more challenging to compare our findings to existing literature. Furthermore, we discussed the Criticism of rating agencies under section 5.2.7, where we found that different rating agencies will provide separate ratings for the same constituent. Therefore, we would expect a variation in the results if we used another rating agency.

The adequacy determines if it reasonable to draw the conclusions that we draw (Olsen & Pedersen, 2003). The analysis aimed to define the relationship between the ESG, E, S, and G scores and financial performance in the Nordic countries. In Part 1 of our analysis, we found that the low-scoring ESG, E, S, and G portfolios had an abnormally low financial performance. In Part 3, the abnormal excess return was explained or partially explained by the GMB factor. The abnormal low returns indicate a positive relationship between low ESG, E, S, and G scores and low financial performance. Furthermore, our analysis in Part 1 and Part 2 found a positive relationship between S screening and financial performance. The high-scoring S portfolio had higher financial performance, and the low scoring S portfolio had a lower performance. To improve the robustness of the analysis, we have divided the analysis into three parts, where each part varies in portfolio allocation or model specification, intending to best determine the relationship between ESG, E, S, and G and financial performance in the Nordics. Since 2005 the number of constituents in the Nordic market with ESG scores has increased. We could have chosen a shorter time frame and had more constituents in our pool, and this method may have led to our results being different.

10 Perspectives

This thesis investigates the relationship between ESG, E, S, and G performance scores and financial performance in the Nordics. Further, this investigation is done based on self-constructed portfolios. However, this thesis conclusion is limited by the refinements made in the delimitation. These refinements have narrowed our investigation area to meet the thesis criteria and to what we found relevant to answer the research question. It is essential to emphasize the methodical decisions made in the thesis and that the conclusion and the overall structure are formed based on these decisions. Hence, it would be interesting to reflect on other methodologies and perspectives that could be made in the present thesis and, in turn, how these considerations could affect our result and conclusion.

In the delimitation, a demarcation was made for the choice of the market. Further, more specified delimitations within the market have been done to narrow the data selection. Accordingly, it would be interesting to extract data from another market and test our assumption and see if the results are comparable to our findings for the Nordic market. For instance, England would be interesting to compare against as both are in Europe, and the ESG reporting is sufficient within the country. It would be interesting to see if the ESG, E, S, and G scores have a more considerable influence on the stock performance than in the Nordics. Furthermore, if so, which of the pillars would have the most influence? This way, one can pinpoint what drives the stock performance in different markets regarding responsible investing.

Further, it would be interesting to select a market, for instance, the emerging market. However, the rating agencies more recently started ESG reporting on this market. Thus, it would be difficult to extract enough ESG, E, S, and G data on the respective market, provoking diversification issues. However, investigating this market would give different results, which would be interesting to compare against our findings.

Further delimitations have been made as we are only looking at the stock market, which delimits us from other sustainable investments, which could affect our conclusion. For instance, by implementing the bond market, we would have green obligations that could diversify our constructed portfolios and influenced the risk-adjusted return. The same applies to implementing the real estate market and includes climate-friendly properties. Consequently, it would be interesting to see how portfolios constructed on different green asset classes performed and, in turn, whether the "greener" the asset class, the better the risk-adjusted return.

In terms of the present thesis stock data, we delimit us to only using constituents in the Nordic stock exchanges, defined in section 5.2.1, in the selected period. Implementing additional exchanges in the Nordics would have given us a broader dataset and hence a lower probability of a selection bias in terms of large-cap constituents, as mentioned in section 5.2.2. This implementation could strengthen the thesis quality as it would match the Fama and French (2015) factor data as this is constructed on large-cap and small-cap constituents. Consequently, this could result in a higher R-squared as the model would fit our data better and explain more of the variation in the excess return by the five factors. However, implementing other exchanges would decrease the probability of extracting sufficient historical ESG, E, S, and G data as ESG reporting was minimal on small-cap constituents dating back to 2005.

We are applying the ESG, E, S, and G performance scores from Refinitiv Eikon, Asset4, and, hence, delimited against other rating agencies. However, implementing several rating agencies would be of little value as the rating agencies have different methodologies, and thus the scores are based on different metrics. Using another rating provider would have given us different portfolio constructions, and therefore our results and conclusion might be different from what we have arrived at in this present thesis. Thus, it would have been interesting to do as Halbritter & dorfleitner (2015). They compared results from different rating providers to emphasize the difference in stock performance due to the choice of ESG rating agencies with new literature from regions that have historically been underrepresented in ESG research.

Lastly, we chose to apply the Fama and French (2015) five-factor model to see whether the variation in ESG, E, S, and G portfolio excess return can be explained by their ESG, E, S, and G scores, respectively. However, it could have been interesting to see how the results would have been affected by using another model. For instance, would we have seen an exposure to the momentum factor if we had applied Carhart's (1997) four-factor model, instead? Another exciting model would have been the Fama and French (1993) three-factor model to see whether the three original factors could have explained the portfolio's excess return any better.

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12 Appendix

Annex 1

Chapter 6.1

Company Name	Identifier	Country of Exchange	Industry

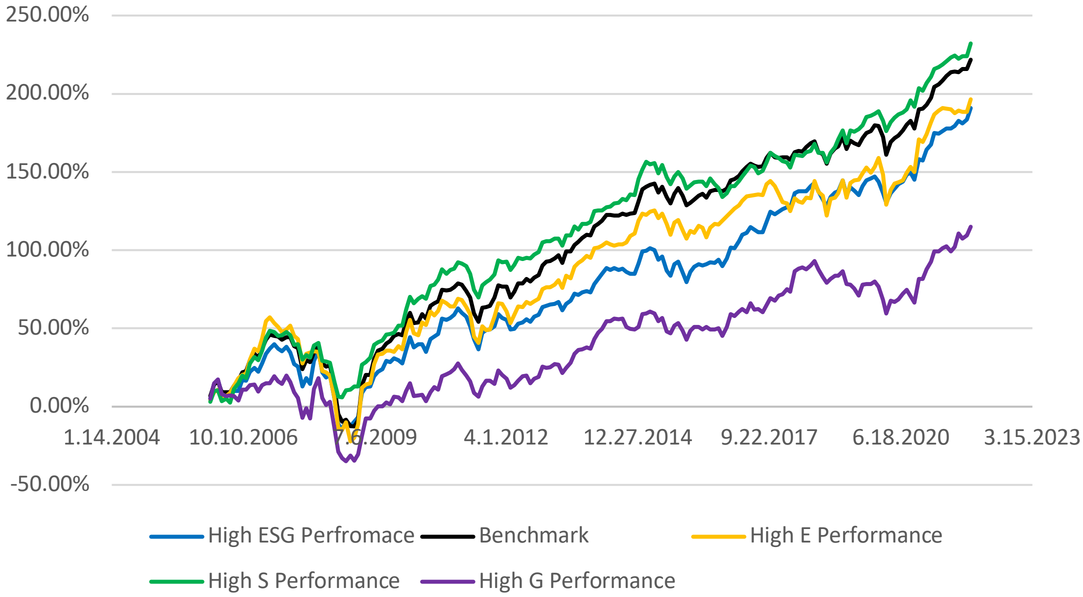
Novozymes A/S	NZYMB	Denmark	healthcare
Carlsberg A/S	CARLb	Denmark	Consumer staples
Novo Nordisk A/S	NOVOb	Denmark	healthcare
DSV A/S	DSV	Denmark	Industrials
Coloplast A/S	COLOb	Denmark	healthcare
Danske Bank A/S	DANSKE	Denmark	financials
FLSmidth & Co A/S	FLS	Denmark	Industrials
AP Moeller - Maersk A/S	MAERSKb	Denmark	Industrials
Vestas Wind Systems A/S	VWS	Denmark	Energy
GN Store Nord A/S	GN	Denmark	healthcare
H Lundbeck A/S	LUN	Denmark	healthcare
Nkt A/S	NKT	Denmark	Industrials
Torm PLC	TRMDa	Denmark	Industrials
Tryg A/S	TRYG	Denmark	financials
Jyske Bank A/S	JYSK	Denmark	financials
Topdanmark A/S	TOP	Denmark	financials
Demant A/S	DEMANT	Denmark	healthcare
Bang & Olufsen A/S	BO	Denmark	Consumer discretionary
EAC Invest A/S	EACI	Denmark	financials
Sydbank A/S	SYDB	Denmark	financials
Nokia Oyj	NOKIA	Finland	communication services
Neles Oyj	NELES	Finland	Industrials
Stora Enso Oyj	STERV	Finland	Materials
UPM-Kymmene Oyj	UPM	Finland	Materials
Wartsila Oyj Abp	WRT1V	Finland	Industrials
Fortum Oyj	FORTUM	Finland	utilities
Outokumpu Oyj	OUT1V	Finland	Materials
Neste Oyj	NESTE	Finland	Energy
Kesko Oyj	KESKOB	Finland	Consumer staples
TietoEVRY Corp	TIETO	Finland	information technology
Cargotec Corp	CGCBV	Finland	Industrials
Konecranes Abp	KCRA	Finland	Industrials
Sanoma Oyj	SAA1V	Finland	Consumer discretionary
Orion Oyj	ORNBV	Finland	healthcare
Kone Oyj	KNEBV	Finland	Industrials
Elisa Oyj	ELISA	Finland	communication services
YIT Oyj	YIT	Finland	Industrials
Nokian Tyres plc	TYRES	Finland	Consumer discretionary
Uponor Oyj	UPONOR	Finland	Industrials
Sampo plc	SAMPO	Finland	financials
Norsk Hydro ASA	NHY	Norway	Materials
Equinor ASA	EQN	Norway	Energy
Orkla ASA	ORK	Norway	Consumer staples
Mowi ASA	MOW	Norway	Consumer staples
Telenor ASA	TEL	Norway	information technology
Yara International ASA	YAR	Norway	Materials

Prosafe SE	PRS	Norway	Energy
Akastor ASA	AKA	Norway	Energy
PGS ASA	PGS	Norway	Energy
TGS ASA	TGS	Norway	Energy
Tomra Systems ASA	TOM	Norway	communication services
Storebrand ASA	STB	Norway	healthcare
Schibsted ASA	SCH	Norway	communication services
Subsea 7 SA	SUB	Norway	Energy
Stolt-Nielsen Ltd	SNI	Norway	Industrials
Dno ASA	DNO	Norway	Energy
Seadrill Ltd	SDR	Norway	Energy
Frontline Ltd	FRO	Norway	Industrials
BillerudKorsnas AB (publ)	BILL	Sweden	Materials
Telefonaktiebolaget LM Ericsson	ERICb	Sweden	communication services
Svenska Cellulosa SCA AB	SCAb	Sweden	Materials
Volvo AB	VOLVb	Sweden	Industrials
AB Skf	SKFb	Sweden	Materials
Atlas Copco AB	ATCOa	Sweden	Industrials
Fabege AB	FABG	Sweden	realestate
Boliden AB	BOL	Sweden	Materials
Swedbank AB	SWEDa	Sweden	financials
Modern Times Group MTG AB	MTGb	Sweden	Consumer discretionary
Elekta AB (publ)	EKTAb	Sweden	healthcare
Telia Company AB	TELIA	Sweden	communication services
Castellum AB	CAST	Sweden	realestate
Electrolux AB	ELUXb	Sweden	Consumer discretionary
Skandinaviska Enskilda Banken AB	SEBa	Sweden	financials
H & M Hennes & Mauritz AB	HMb	Sweden	Consumer discretionary
Swedish Match AB	SWMA	Sweden	Consumer staples
SAS AB	SAS	Sweden	Industrials
Sandvik AB	SAND	Sweden	Industrials
Husqvarna AB	HUSQb	Sweden	Consumer discretionary
Alfa Laval AB	ALFA	Sweden	Industrials
Axfood AB	AXFO	Sweden	Consumer staples
Nordea Bank Abp	NDASE	Sweden	financials
SSAB AB	SSABa	Sweden	Materials
Tele2 AB	TEL2b	Sweden	communication services
Assa Abloy AB	ASSAb	Sweden	Industrials
Holmen AB	HOLMb	Sweden	Materials
Wihlborgs Fastigheter AB	WIHL	Sweden	realestate
Skanska AB	SKAb	Sweden	Industrials
Lundin Energy AB	LUNE	Sweden	Energy
Svenska Handelsbanken AB	SHBa	Sweden	financials
Trelleborg AB	TRELb	Sweden	Industrials
Nobia AB	NOBI	Sweden	Consumer discretionary
Ratos AB	RATOb	Sweden	financials

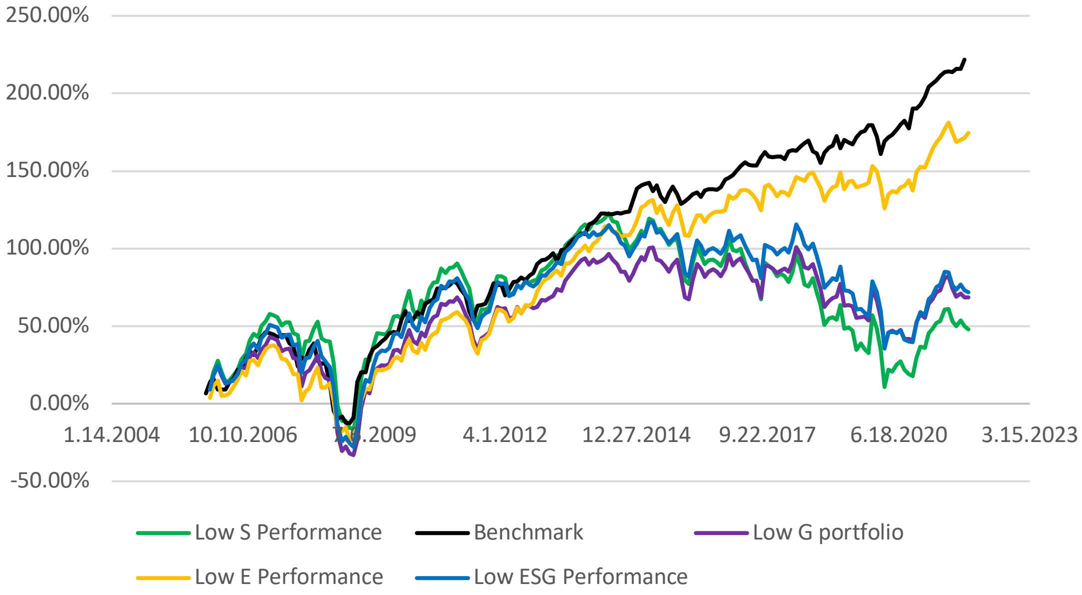
Securitas AB	SECUb	Sweden	Industrials
Getinge AB	GETIb	Sweden	healthcare
Kinnevik AB	KINVb	Sweden	financials
Eniro Group AB	ENRO	Sweden	Consumer discretionary
Hexagon AB	HEXAb	Sweden	information technology
Investor AB	INVEb	Sweden	financials
Industrivarden AB	INDUa	Sweden	financials

Annex 2

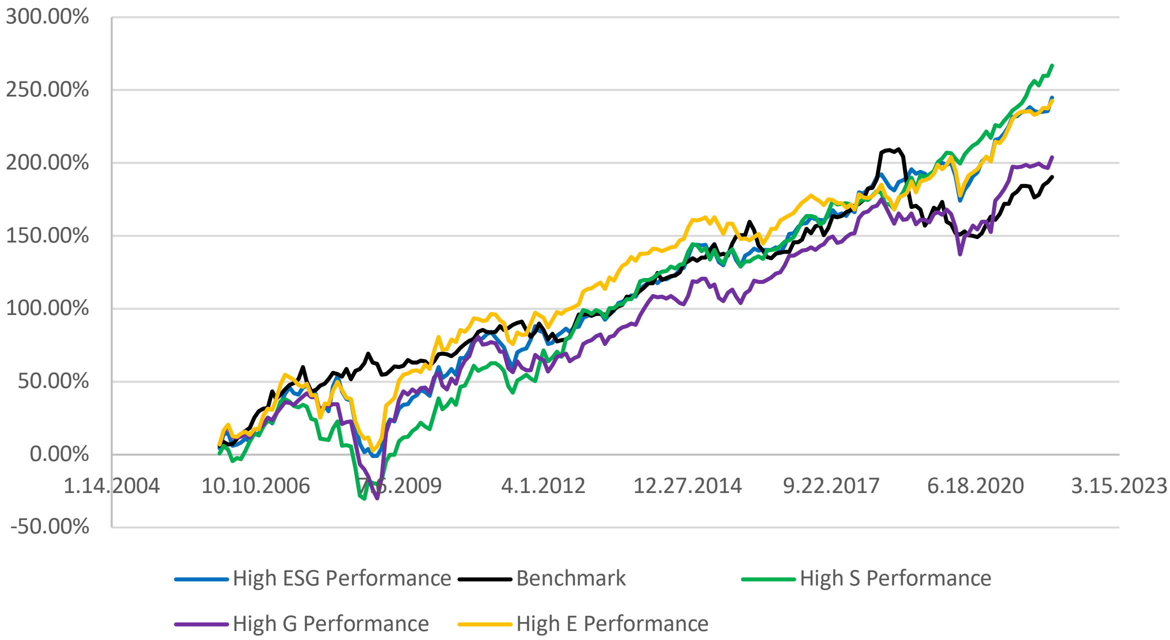
High Average Allocated ESG, E, S, and G Performance against the benchmark



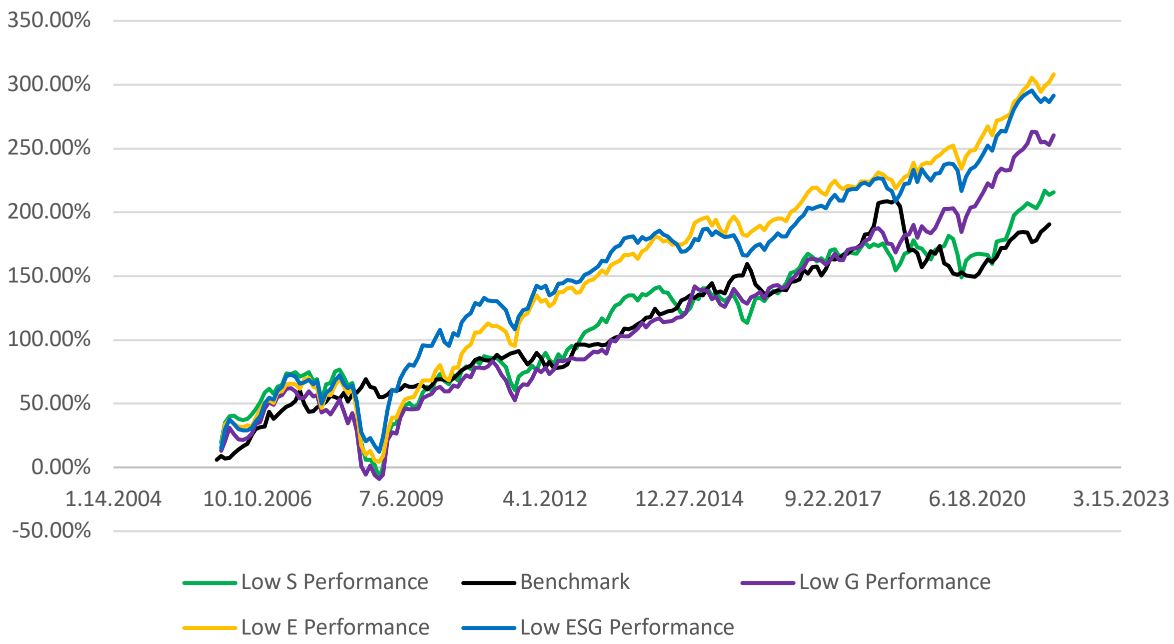
Low Average Allocated ESG, E, S, and G Performance against the benchmark



High Yearly Allocated ESG, E, S, and G Performance against the benchmark



Low Yearly Allocated ESG, E, S, and G Performance against the benchmark



Annex 3

The 2x3 sorting from Fama and French (2015) five-factor model defines the factors SMB, HML, RMW and CMA in the following way:

SMB – SMB is based on the average return of nine small-cap portfolios minus the average return of nine large-cap portfolios:

$$SMB_{\frac{B}{M}} = \frac{1}{3} * (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} * (Big\ Value + Big\ Neutral + Big\ Growth)$$

$$SMB_{OP} = \frac{1}{3} * (Small\ Robust + Small\ Neutral + Small\ Weak) - \frac{1}{3} * (Big\ Robust + Big\ Neutral + Big\ Weak)$$

$$SMB_{INV} = \frac{1}{3} * (Small\ Conservative + Small\ Neutral + Small\ Agressive) - \frac{1}{3} * (Big\ Conservative + Big\ Neutral + Big\ Agressive)$$

HML – HML is based on the average return of two low book-to-market portfolios minus the average return of two high book-to-market portfolios:

$$HML = \frac{1}{2} * (Small\ Value + Big\ Value) - \frac{1}{2} * (Small\ Growth + \ Big\ Growth)$$

RMW – RMW is based on the average return of two robust operating profitability portfolios minus the average return of two weak operating profitability portfolios:

$$RMW = \frac{1}{2} * (Small\ Robust + Big\ Robust) - \frac{1}{2} * (Small\ Weak + \ Big\ Weak)$$

CMA – CMA is based on the average return of two conservative investment portfolios minus the average return of two aggressive investment portfolios:

$$CMA = \frac{1}{2} * (Small\ Conservative + Big\ Conservative) - \frac{1}{2} * (Small\ Agressive + \ Big\ Agressive)$$

Annex 4

PART 1 – AVERAGE ALLOCATED HIGH AND LOW ESG, E, S, AND G PORTFOLIOS

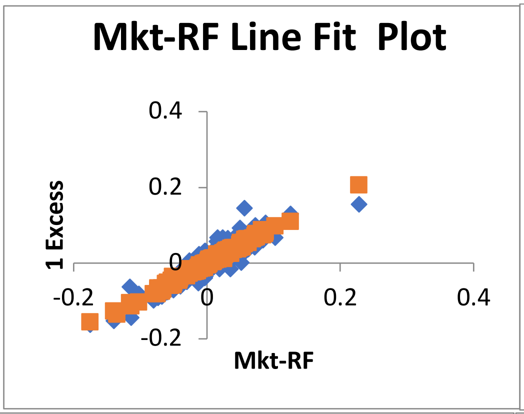
Assumption 5

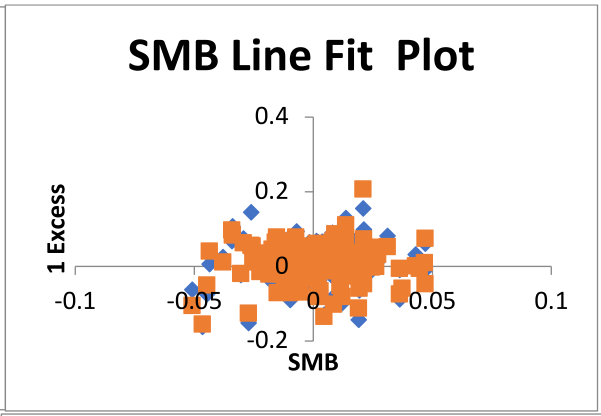
	mktrf	smb	hml	rmw	cma
mktrf	1.0000				
smb	0.1142	1.0000			
hml	0.3779	0.0113	1.0000		
rmw	-0.2136	-0.0783	-0.7764	1.0000	
cma	-0.2703	-0.2369	0.4467	-0.3659	1.0000

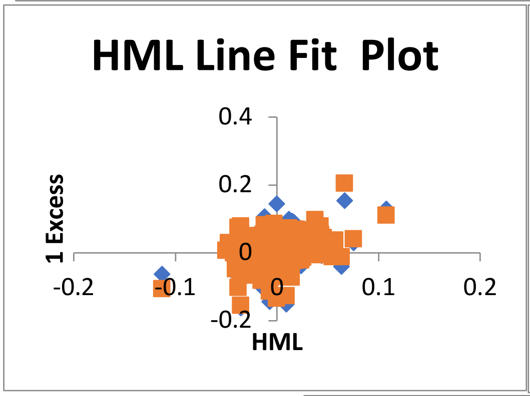
Variable	VIF	1/VIF
hml	3.68	0.272068
rmw	2.61	0.383259
cma	1.85	0.540421
mktrf	1.66	0.604050
smb	1.10	0.912291
Mean VIF	2.18	

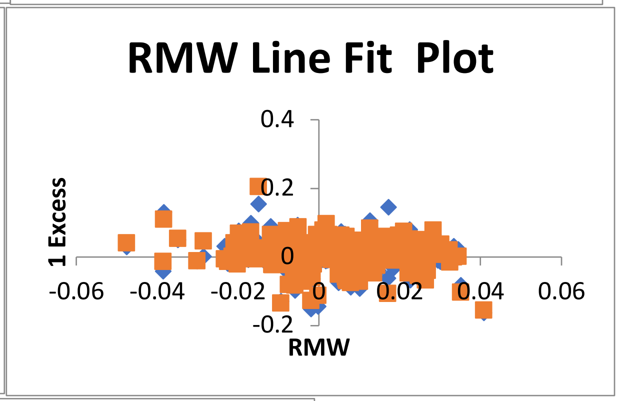
HIGH ESG

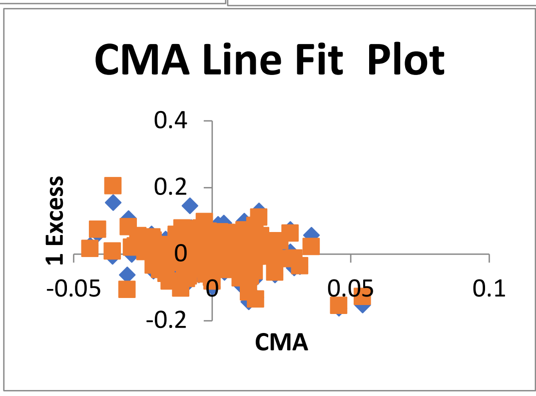
Assumption 1 – Linearity



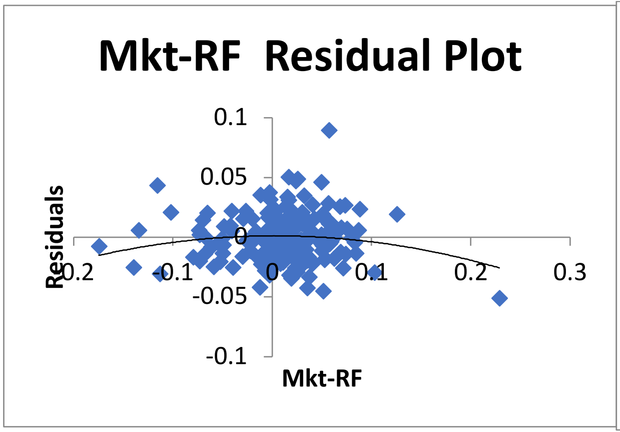


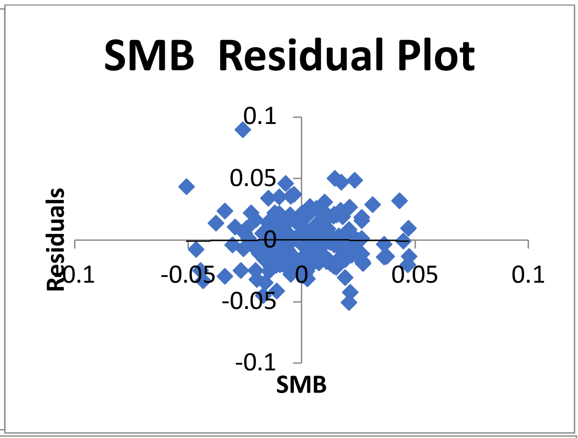


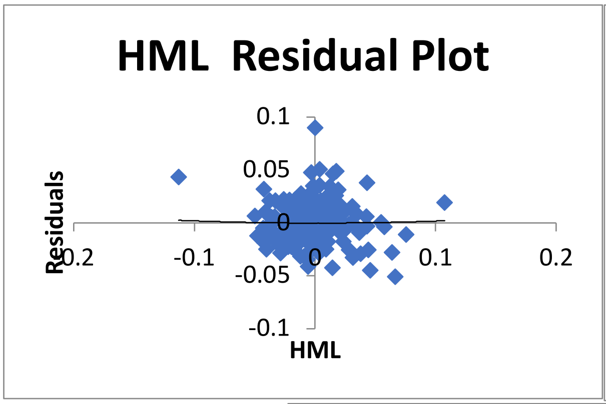


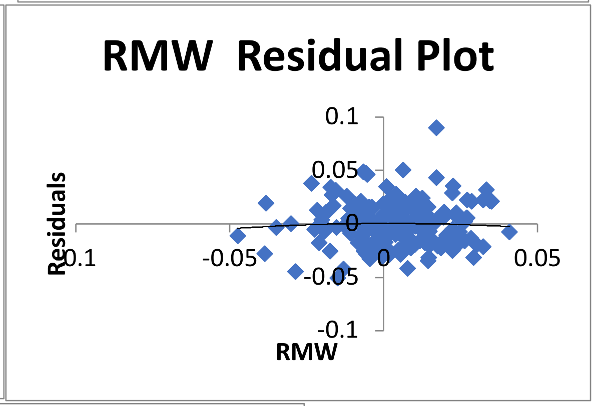


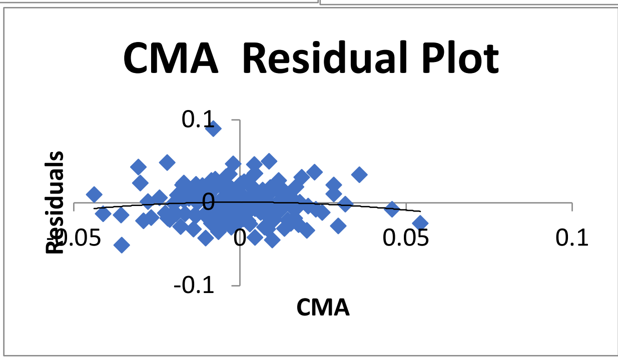
Assumption 2 – Zero conditional mean error





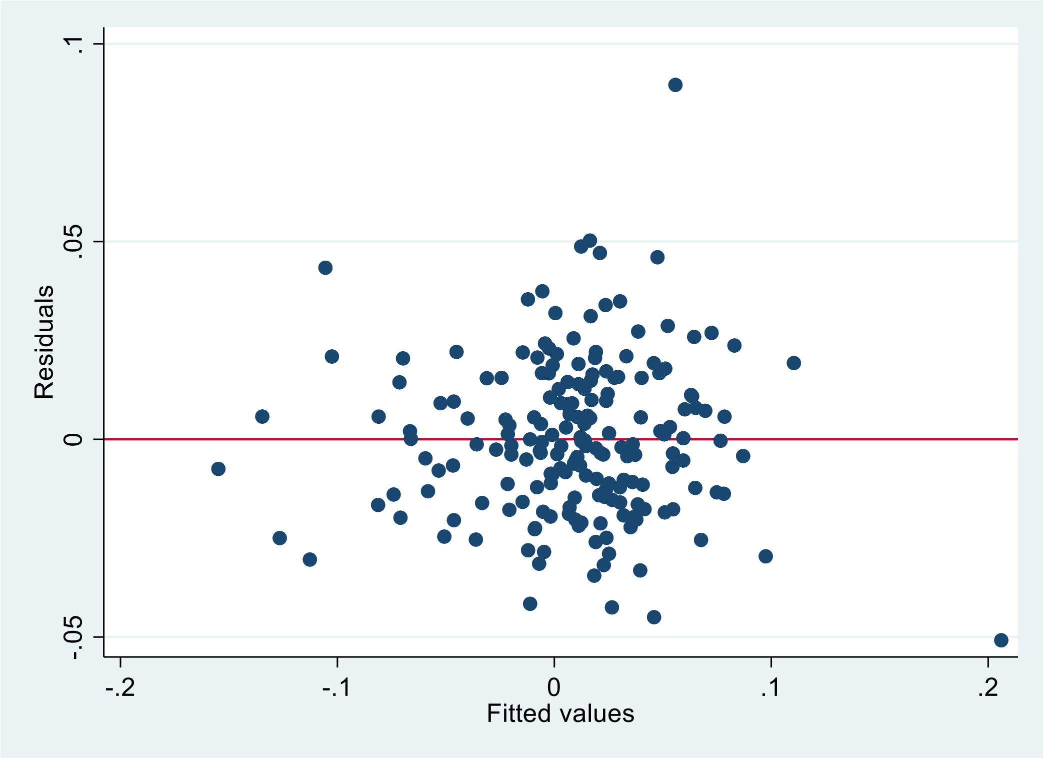






	Mean residuals
High ESG portfolio	9,39642E-19

Assumption 3 – Homoscedasticity

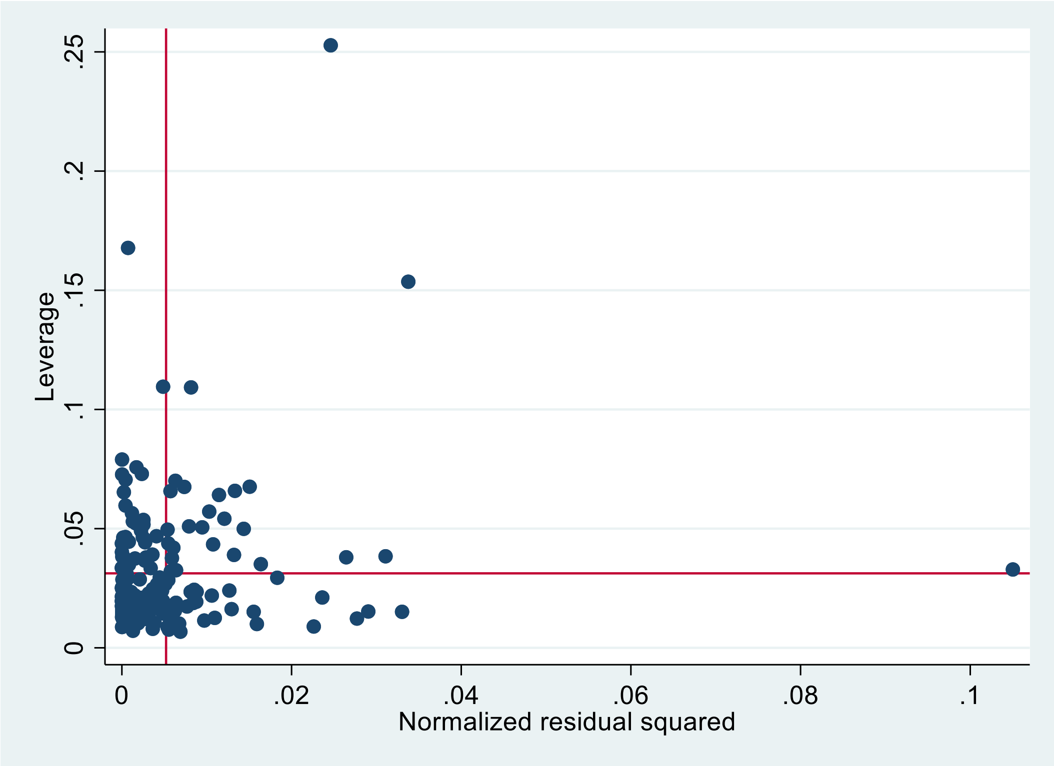


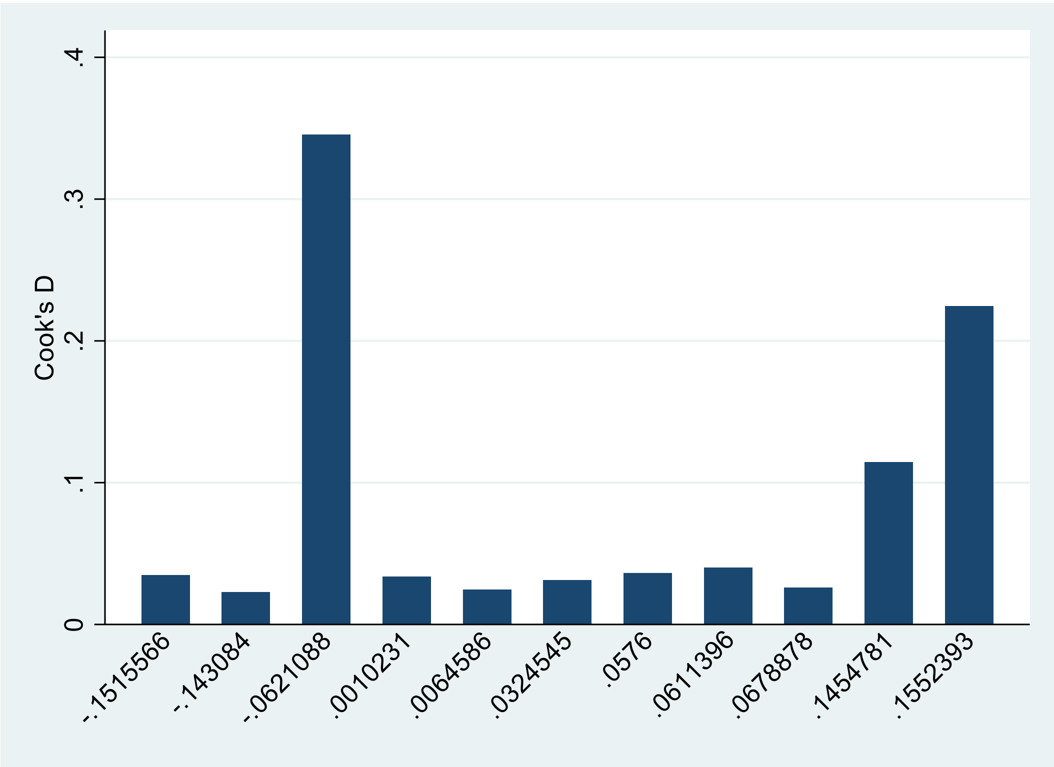

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     6.16
         Prob > chi2  =   0.0131
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     151.78
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8348
                                                Root MSE          =     .02028
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.018605	.0379575	26.84	0.000	.9437229	1.093488
smb	-.0641058	.0996464	-0.64	0.521	-.2606883	.1324767
hml	-.1787864	.1281861	-1.39	0.165	-.431672	.0740991
rmw	.0264126	.1823109	0.14	0.885	-.3332504	.3860756
cma	.3184645	.1434826	2.22	0.028	.035402	.601527
_cons	-.0018749	.0015913	-1.18	0.240	-.0050143	.0012644

Assumption 4 - Large outliers are unlikely





Assumption 5 - No perfect multicollinearity

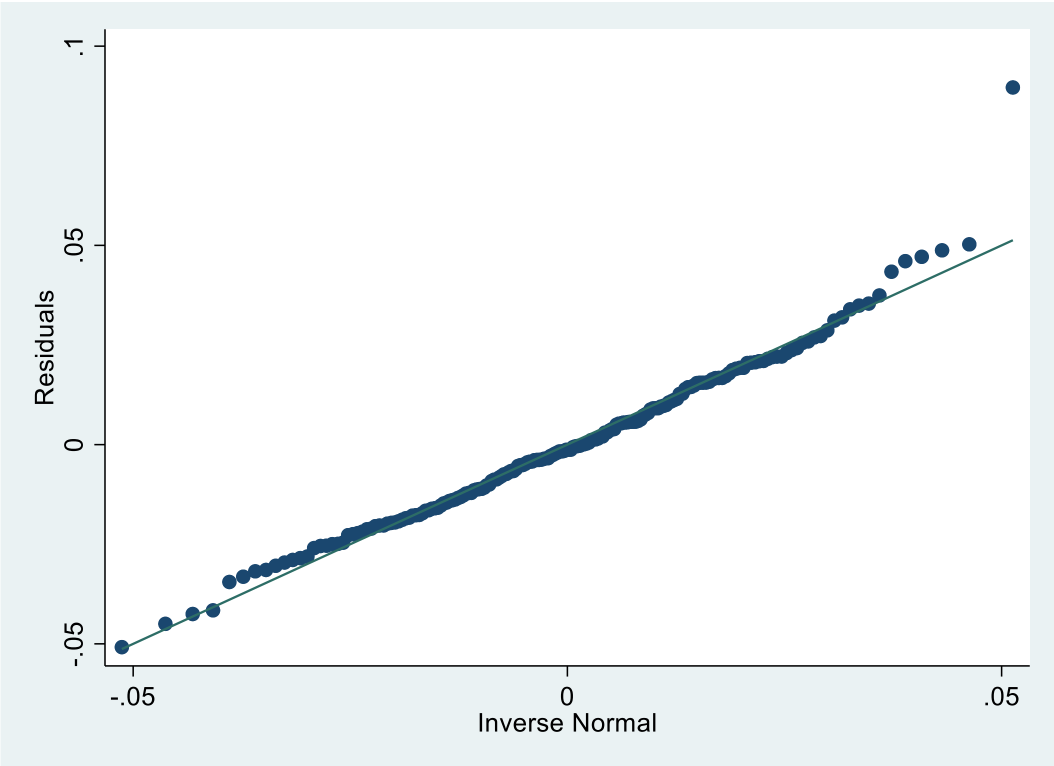
Assumption 6 - No serial correlation

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.512**	**1**	**0.4742**

H0: no serial correlation

Assumption 7 - Normality of Errors

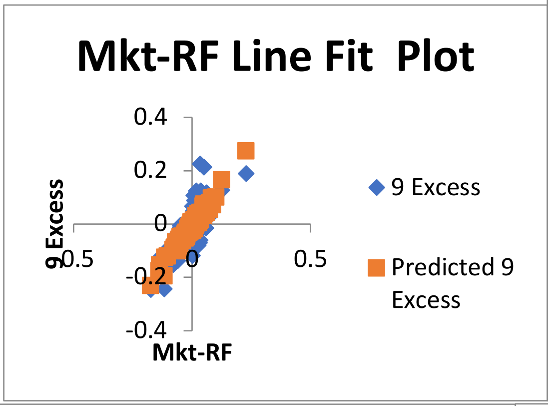


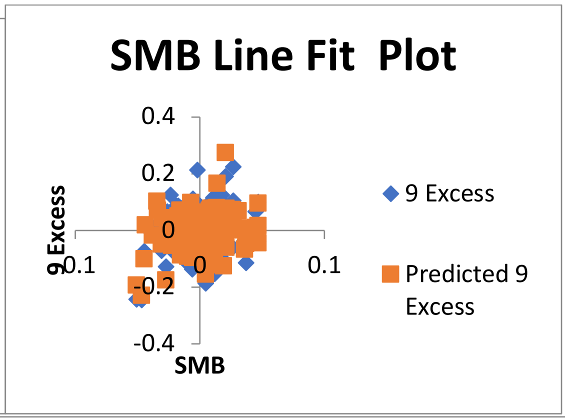
Shapiro-Wilk W test for normal data

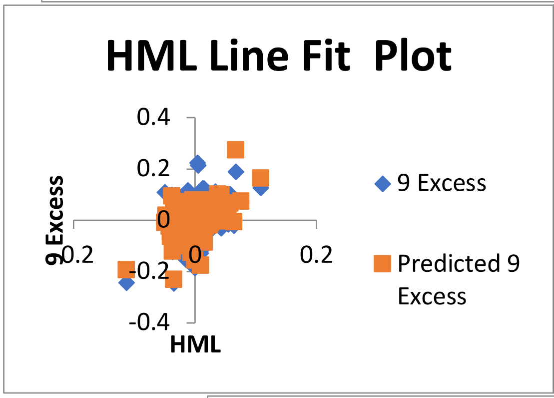
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.97977**	**2.913**	**2.455**	**0.00705**

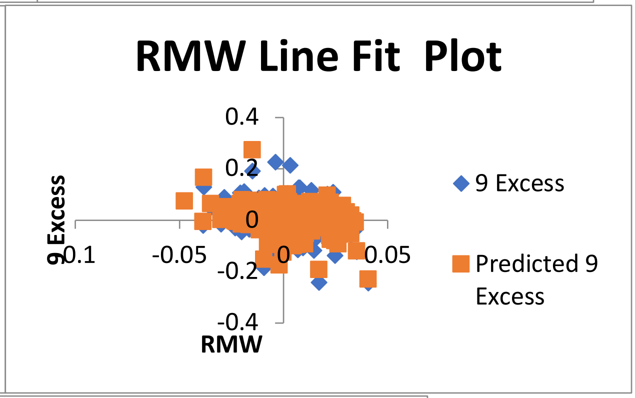
LOW ESG

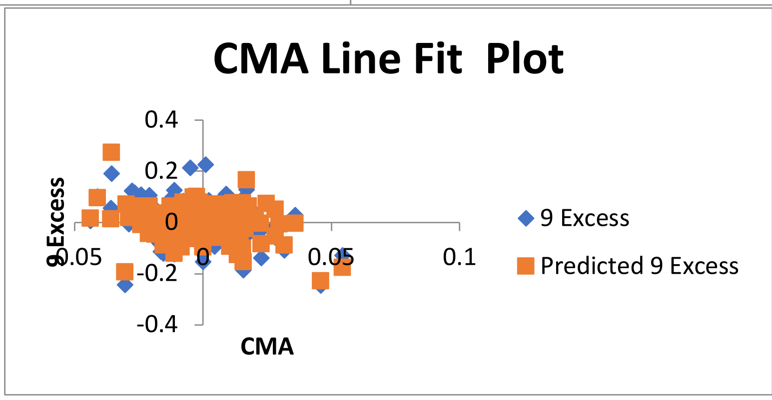
Assumption 1



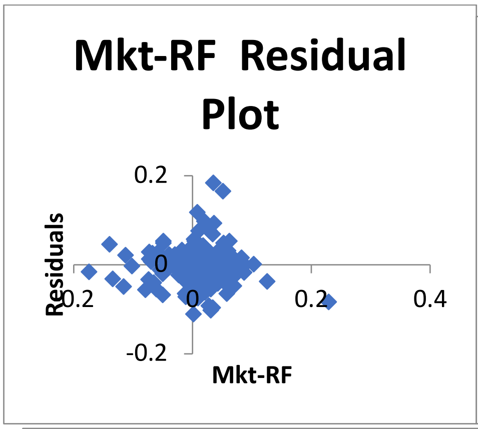


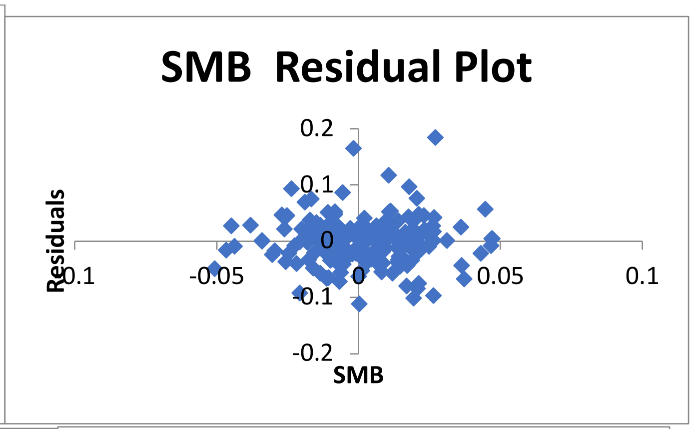


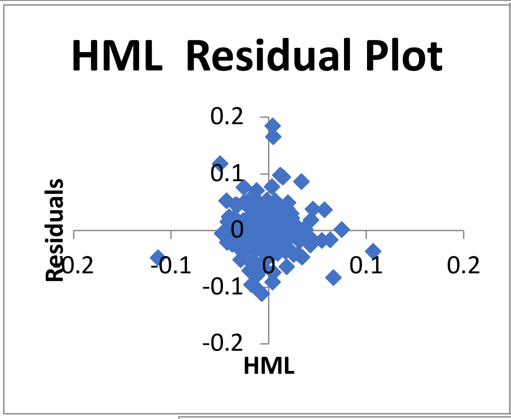


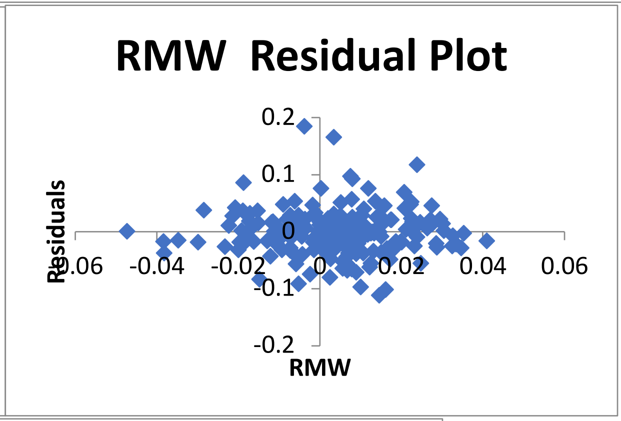


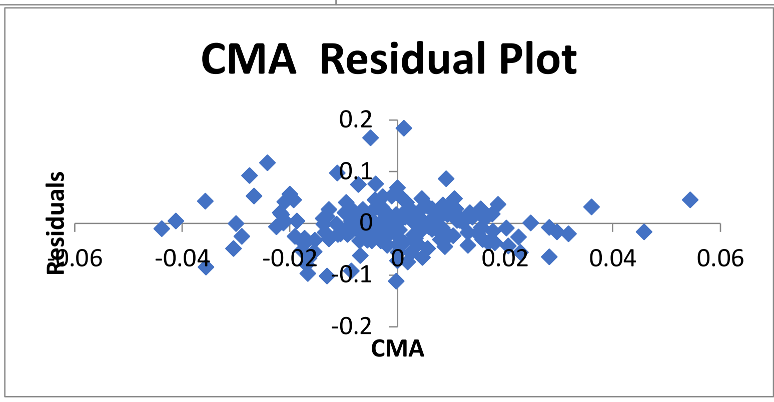
Assumption 2





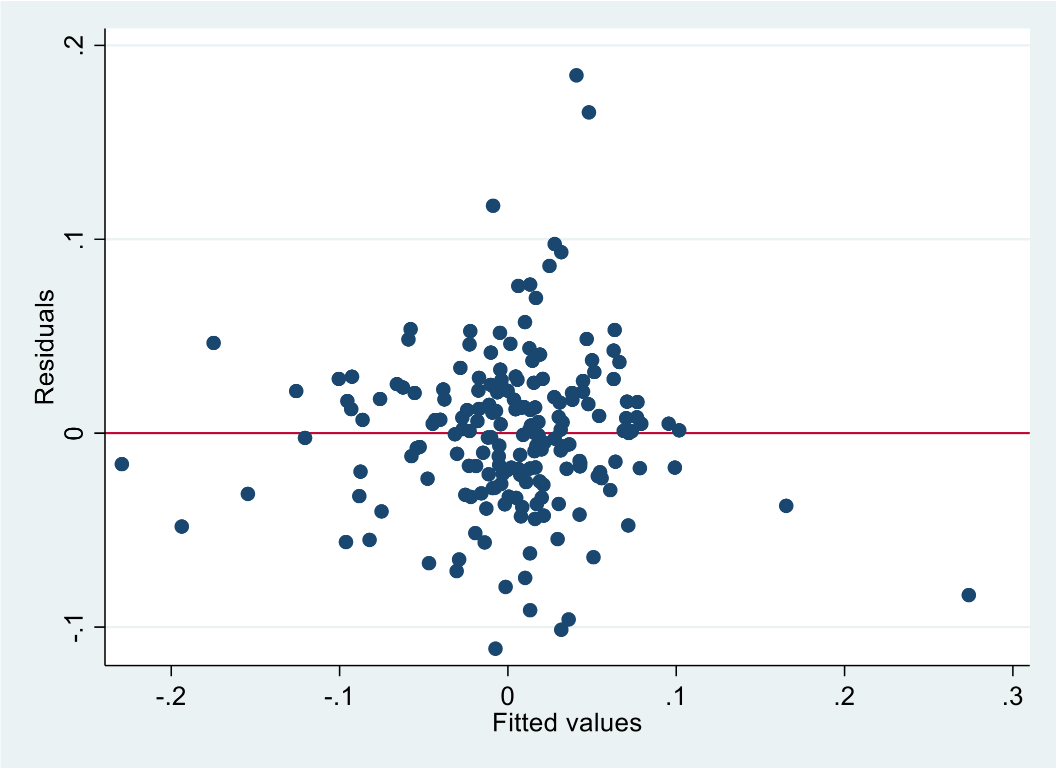






	Mean residuals
Low ESG portfolio	1,8735E-16

Assumption 3

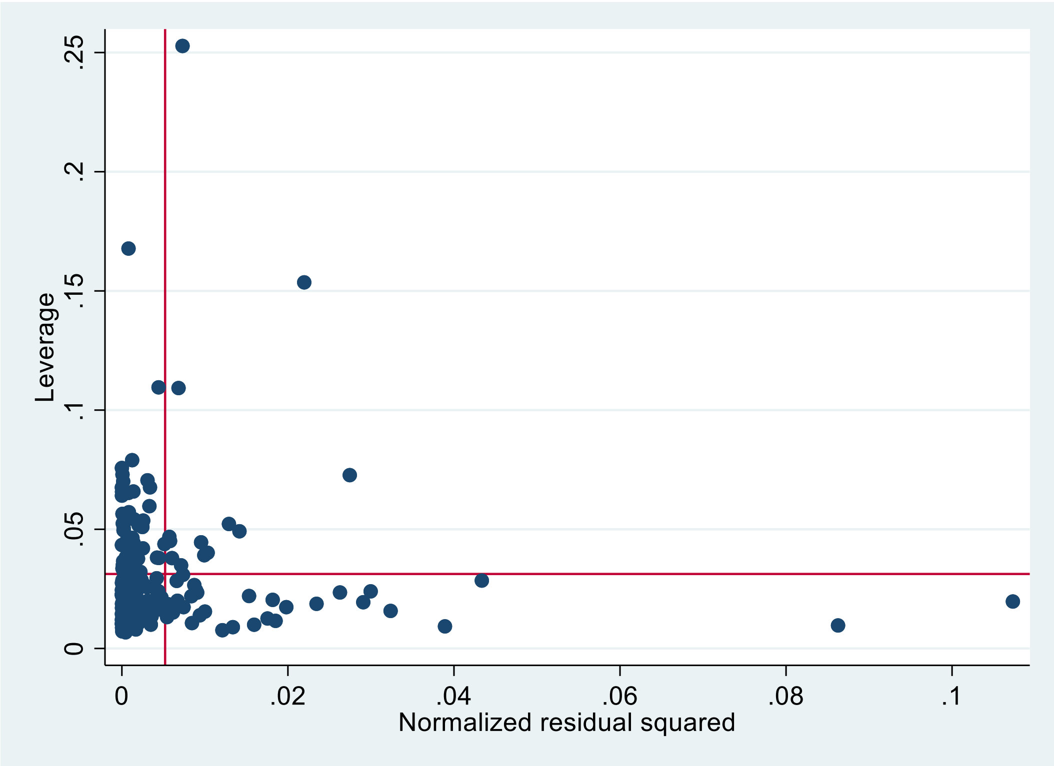


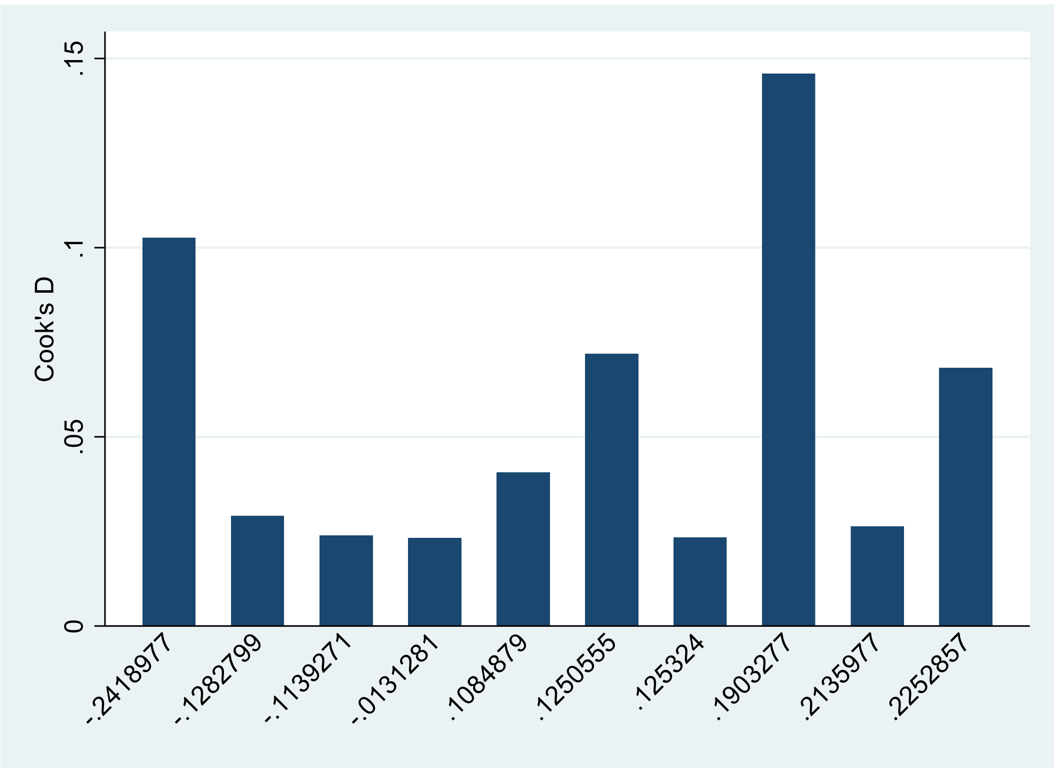

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     4.85
         Prob > chi2  =   0.0277
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      66.46
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6533
                                                Root MSE          =     .04131
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.055839	.0706414	14.95	0.000	.9164775	1.1952
smb	.4380265	.173289	2.53	0.012	.0961619	.7798911
hml	.4372758	.2128746	2.05	0.041	.0173168	.8572347
rmw	.2126268	.2581594	0.82	0.411	-.2966702	.7219237
cma	-.1851189	.2819257	-0.66	0.512	-.741302	.3710642
_cons	-.0092975	.0030375	-3.06	0.003	-.0152899	-.0033051

Assumption 4





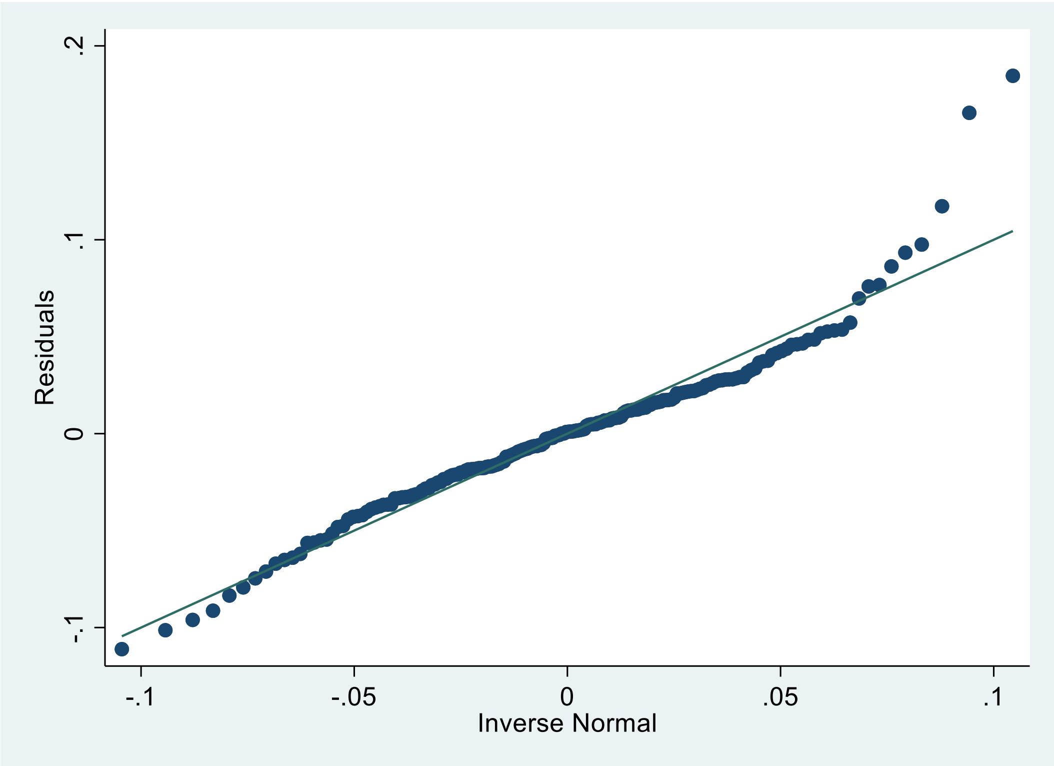
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**3.640**	**1**	**0.0564**

H0: no serial correlation

Assumption 7

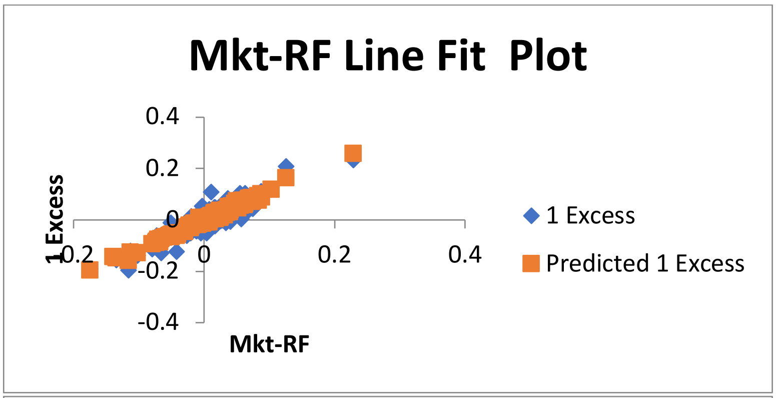


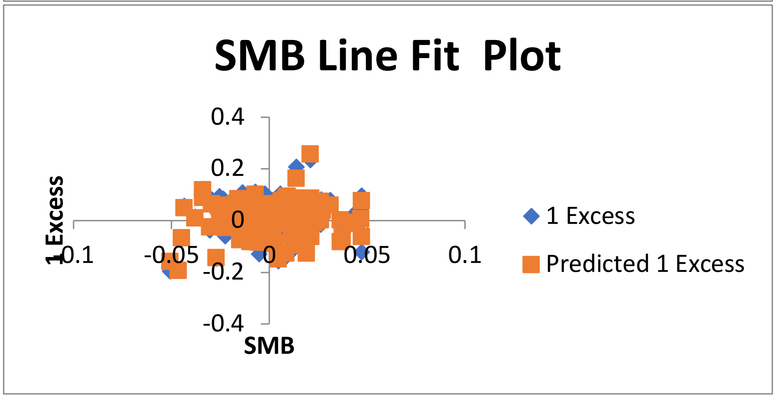
Shapiro-Wilk W test for normal data

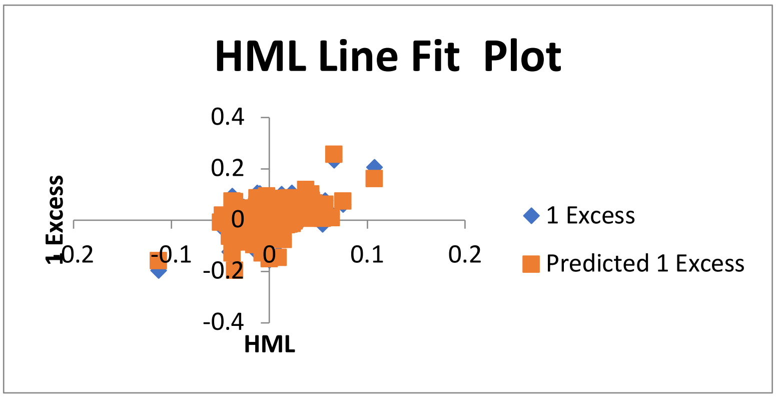
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.95223**	**6.878**	**4.428**	**0.00000**

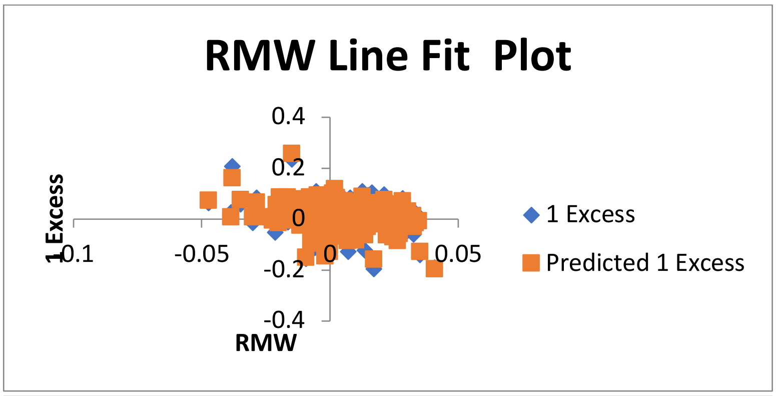
HIGH E

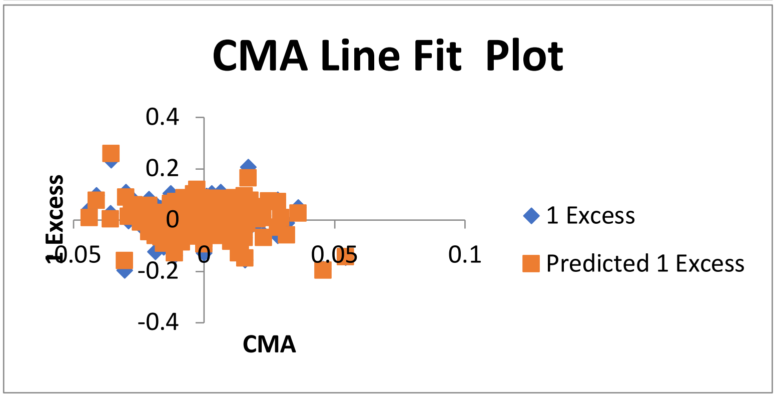
Assumptions 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

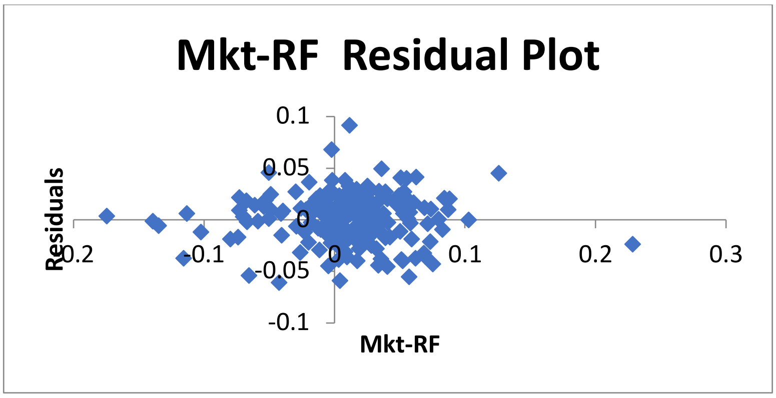

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

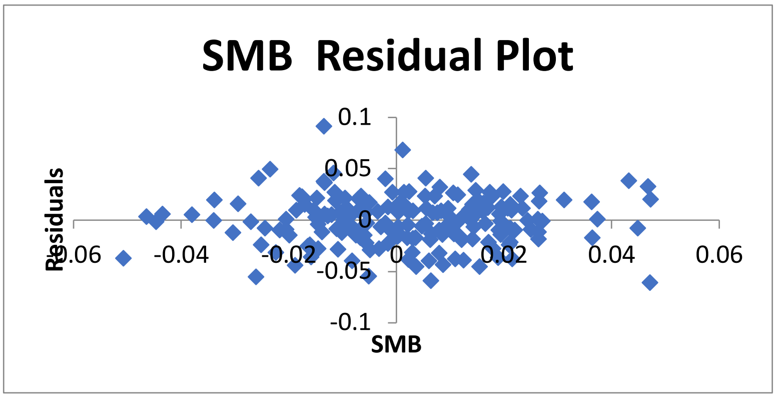

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

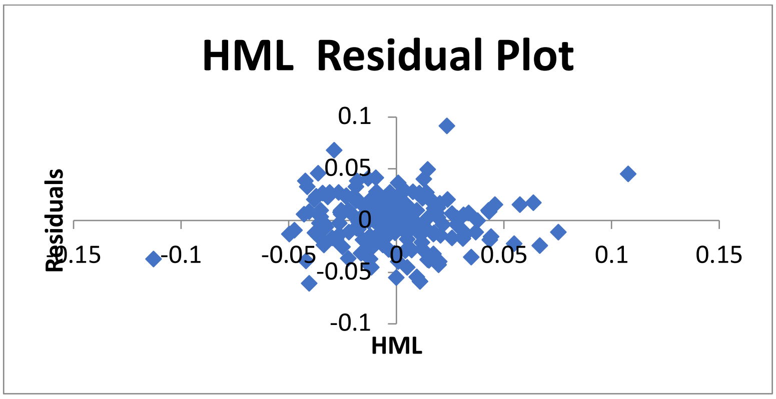


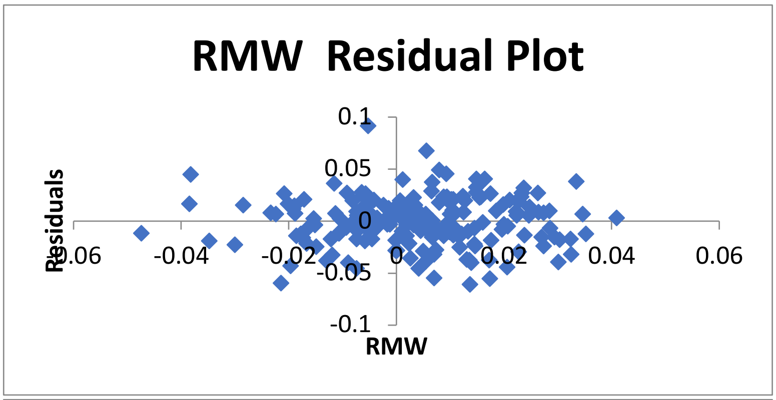


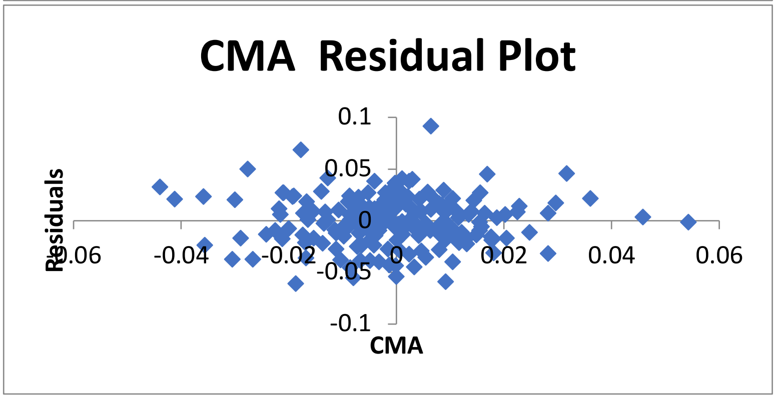
Assumptions 2





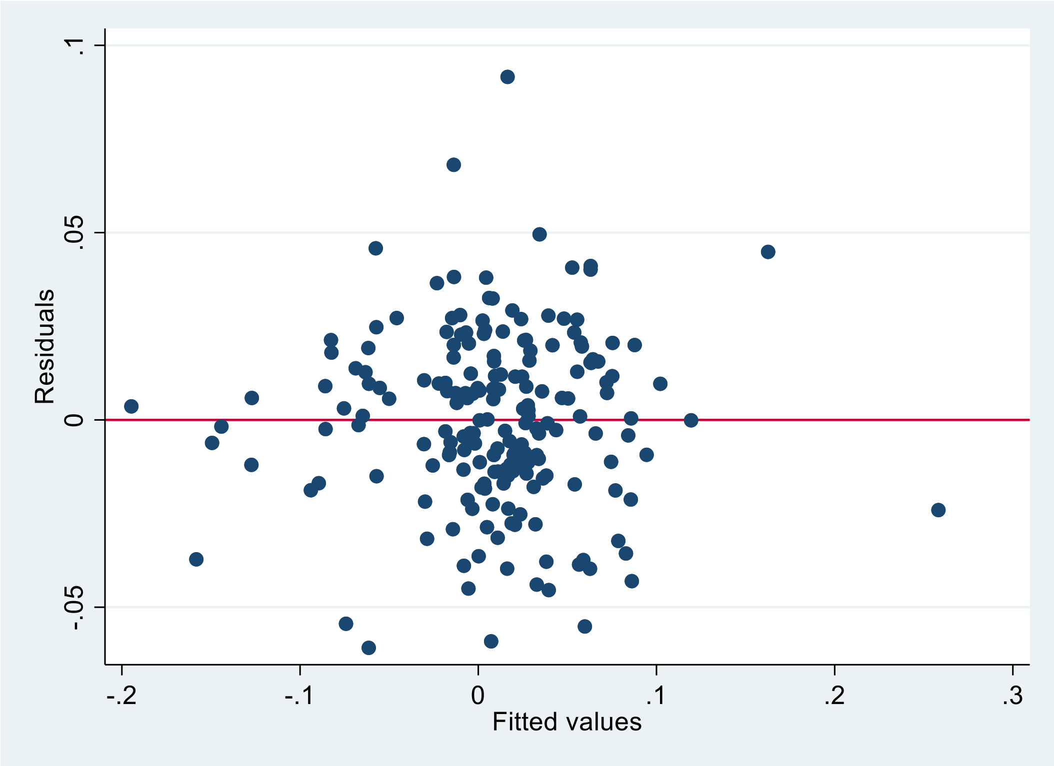






	Mean residuals
High E portfolio	1,78677E-16

Assumptions 3

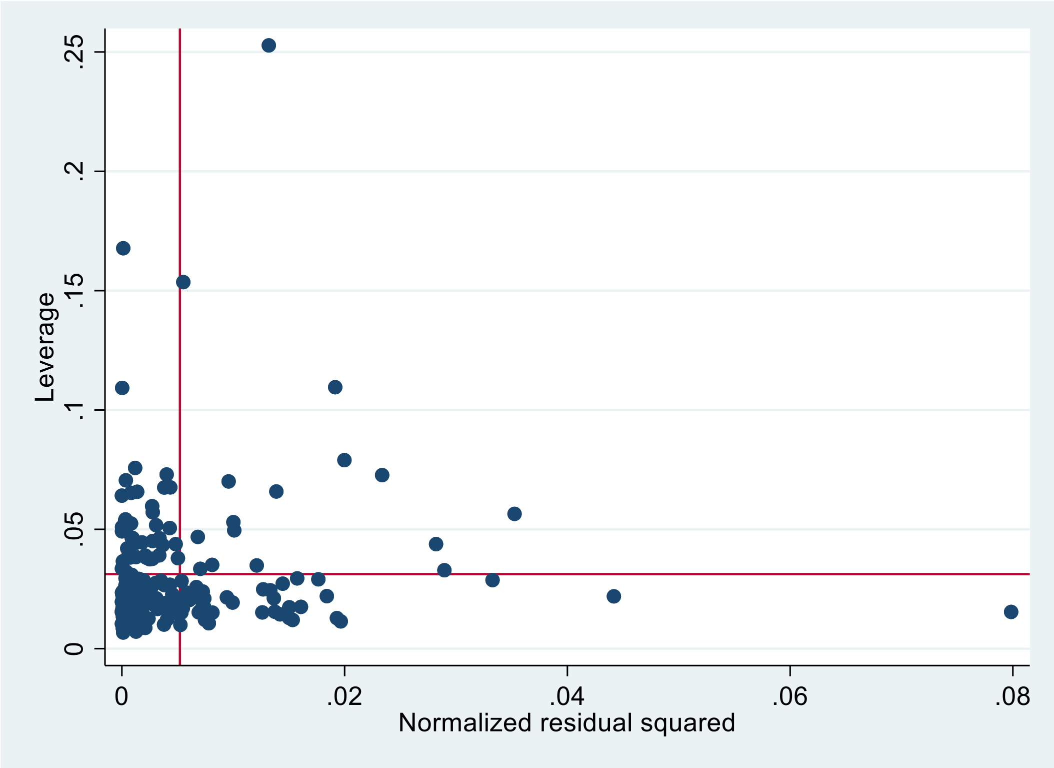


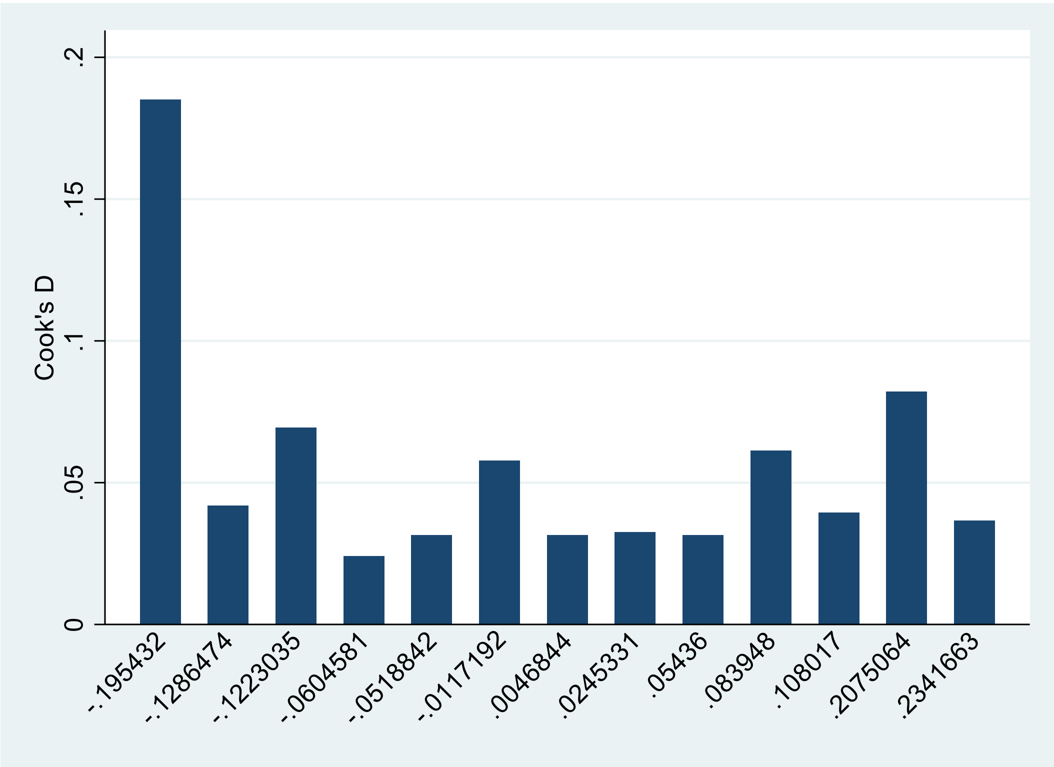

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     0.70
         Prob > chi2  =   0.4043
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     236.11
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8425
                                                Root MSE          =     .02376
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.124562	.0435289	25.83	0.000	1.038688	1.210435
smb	-.00633	.1066054	-0.06	0.953	-.2166411	.2039811
hml	.1649674	.1534143	1.08	0.284	-.1376885	.4676232
rmw	-.0394087	.194042	-0.20	0.839	-.4222148	.3433975
cma	.236783	.1771342	1.34	0.183	-.1126673	.5862333
_cons	-.0019162	.0018798	-1.02	0.309	-.0056247	.0017922

Assumptions 4





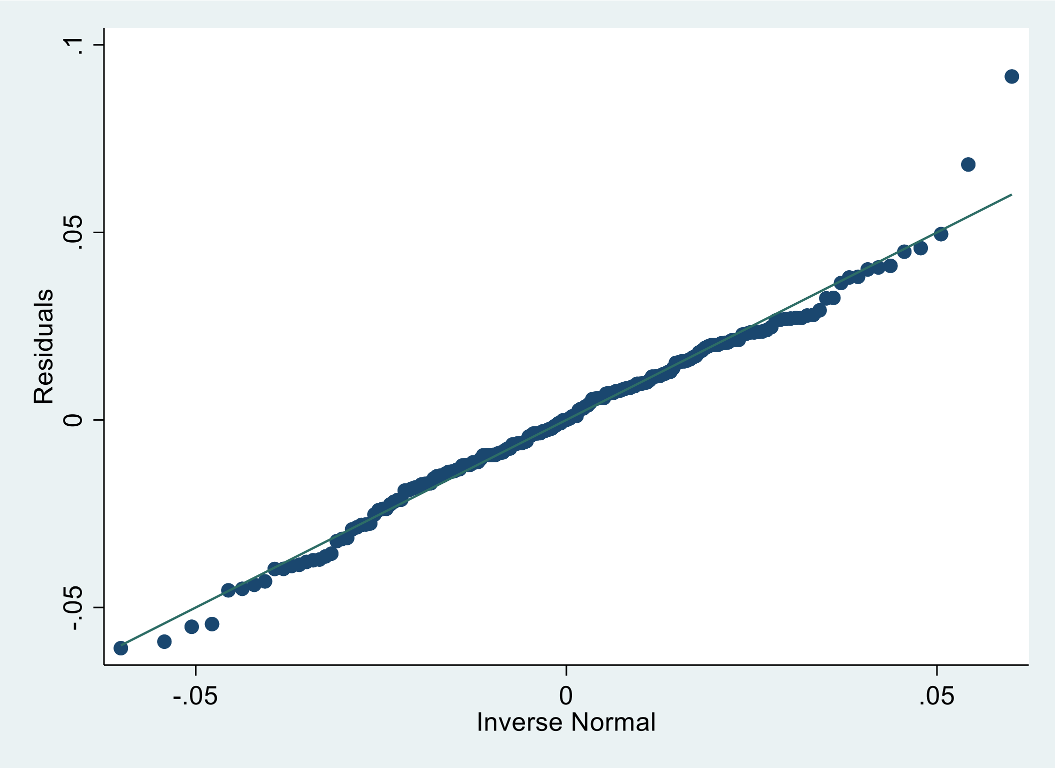
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.001**	**1**	**0.9707**

H0: no serial correlation

Assumptions 7

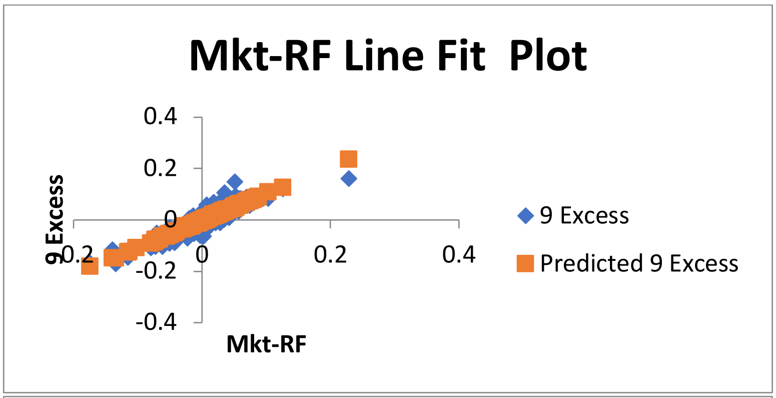


Shapiro-Wilk W test for normal data

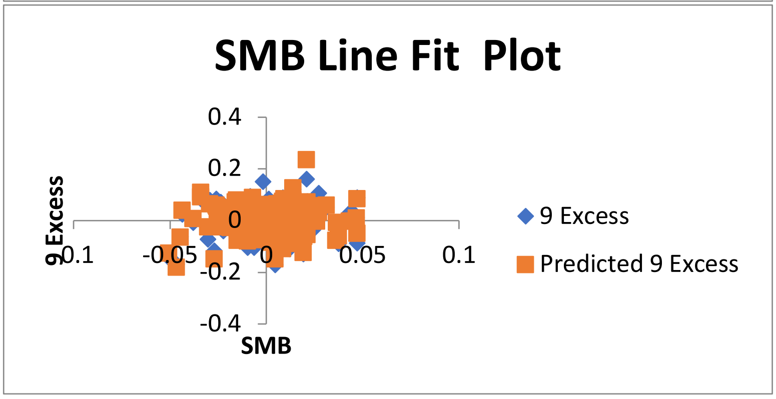
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.98799**	**1.730**	**1.258**	**0.10412**

LOW E

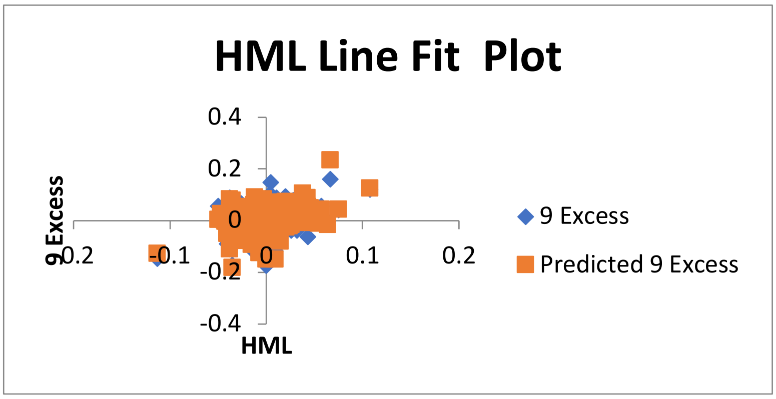
Assumptions 1



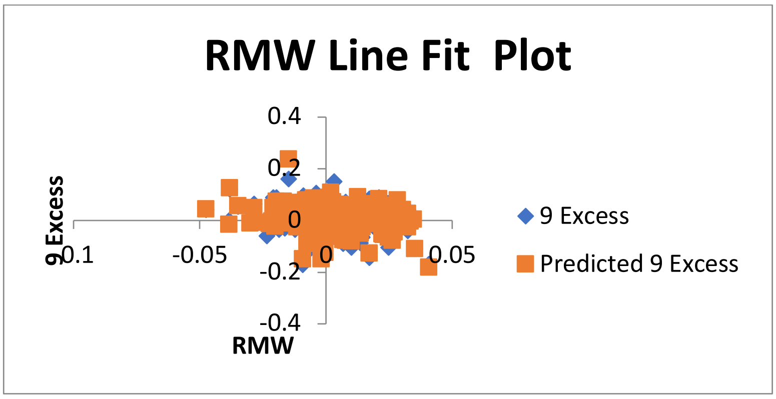
Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

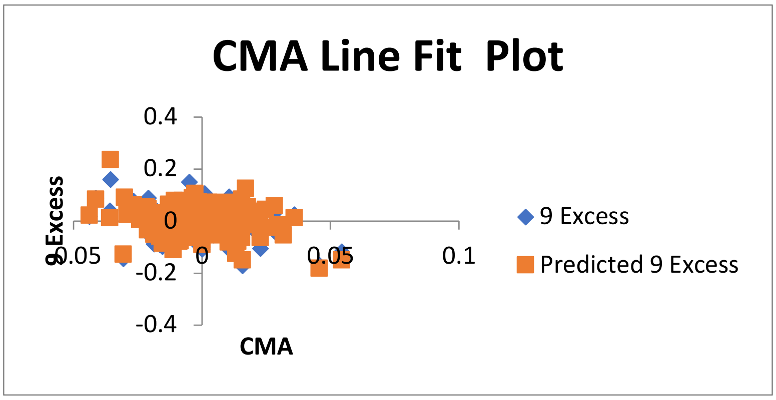


SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

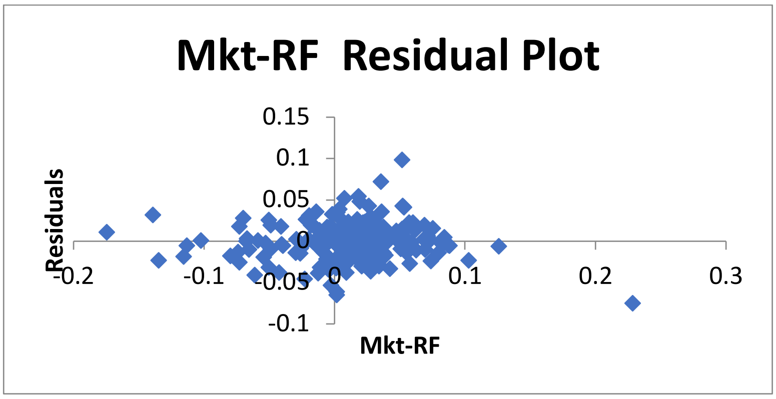


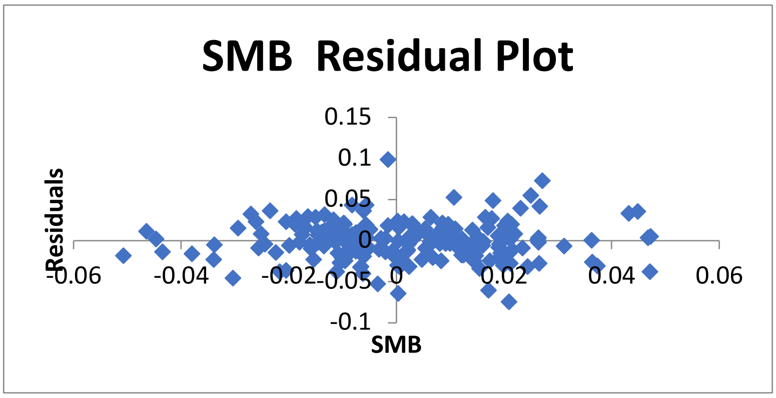
HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

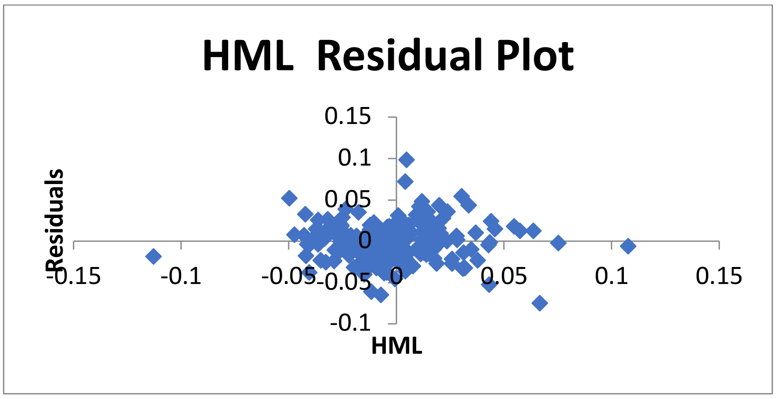


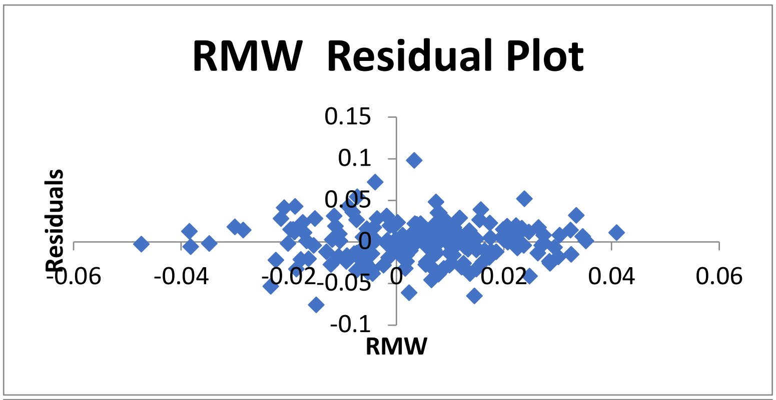


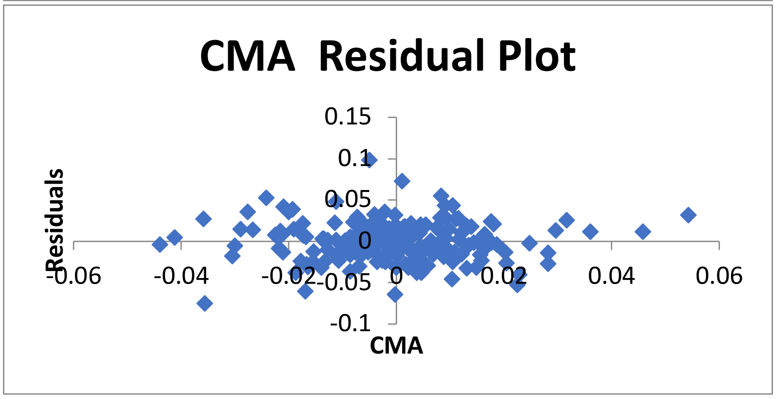
Assumptions 2





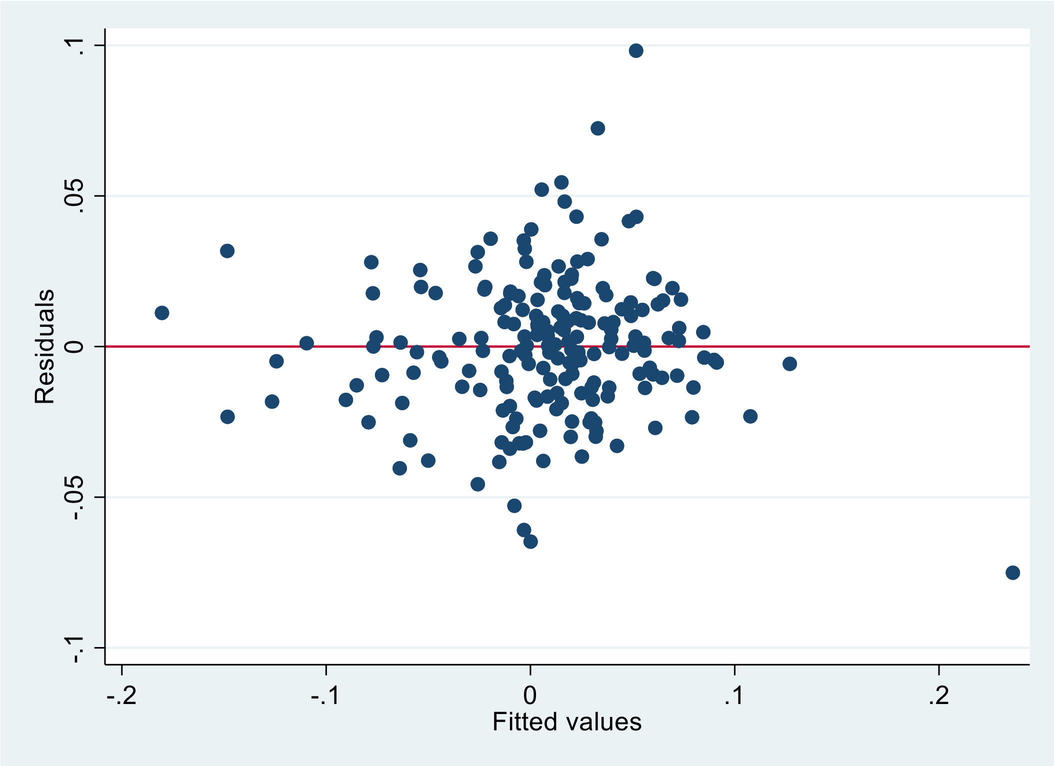






	Mean residuals
Low E portfolio	3,81639E-16

Assumptions 3

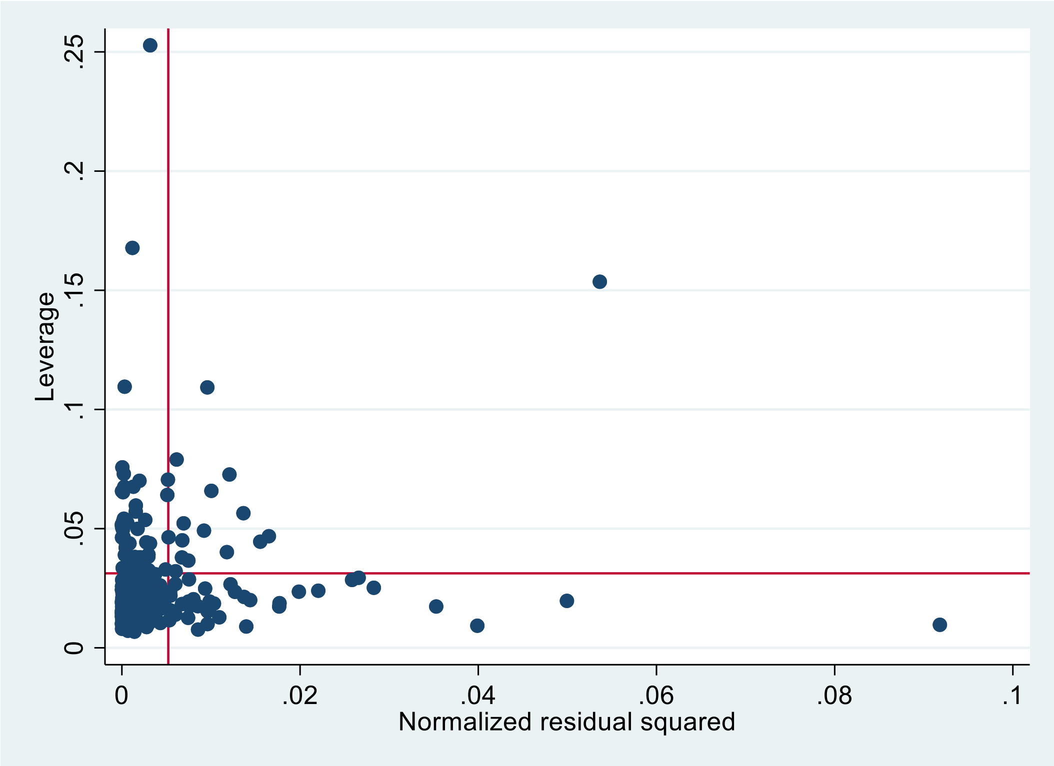


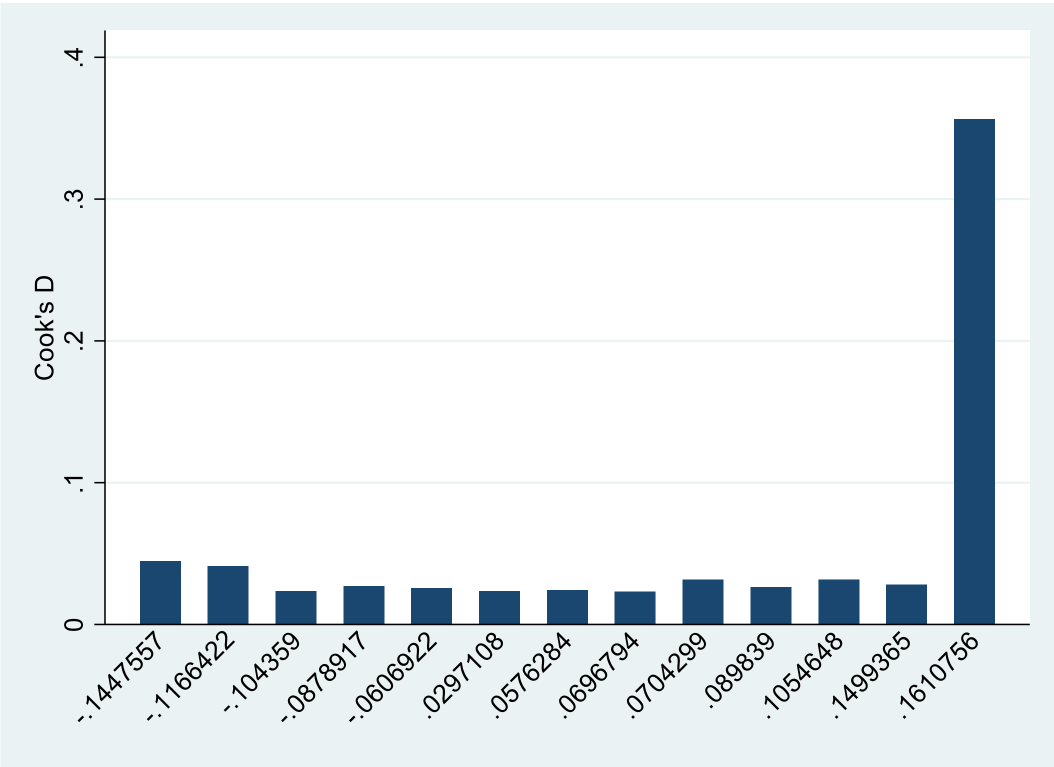

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     5.34
         Prob > chi2  =   0.0209
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     124.27
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8180
                                                Root MSE          =     .02377
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.071048	.0438043	24.45	0.000	.9846313	1.157465
smb	-.0291114	.0970771	-0.30	0.765	-.2206251	.1624024
hml	.0047906	.1212561	0.04	0.969	-.2344234	.2440046
rmw	.1418012	.1507866	0.94	0.348	-.1556706	.4392731
cma	.0750783	.1669984	0.45	0.654	-.2543762	.4045327
_cons	-.0036756	.0018493	-1.99	0.048	-.007324	-.0000273

Assumptions 4





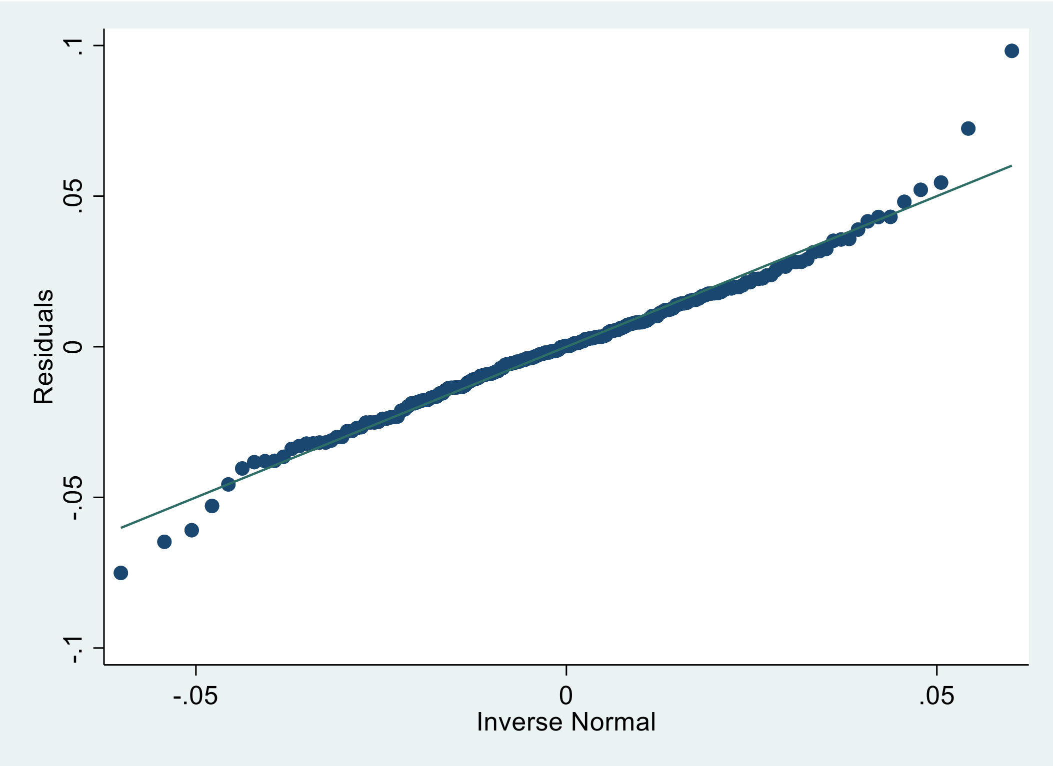
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**2.486**	**1**	**0.1148**

H0: no serial correlation

Assumptions 7

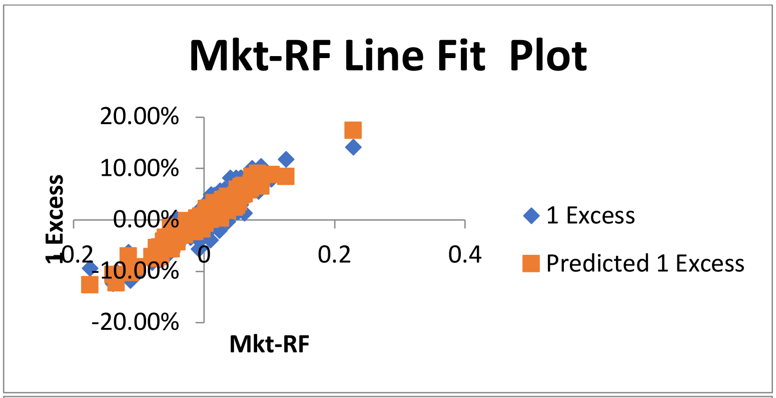


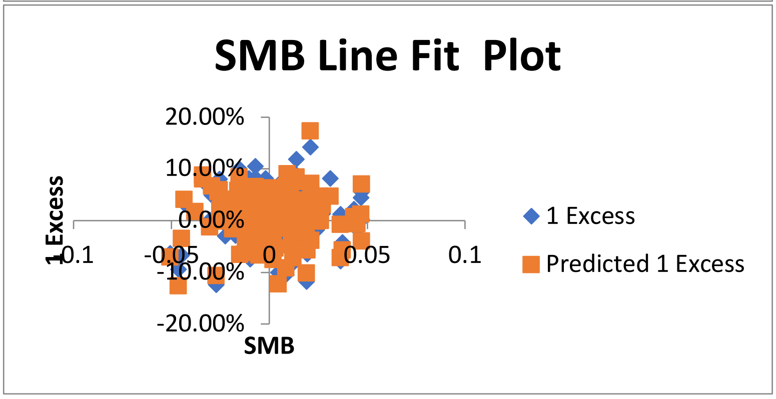
Shapiro-Wilk W test for normal data

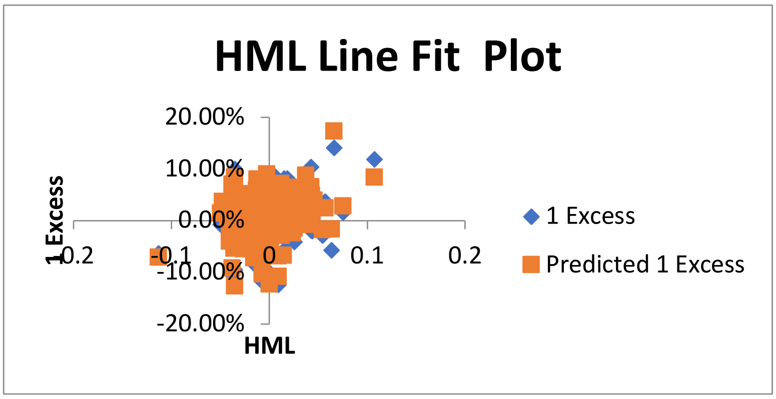
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.98157**	**2.653**	**2.241**	**0.01252**

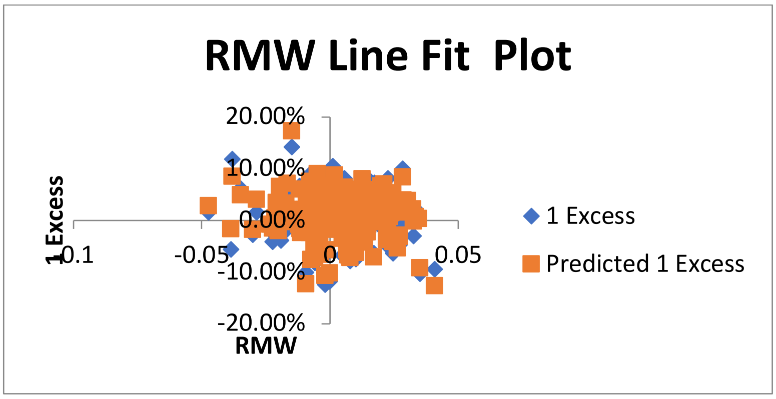
HIGH S

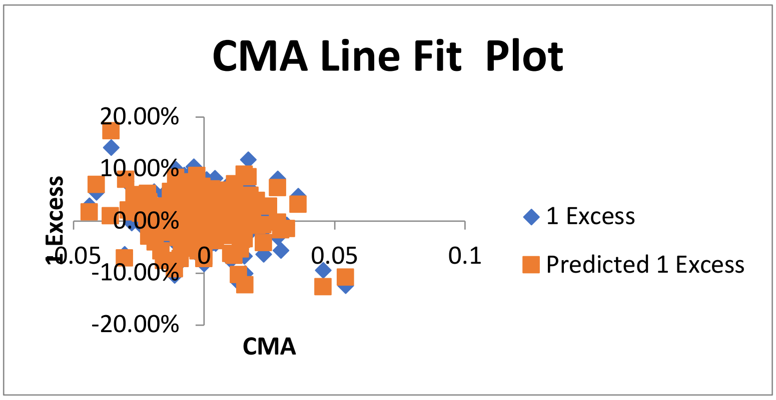
Assumptions 1


Mkt-RF Line Fit Plot
20.00%
10.00%
0.00%
-10.00%
-20.00%
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

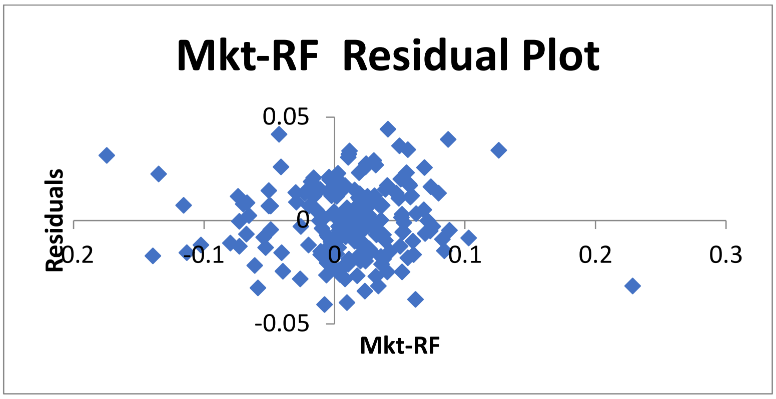

SMB Line Fit Plot
20.00%
10.00%
0.00%
-10.00%
-20.00%
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

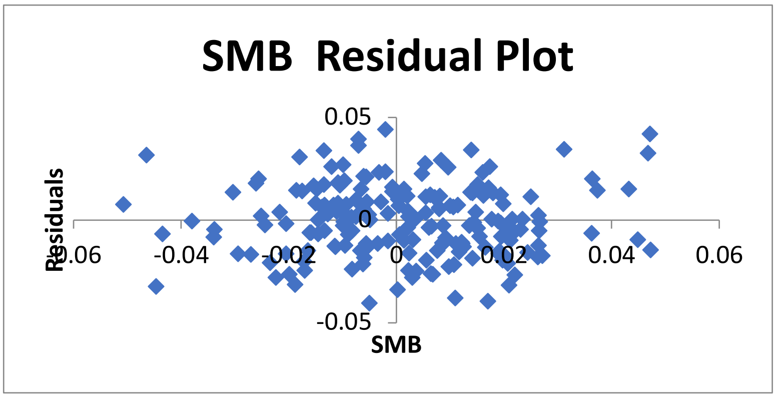

HML Line Fit Plot
20.00%
10.00%
0.00%
-10.00%
-20.00%
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

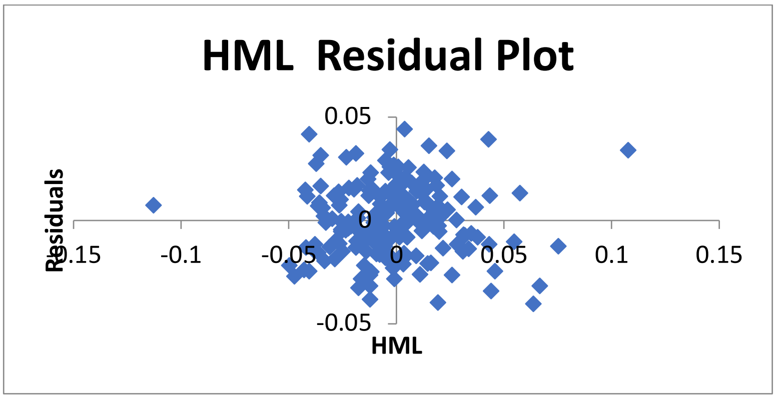


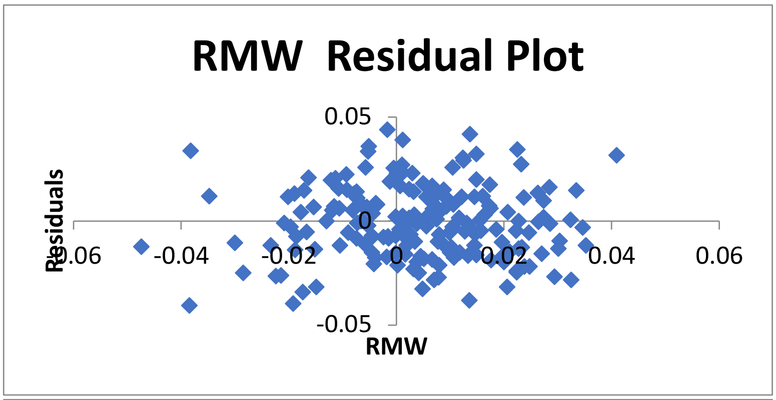


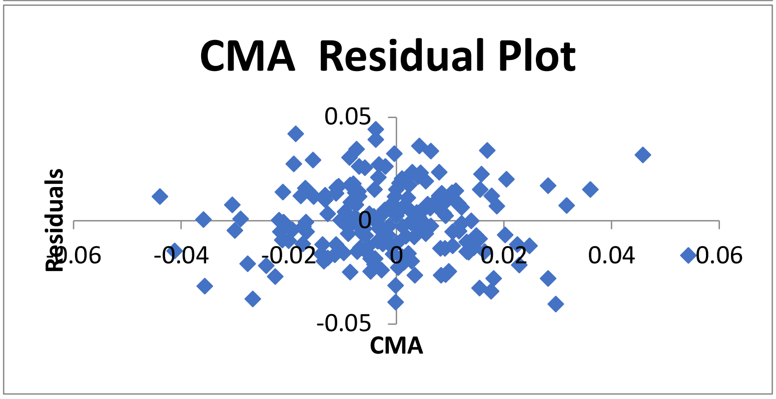
Assumptions 2





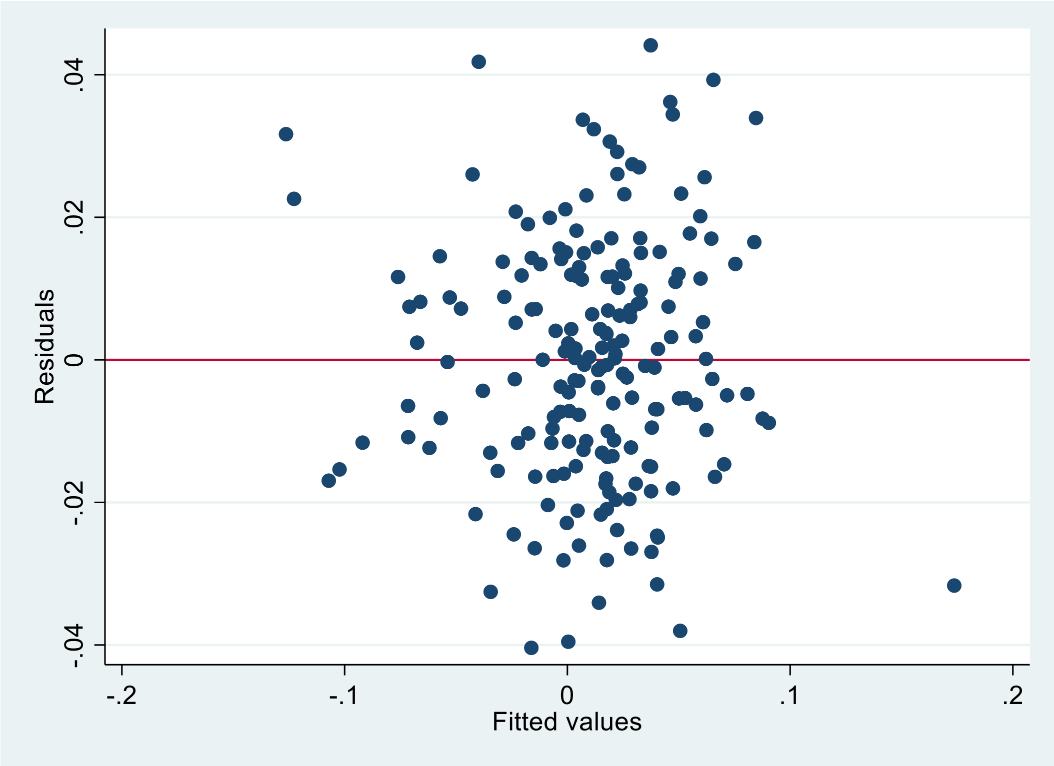






	Mean residuals
High S portfolio	-4,51606E-16

Assumptions 3

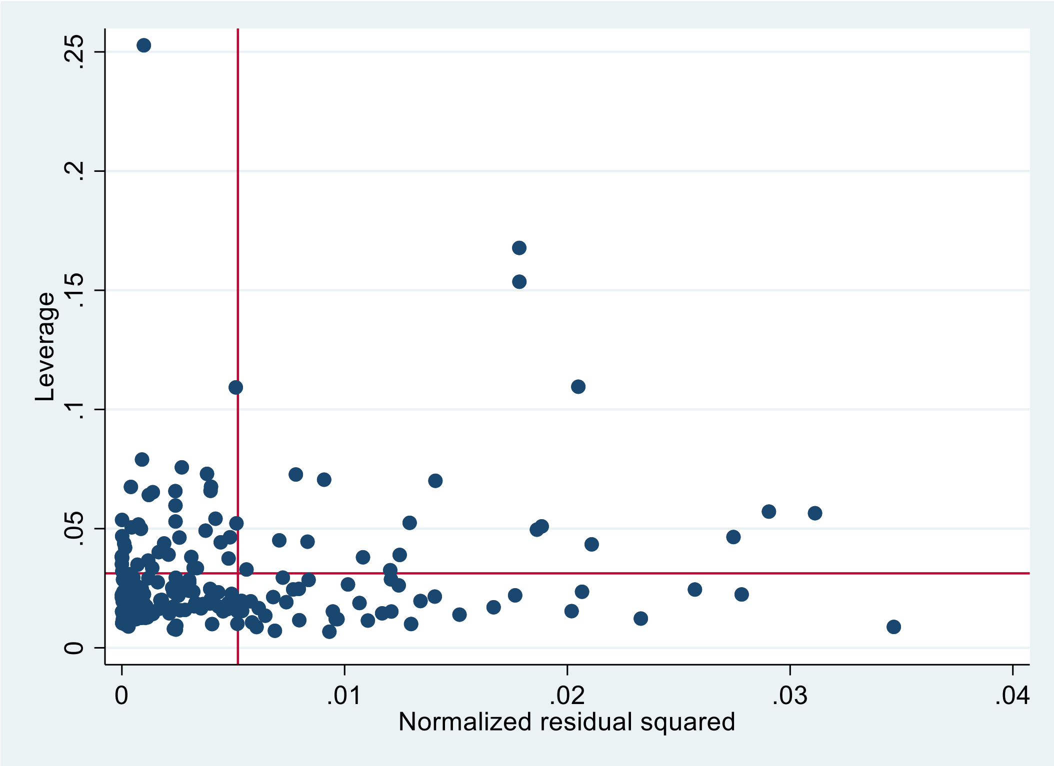


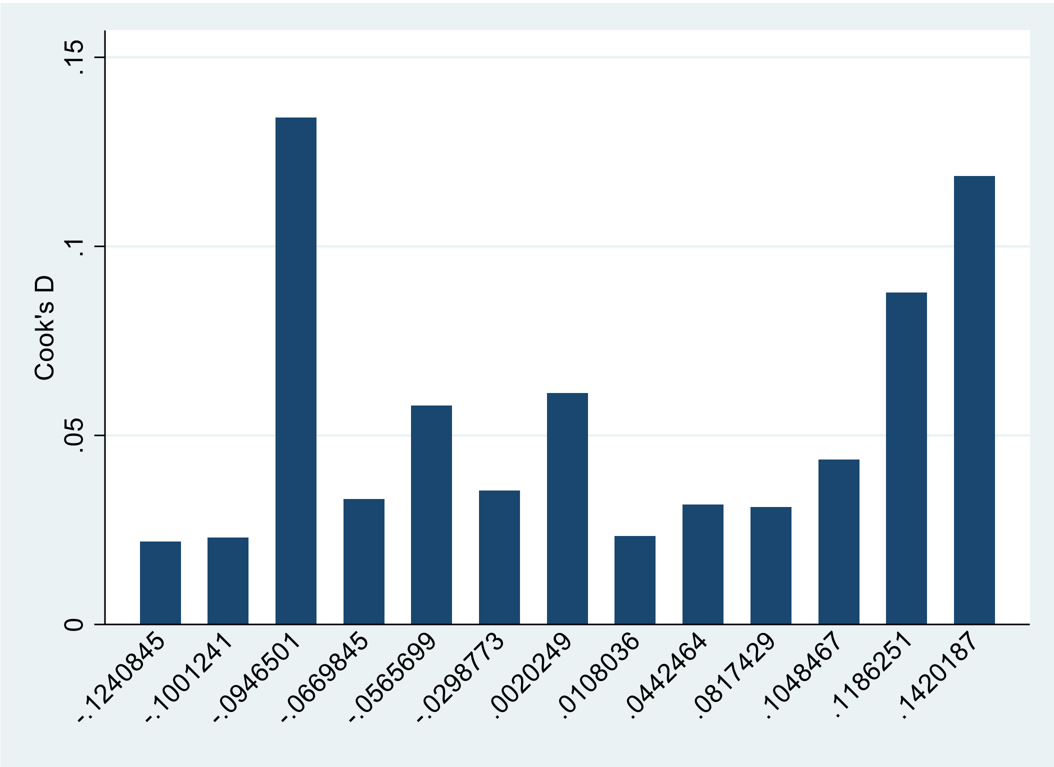

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     0.67
         Prob > chi2  =   0.4135
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     188.06
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8482
                                                Root MSE          =     .01738
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.9801209	.032683	29.99	0.000	.9156439	1.044598
smb	-.1437087	.0745987	-1.93	0.056	-.2908769	.0034596
hml	-.4585765	.0948733	-4.83	0.000	-.6457427	-.2714104
rmw	-.0770471	.1308107	-0.59	0.557	-.3351104	.1810161
cma	.5310249	.1142644	4.65	0.000	.3056041	.7564457
_cons	.0008749	.0013615	0.64	0.521	-.0018111	.0035609

Assumptions 4





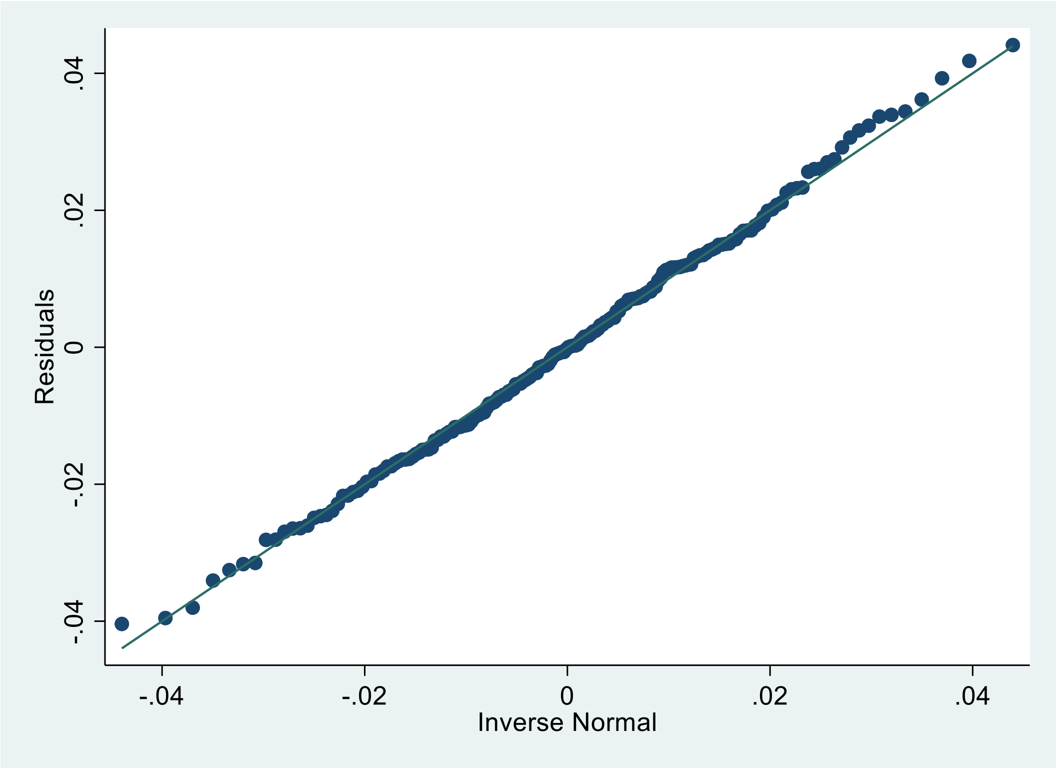
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.226**	**1**	**0.6343**

H0: no serial correlation

Assumptions 7

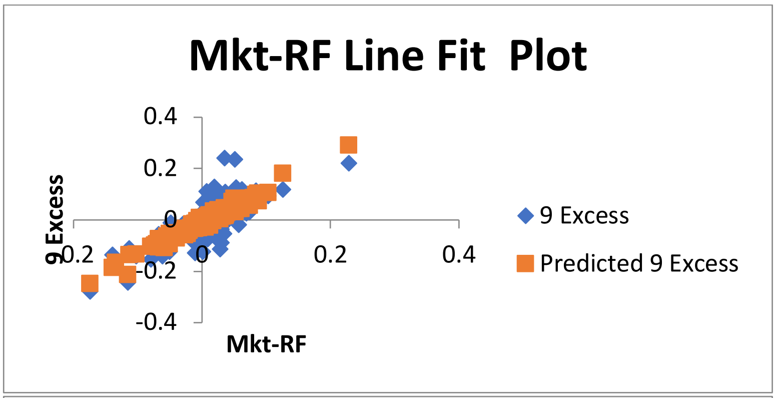


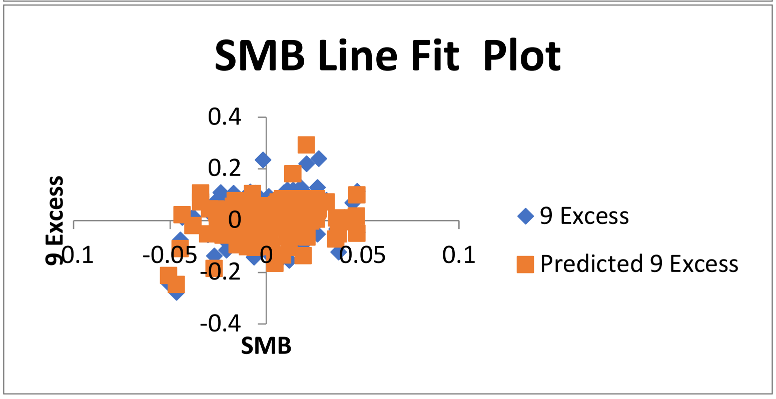
Shapiro-Wilk W test for normal data

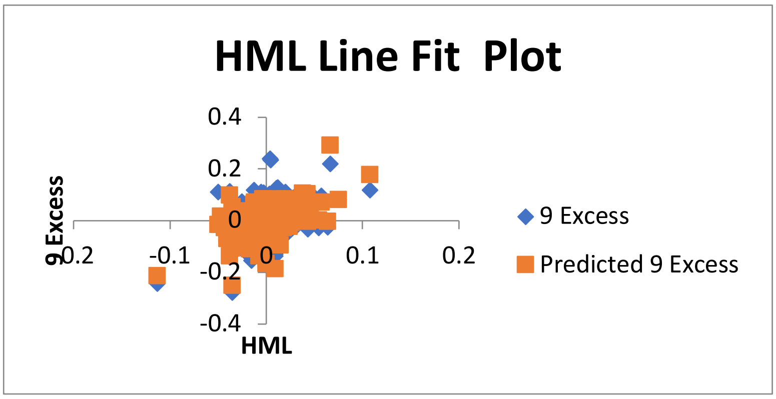
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.99540**	**0.663**	**-0.944**	**0.82739**

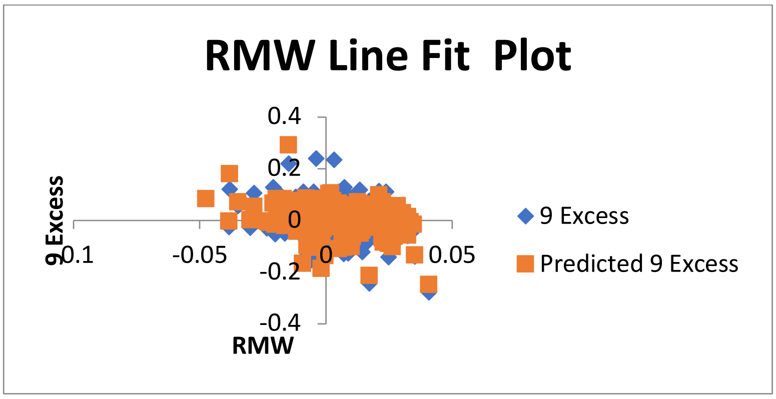
LOW S

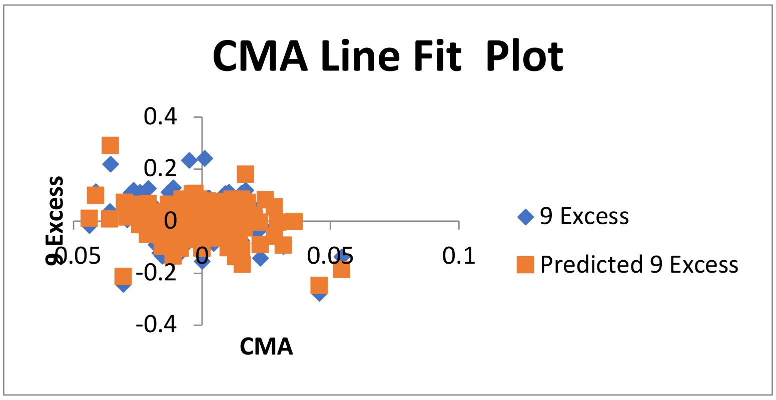
Assumptions 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

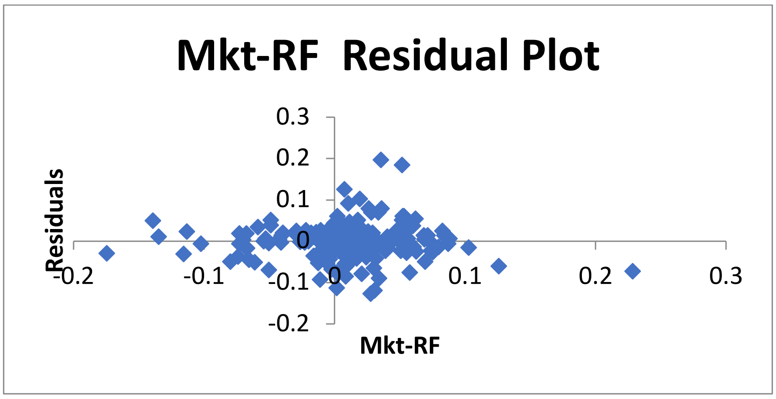

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

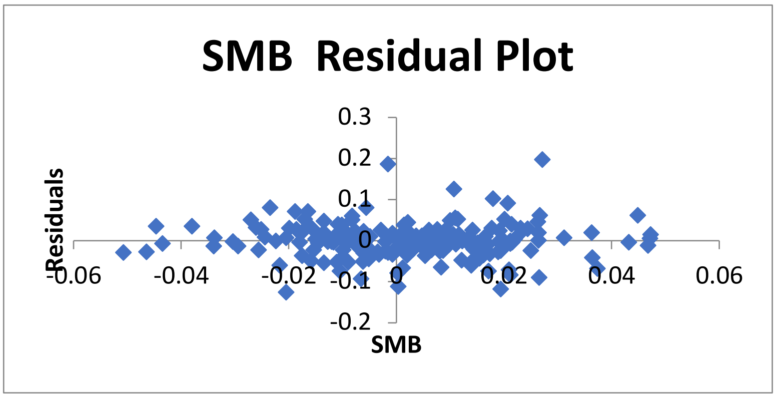

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

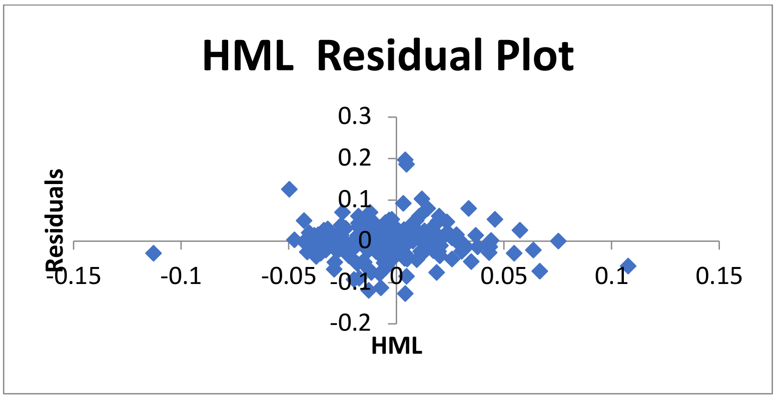


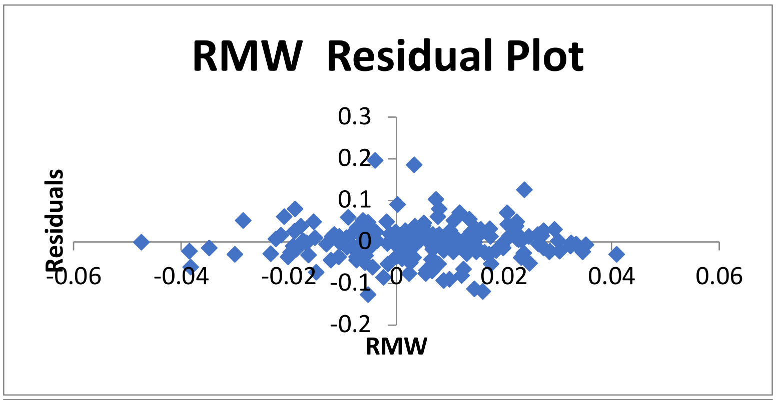


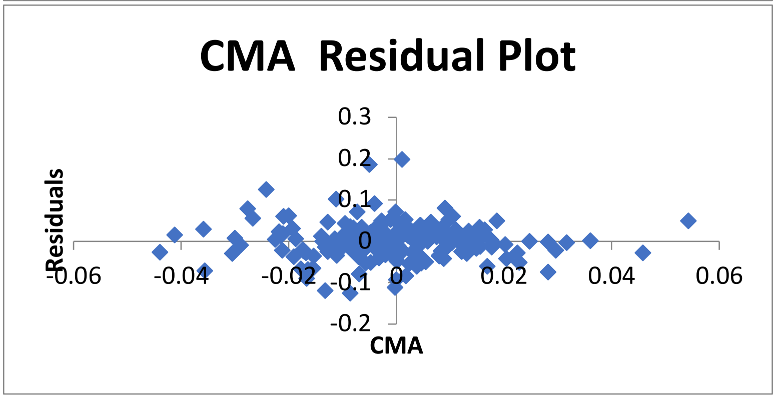
Assumptions 2





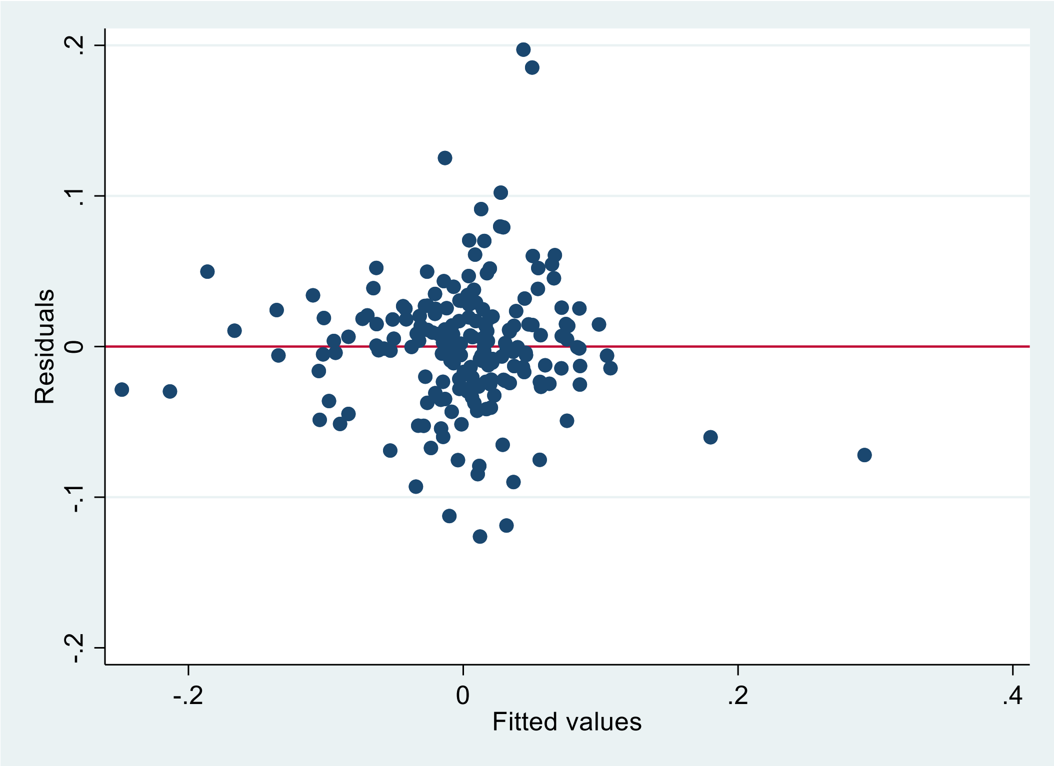






	Mean residuals
Low S portfolio	1,6769E-16

Assumptions 3

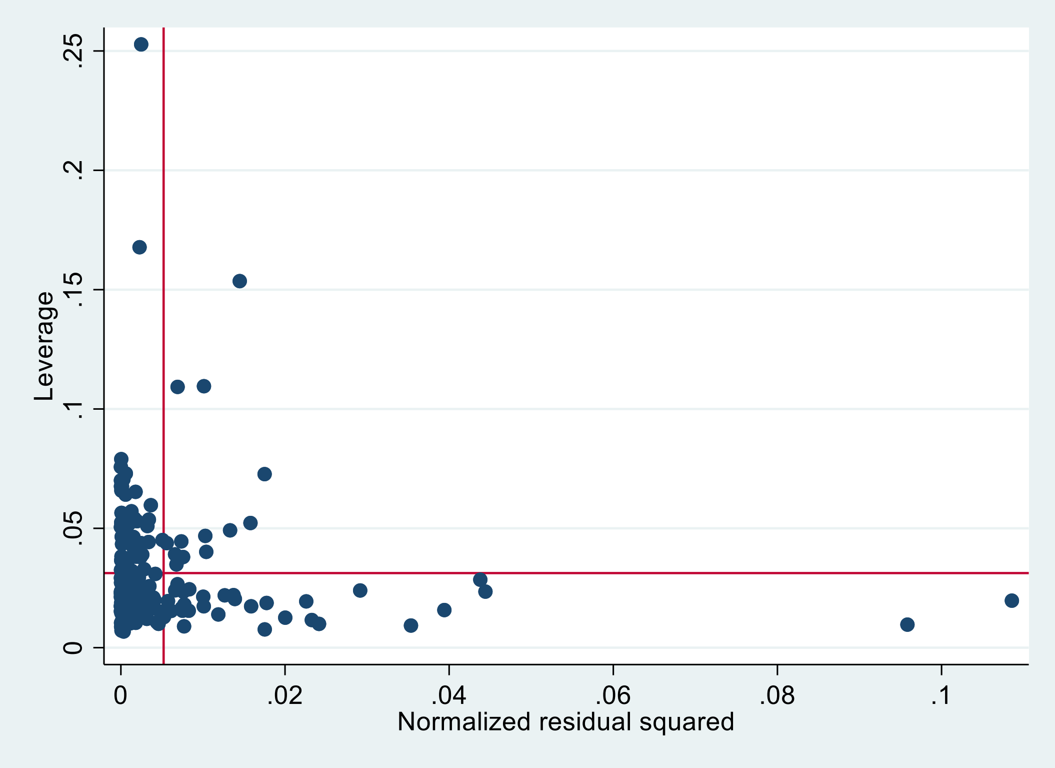


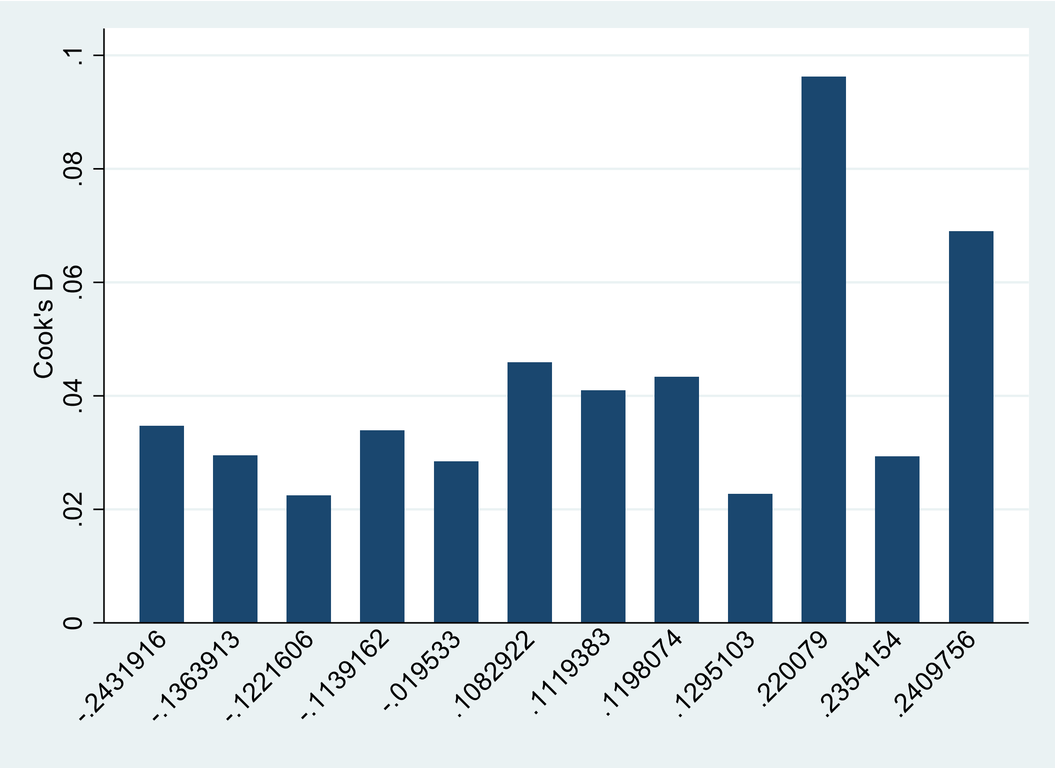

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     6.16
         Prob > chi2  =   0.0130
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      80.33
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6609
                                                Root MSE          =     .04387
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.145815	.0702279	16.32	0.000	1.00727	1.284361
smb	.4936132	.1797443	2.75	0.007	.1390136	.8482129
hml	.4461018	.2053475	2.17	0.031	.0409922	.8512115
rmw	.1557943	.2623563	0.59	0.553	-.3617822	.6733709
cma	-.1022592	.2760529	-0.37	0.711	-.6468564	.442338
_cons	-.0112517	.0032383	-3.47	0.001	-.0176403	-.0048631

Assumptions 4





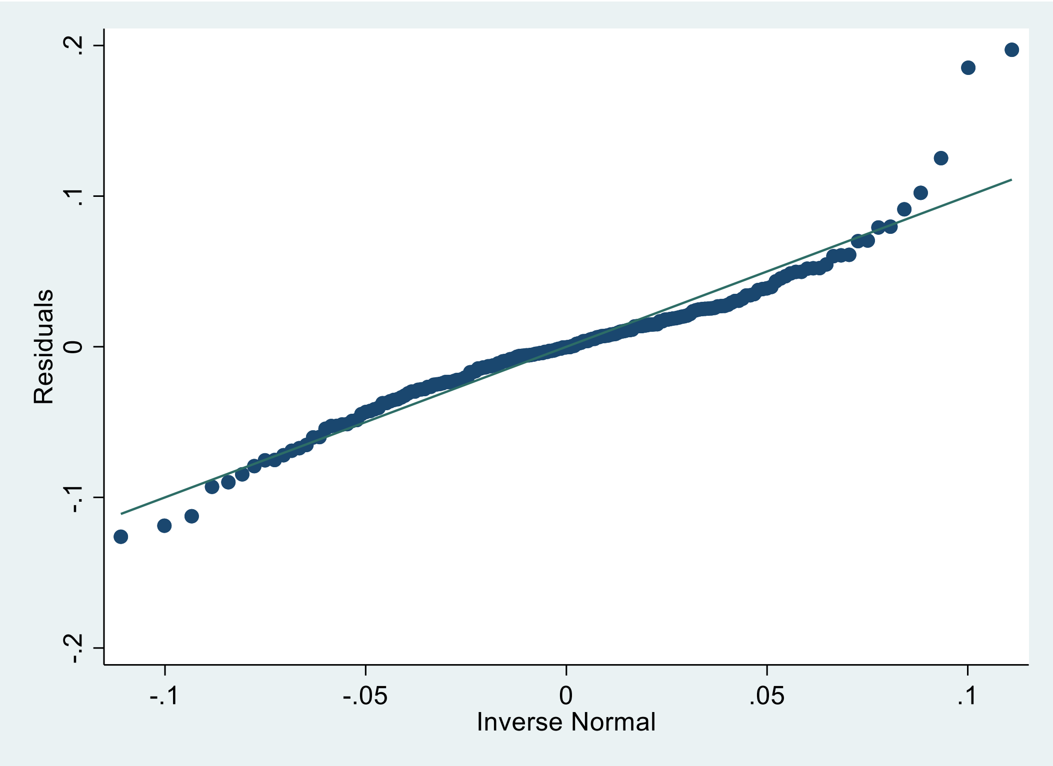
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**3.268**	**1**	**0.0706**

H0: no serial correlation

Assumptions 7

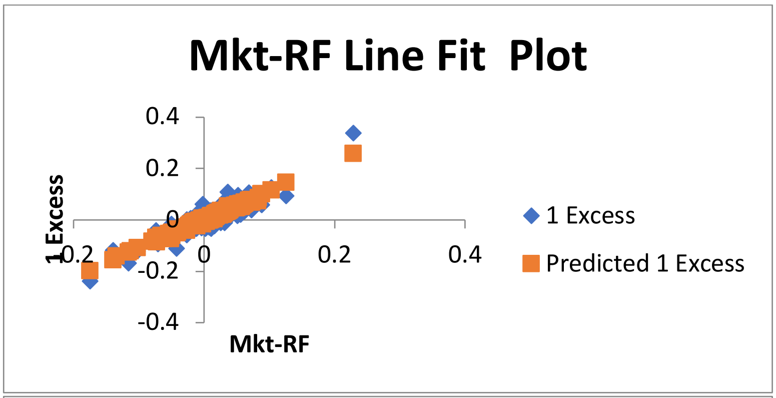


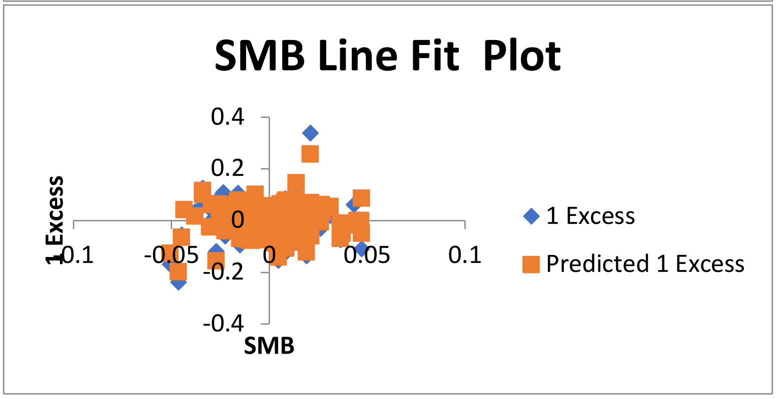
Shapiro-Wilk W test for normal data

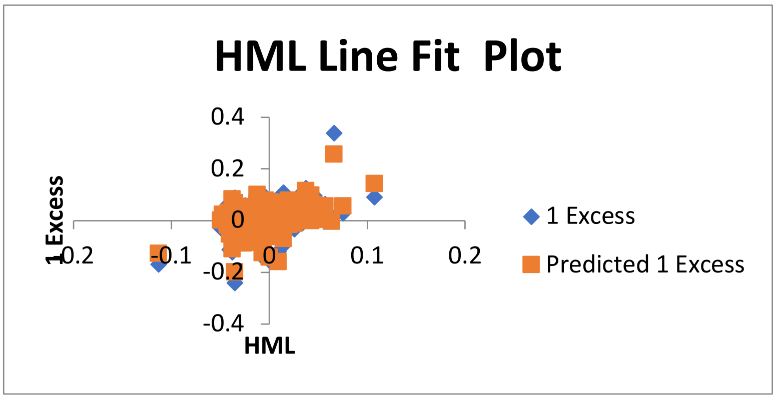
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.94235**	**8.301**	**4.859**	**0.00000**

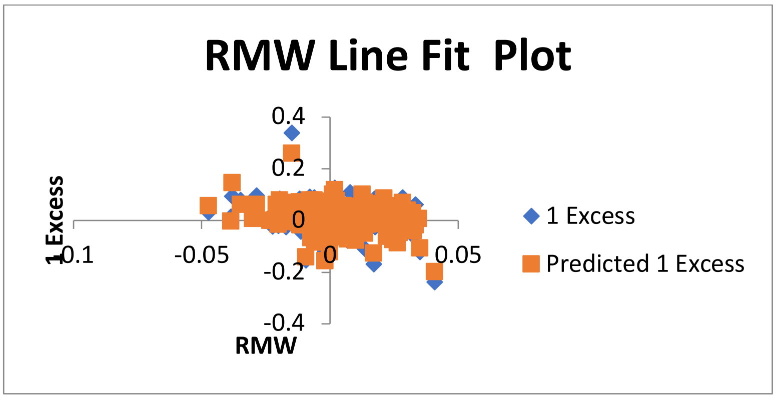
HIGH G

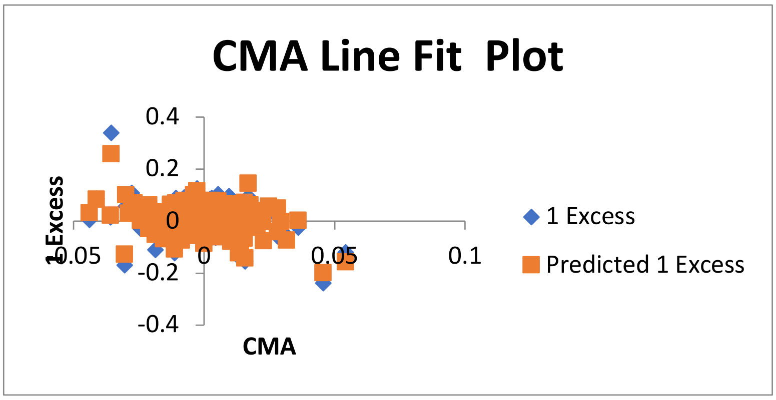
Assumptions 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

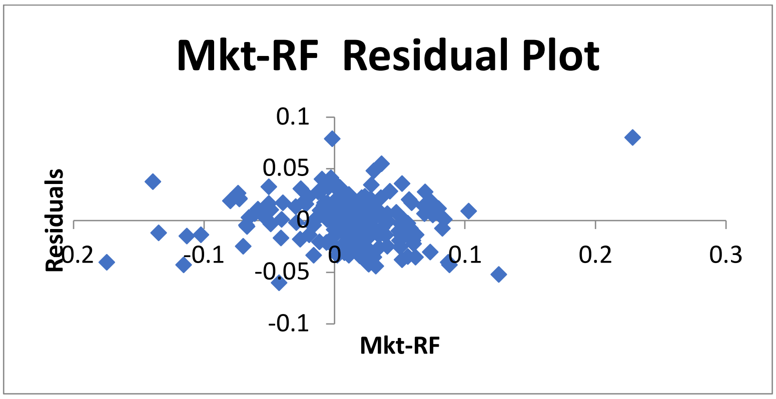

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

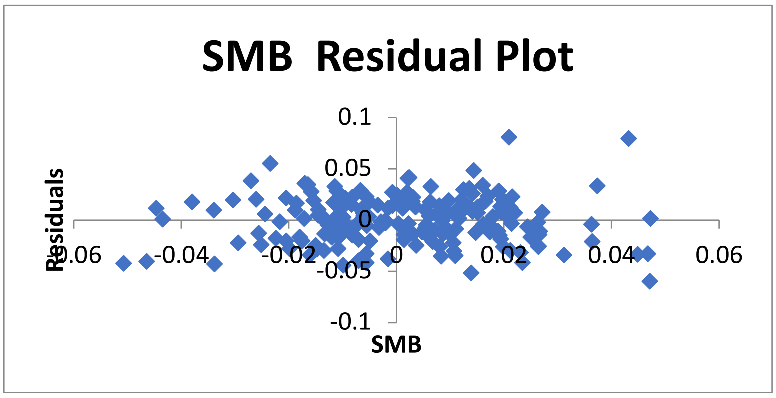

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

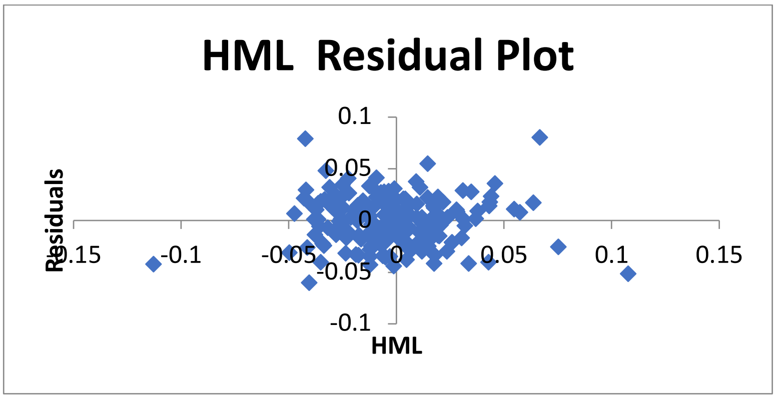


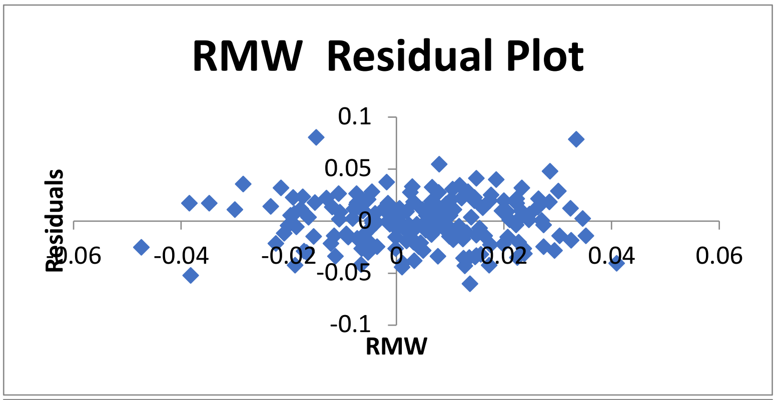


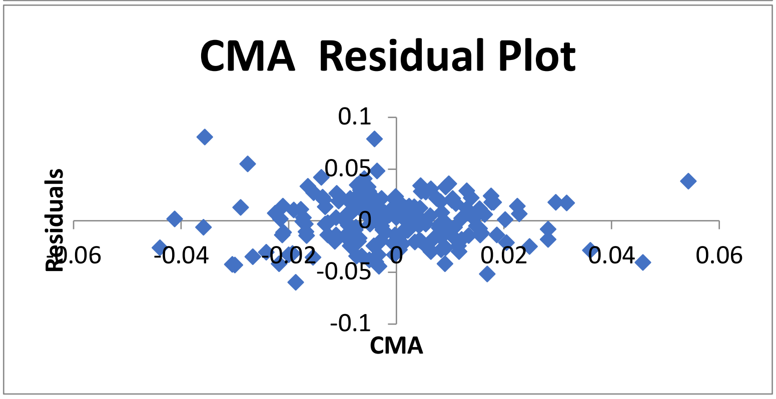
Assumptions 2





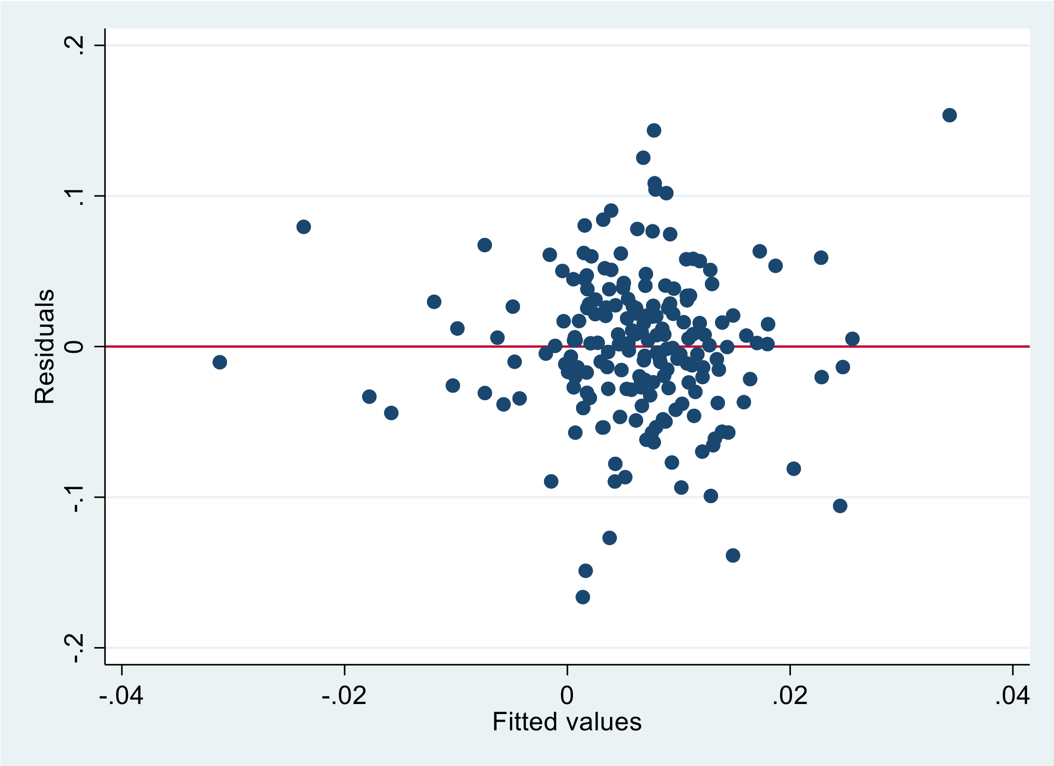






	Mean residuals
High G portfolio	5,14093E-18

Assumptions 3

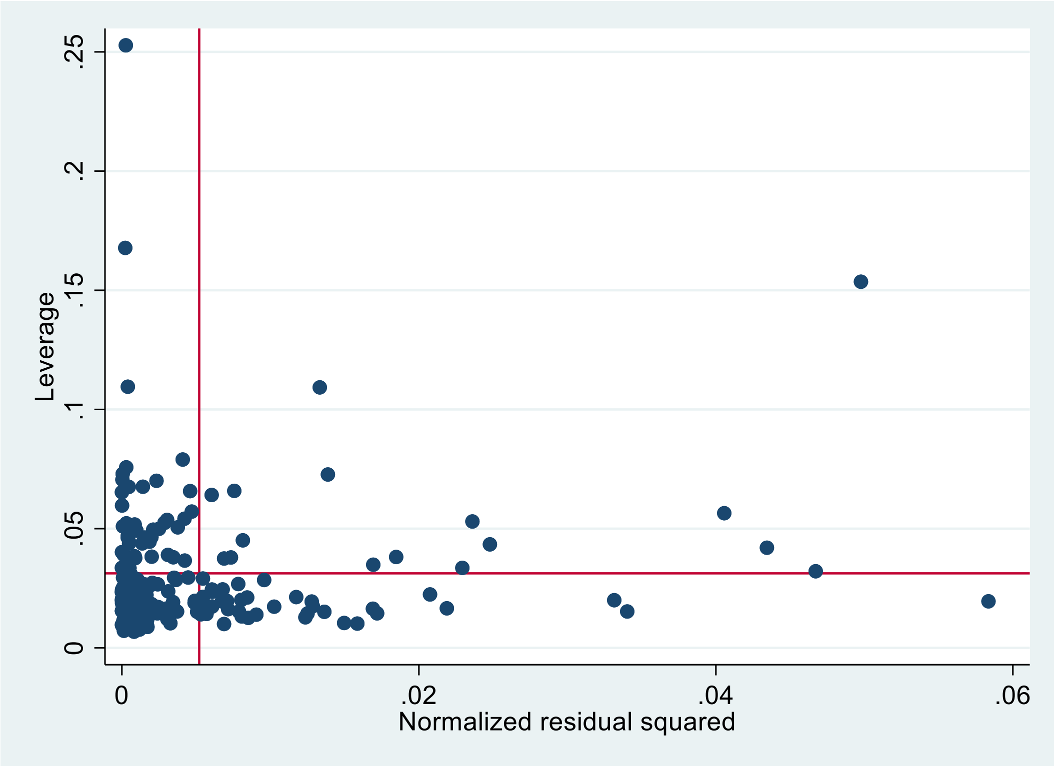


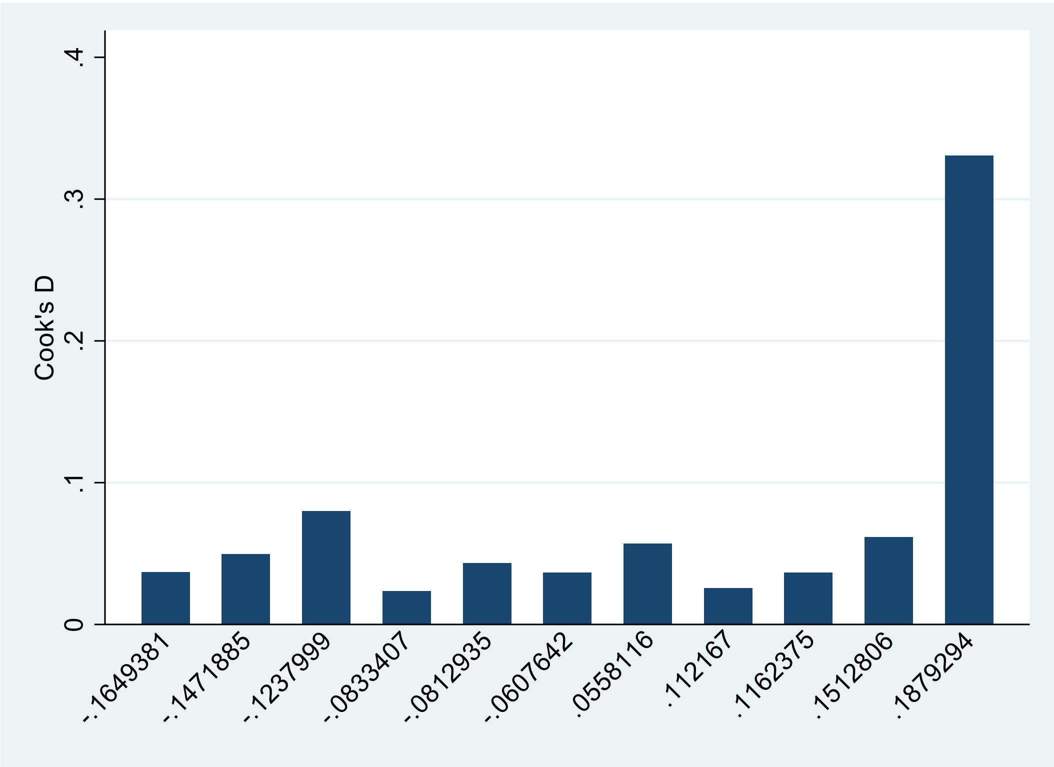

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =    12.80
         Prob > chi2  =   0.0003
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      58.20
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6582
                                                Root MSE          =     .02961
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.8564277	.0540323	15.85	0.000	.7498329	.9630226
smb	.0026248	.1305765	0.02	0.984	-.2549766	.2602262
hml	.0990709	.1556141	0.64	0.525	-.2079248	.4060665
rmw	.1085276	.220488	0.49	0.623	-.3264512	.5435064
cma	.1306327	.1996678	0.65	0.514	-.263272	.5245374
_cons	-.0032927	.0022502	-1.46	0.145	-.0077319	.0011465

Assumptions 4





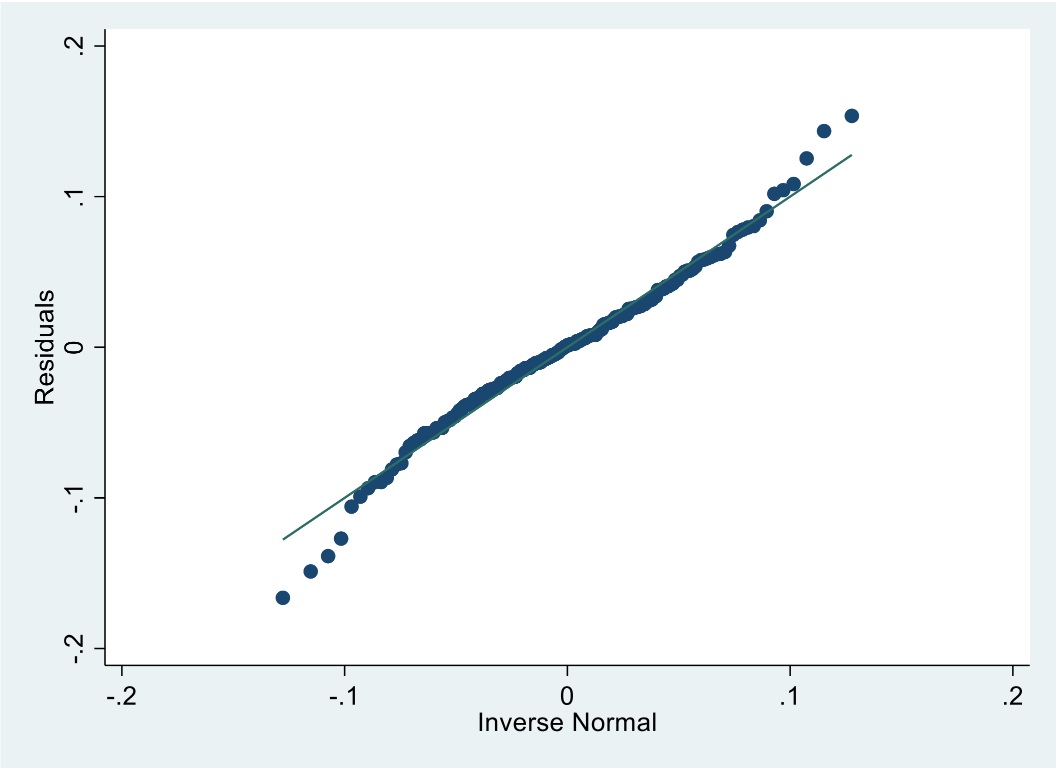
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**7.310**	**1**	**0.0069**

H0: no serial correlation

Assumptions 7

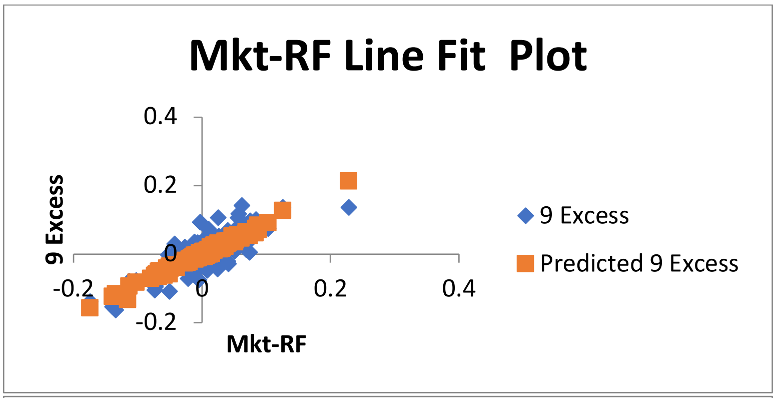


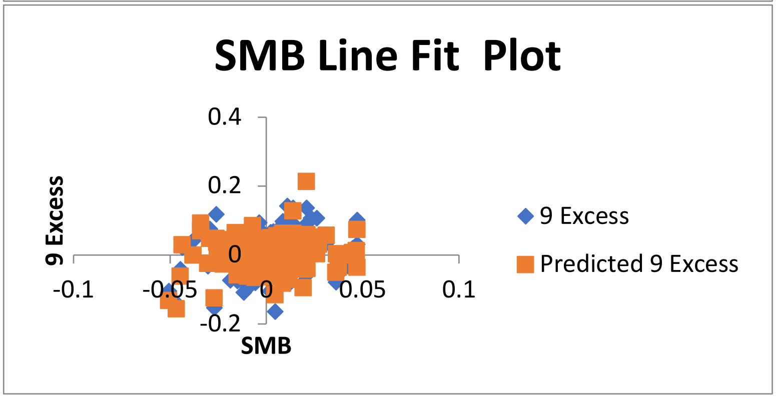
Shapiro-Wilk W test for normal data

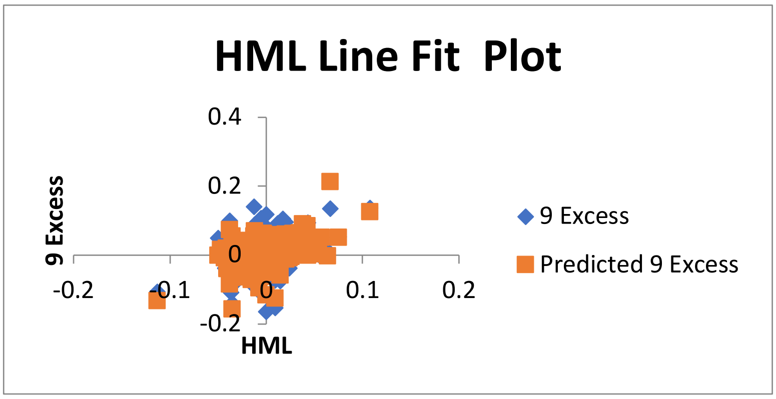
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.96210**	**5.458**	**3.897**	**0.00005**

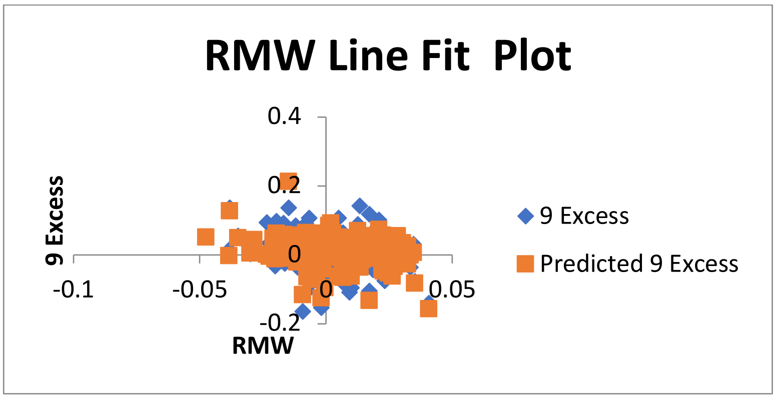
LOW G

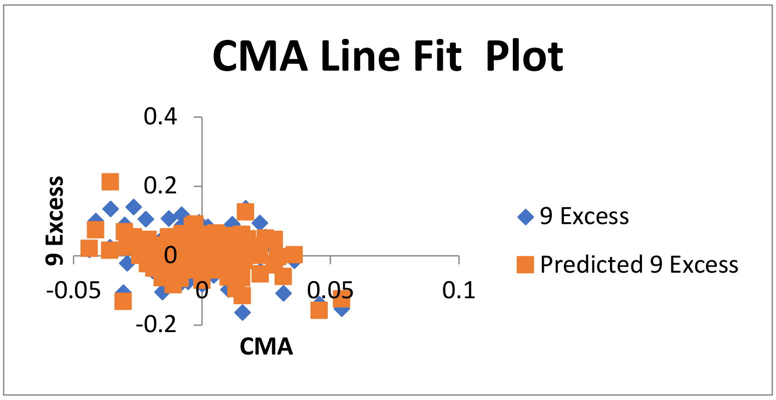
Assumptions 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

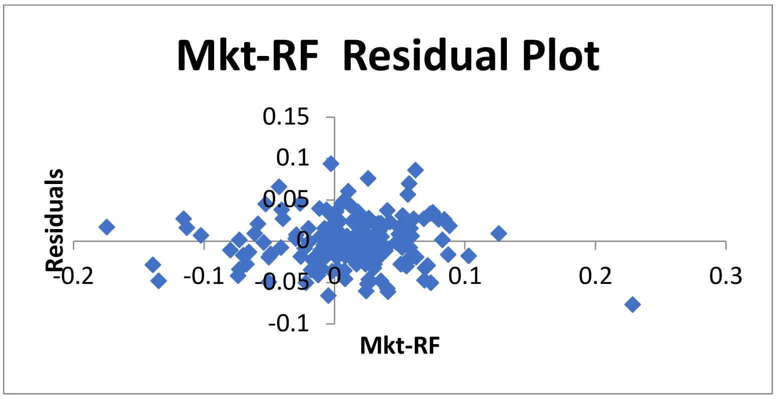

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

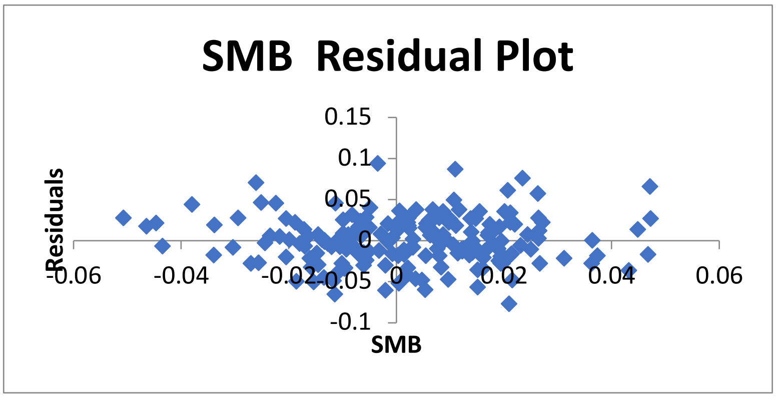

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

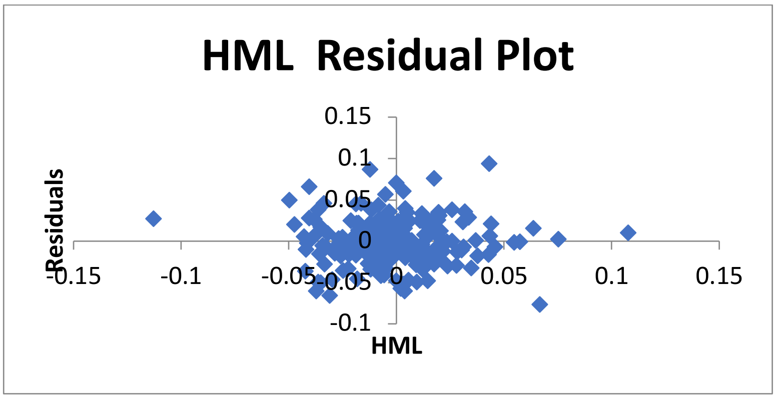


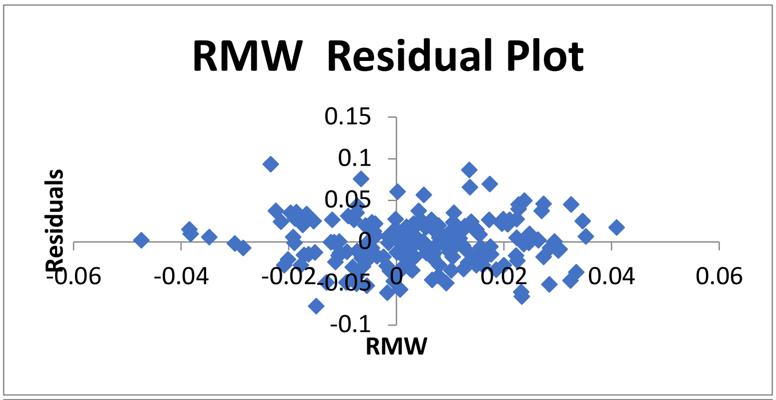


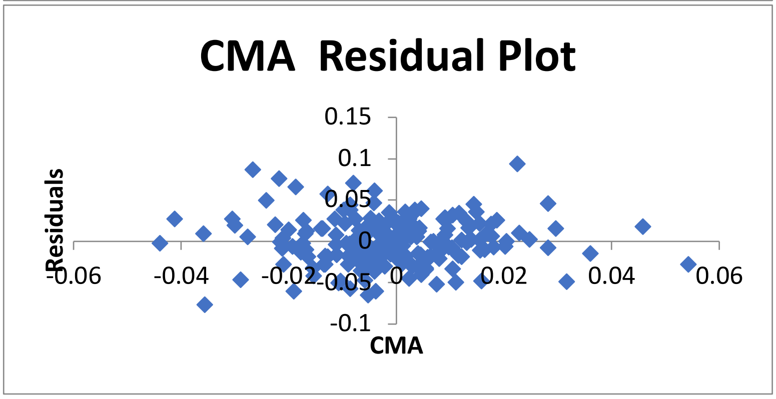
Assumptions 2





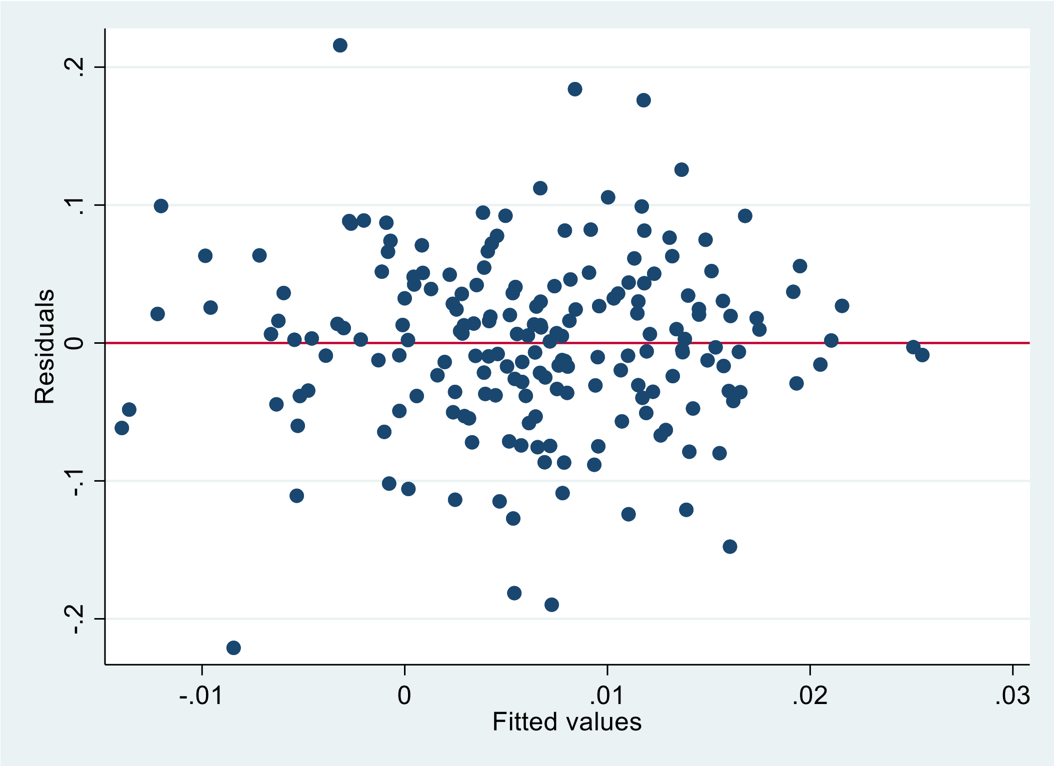






	Mean residuals
Low G portfolio	3,68629E-18

Assumptions 3

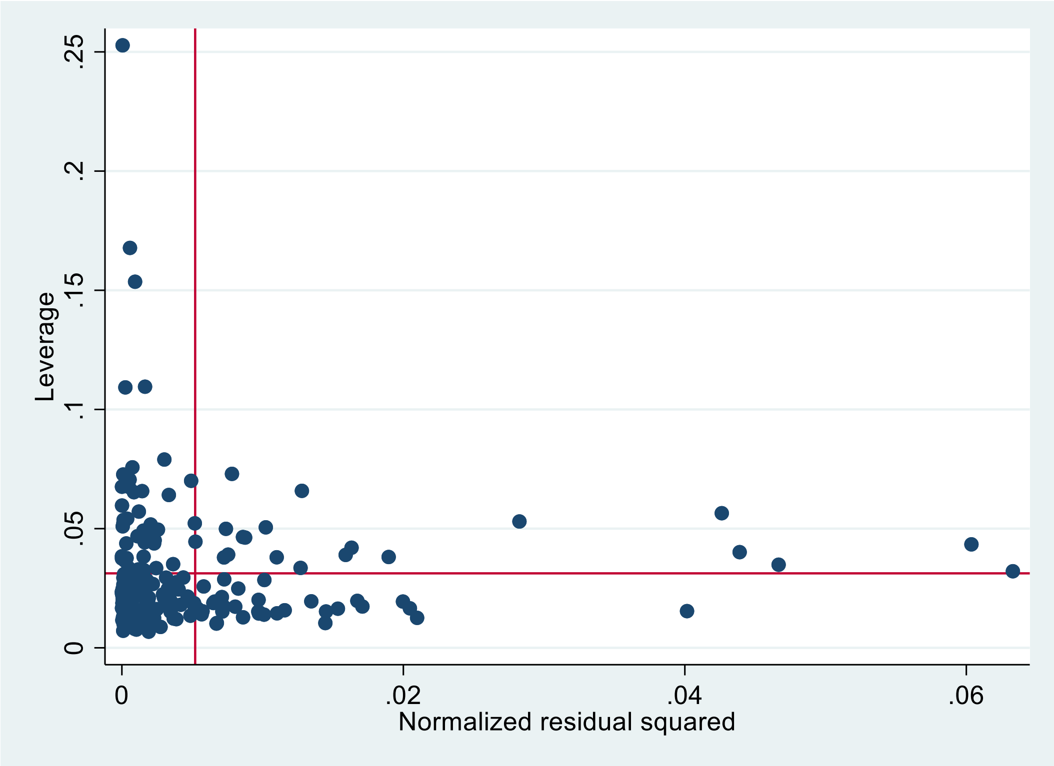


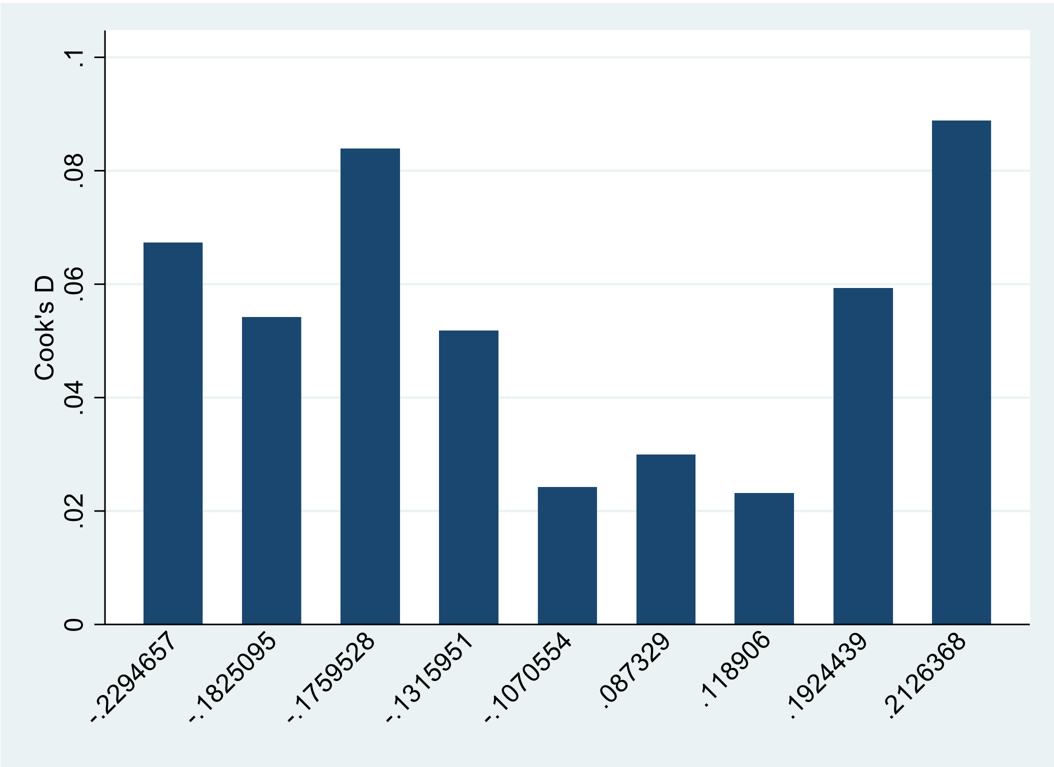

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     1.80
         Prob > chi2  =   0.1791
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      87.01
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6705
                                                Root MSE          =     .03784
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.032841	.0641383	16.10	0.000	.9063089	1.159373
smb	.3282308	.1527891	2.15	0.033	.0268083	.6296532
hml	.3338751	.1724772	1.94	0.054	-.0063879	.6741382
rmw	.246136	.2139336	1.15	0.251	-.1759122	.6681842
cma	-.2350603	.2432045	-0.97	0.335	-.7148541	.2447336
_cons	-.008565	.0028335	-3.02	0.003	-.0141549	-.0029751

Assumptions 4





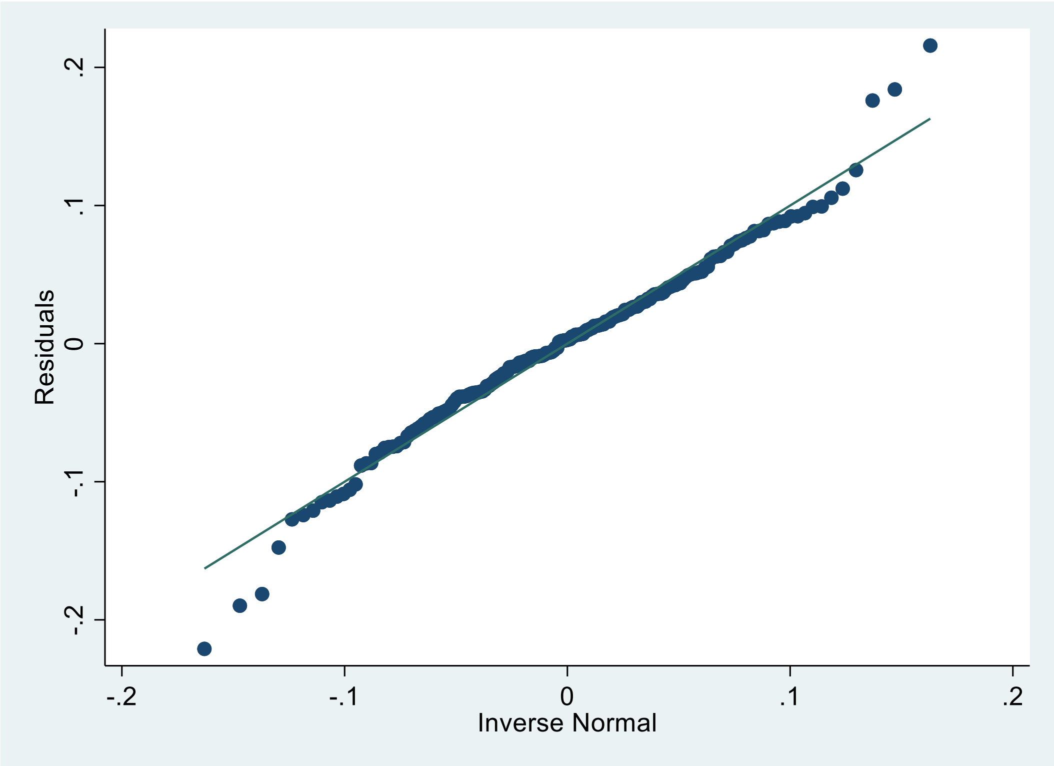
Assumptions 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**3.642**	**1**	**0.0563**

H0: no serial correlation

Assumptions 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.94798**	**7.490**	**4.623**	**0.00000**

Annex 5

PART 2 – YEARLY ALLOCATED HIGH AND LOW ESG, E, S, AND G PORTFOLIOS

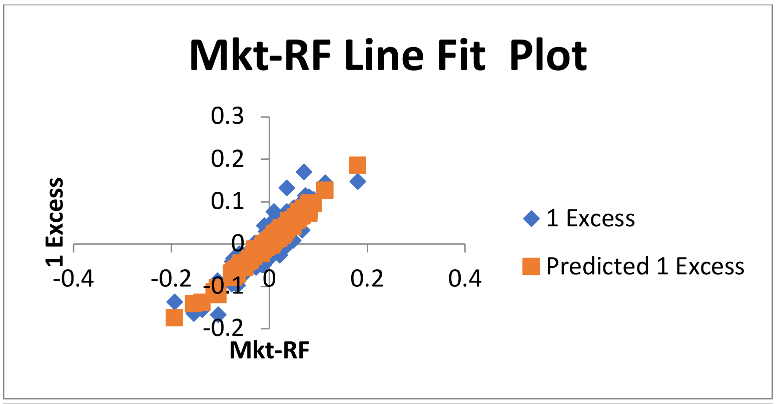
Assumption 5

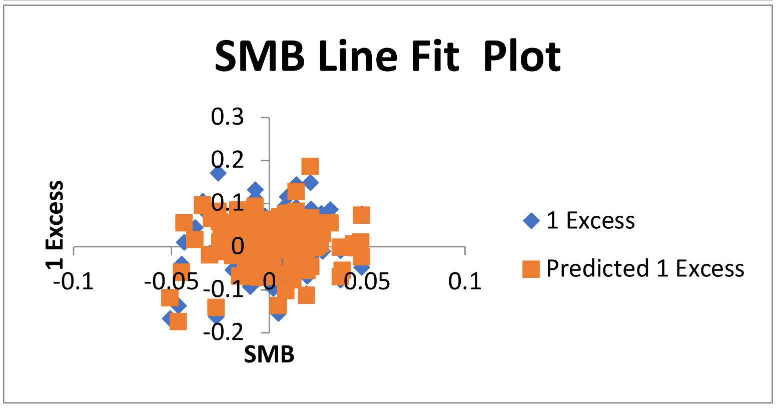
	mktrf	smb	hml	rmw	cma
mktrf	1.0000				
smb	0.1257	1.0000			
hml	0.3230	0.0113	1.0000		
rmw	-0.1829	-0.0783	-0.7764	1.0000	
cma	-0.3050	-0.2369	0.4467	-0.3659	1.0000

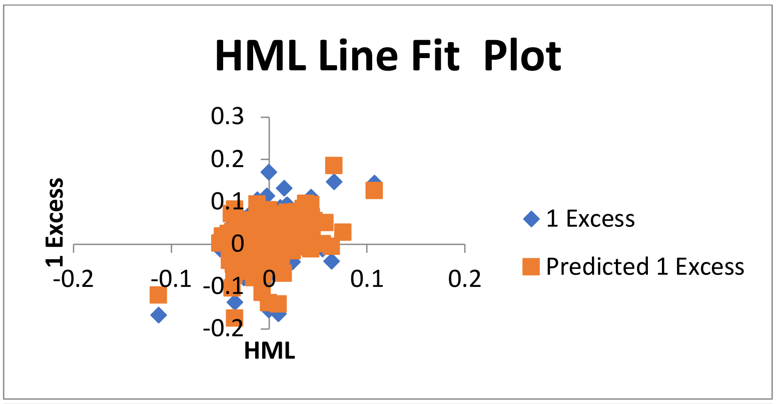
Variable	VIF	1/VIF
hml	3.46	0.288712
rmw	2.59	0.385785
cma	1.85	0.541835
mktrf	1.57	0.635248
smb	1.10	0.912430
Mean VIF	2.11	

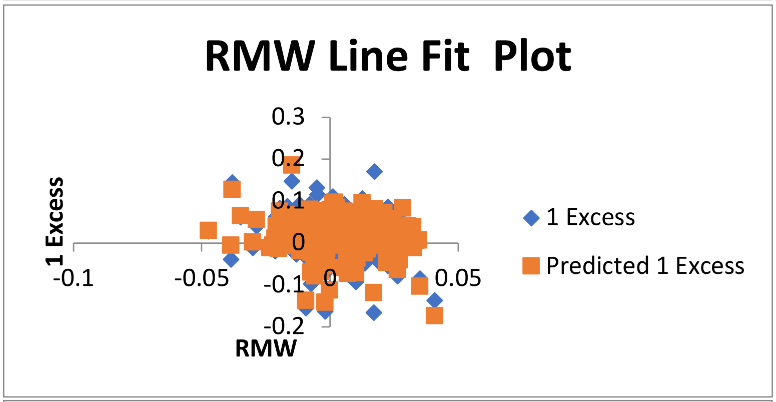
HIGH ESG

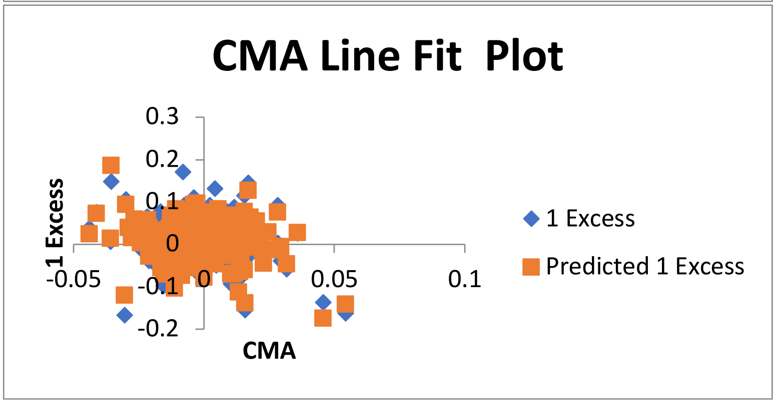
Assumption 1



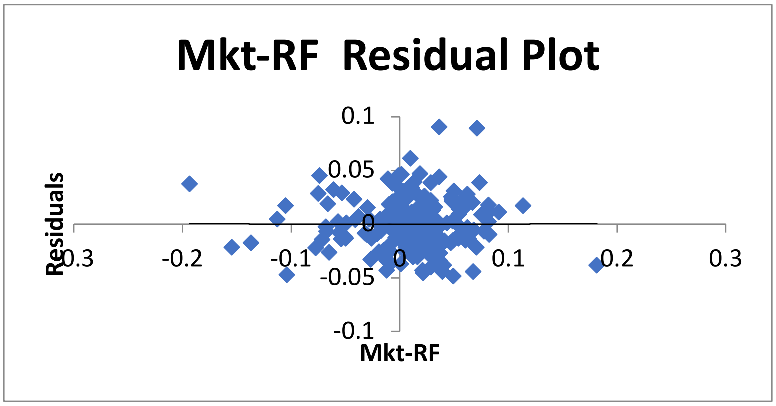
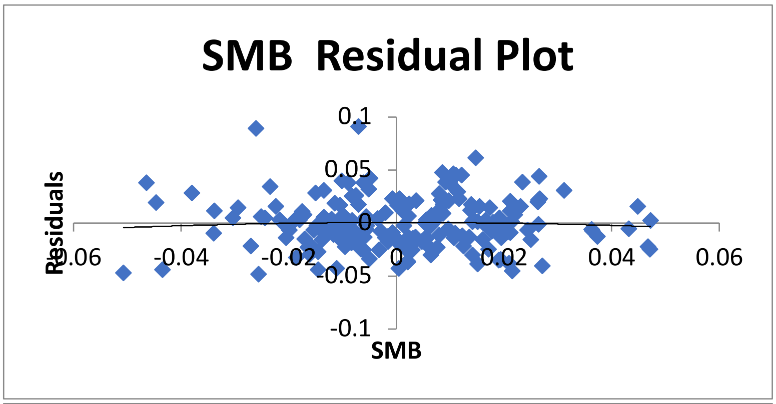
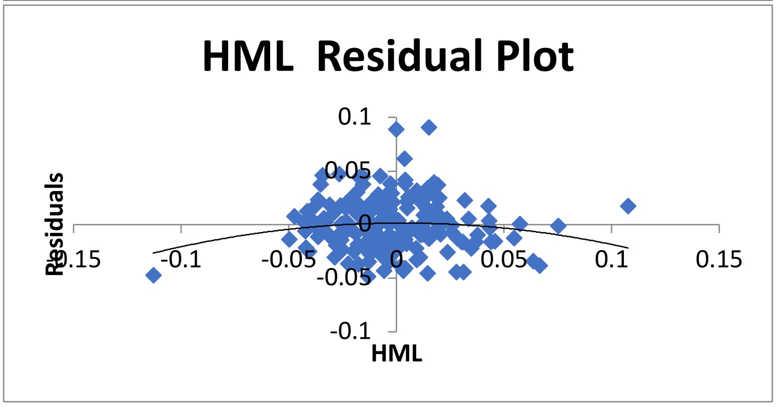


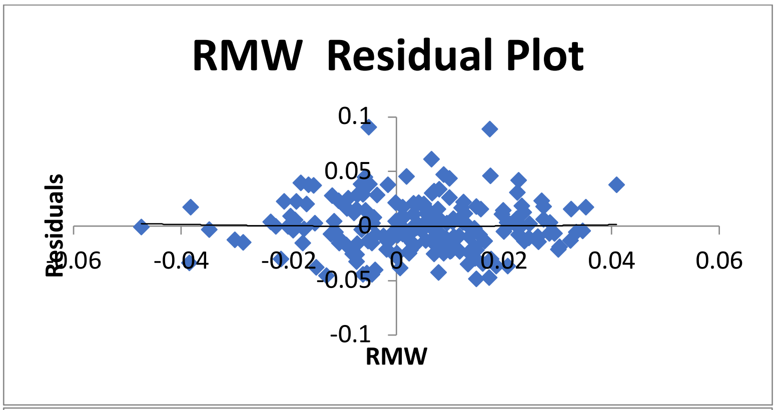


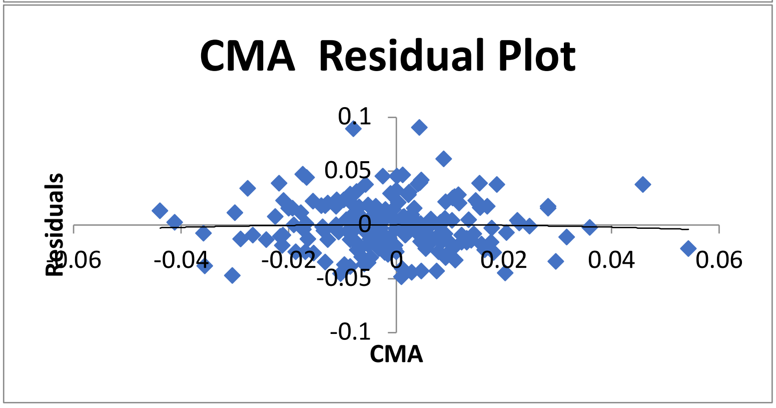




Assumption 2

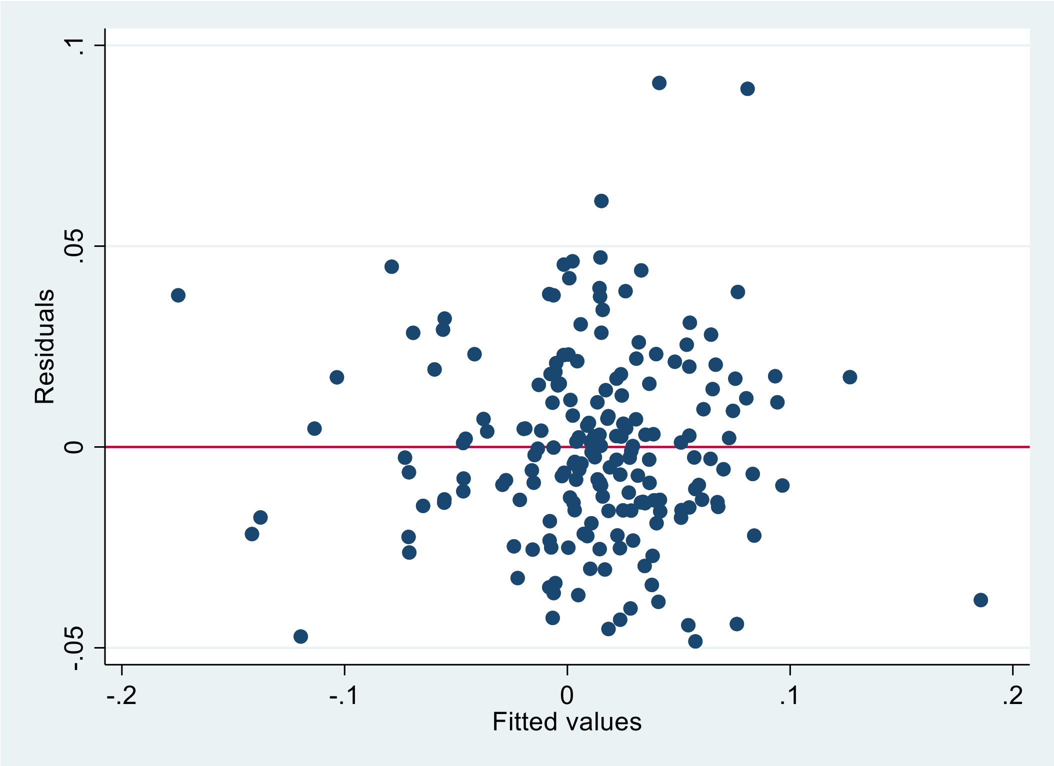

Mkt-RF Residual Plot
Residuals
Mkt-RF
0.1
0.05
0
-0.05
-0.1
-0.3
-0.2
-0.1
0
0.1
0.2
0.3

SMB Residual Plot
Residuals
SMB
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06

HML Residual Plot
Residuals
HML
0.1
0.05
0
-0.05
-0.1
-0.15
-0.1
-0.05
0
0.05
0.1
0.15





	Mean residuals
High ESG	-1,59016E-18

Assumption 3

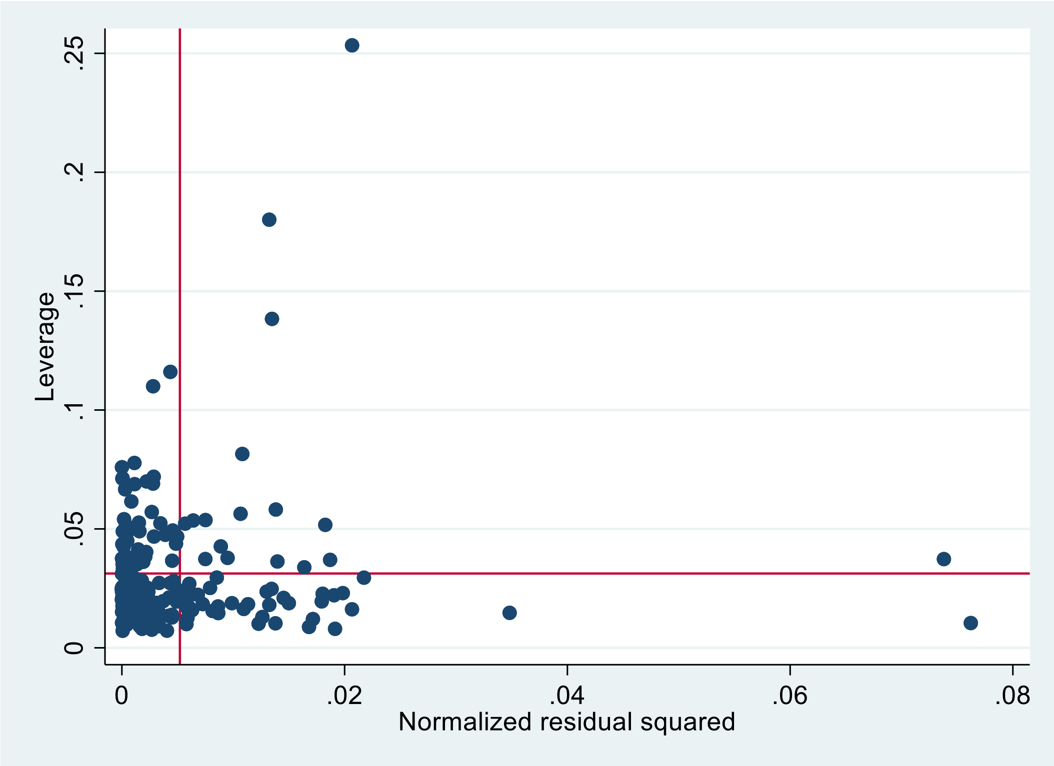


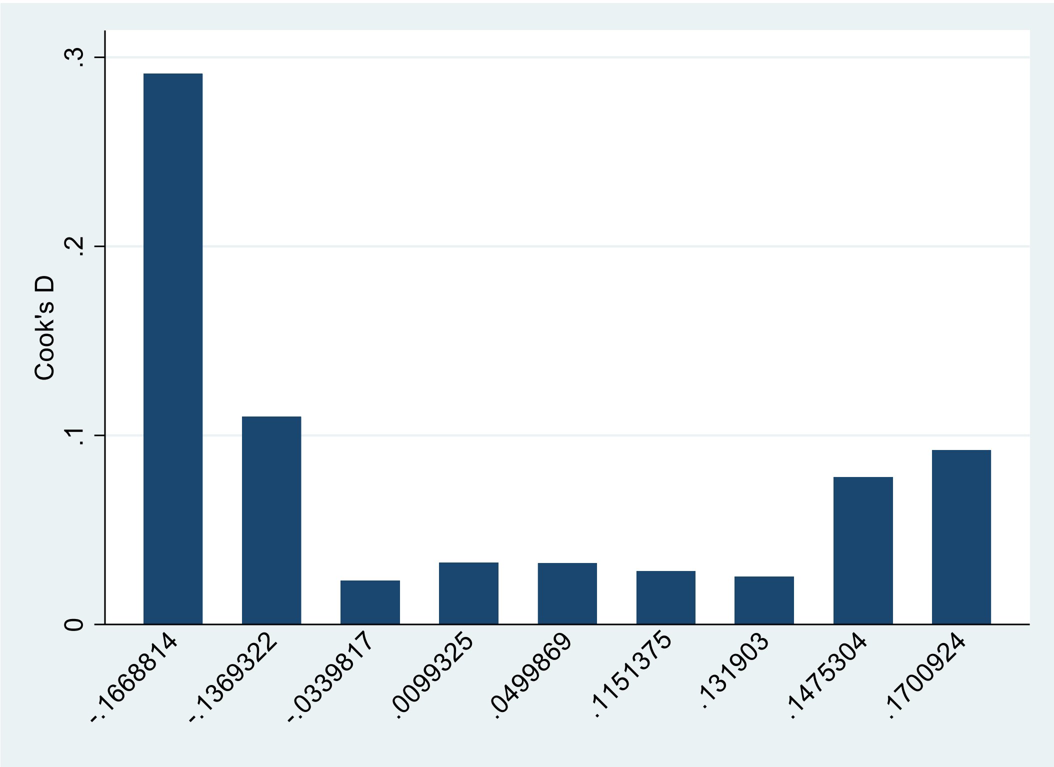

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     1.08
         Prob > chi2  =   0.2990
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     114.58
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7938
                                                Root MSE          =     .02407
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.017572	.0476993	21.33	0.000	.9234708	1.111673
smb	-.0979612	.1104024	-0.89	0.376	-.315763	.1198407
hml	.1870685	.1404054	1.33	0.184	-.0899234	.4640604
rmw	.3324729	.2045377	1.63	0.106	-.0710391	.7359848
cma	.1823806	.1600908	1.14	0.256	-.1334465	.4982078
_cons	.0020315	.0019301	1.05	0.294	-.0017762	.0058392

Assumption 4





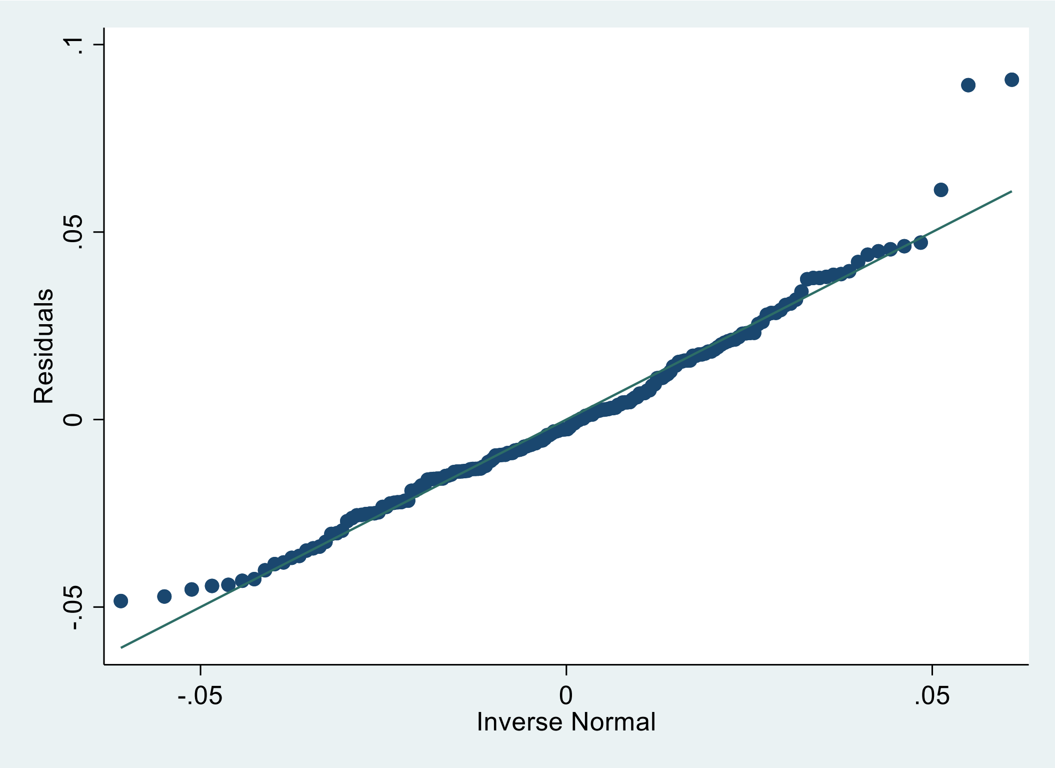
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**2.585**	**1**	**0.1079**

H0: no serial correlation

Assumption 7

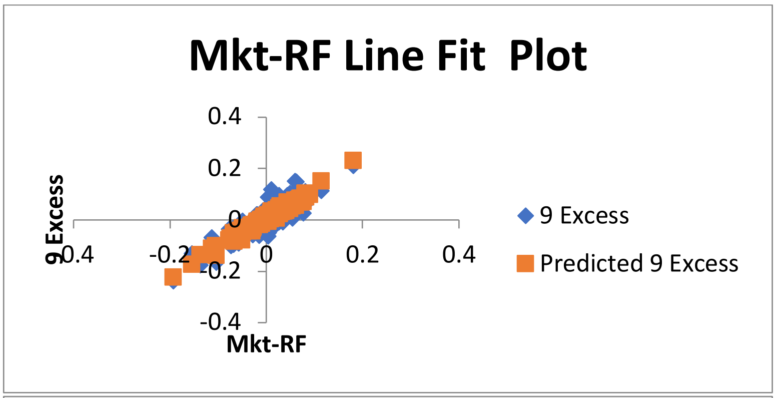


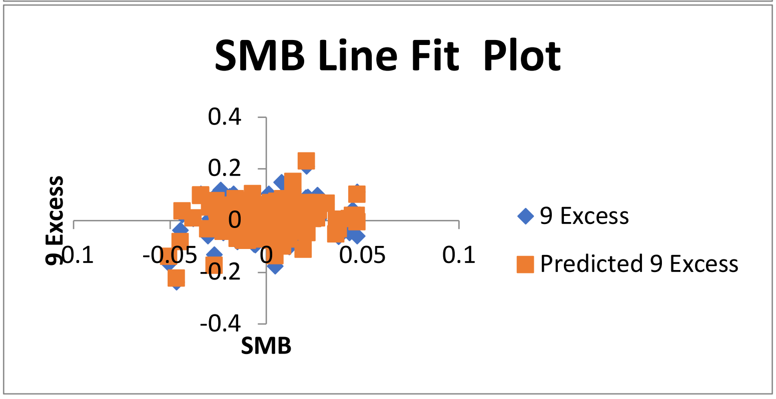
Shapiro-Wilk W test for normal data

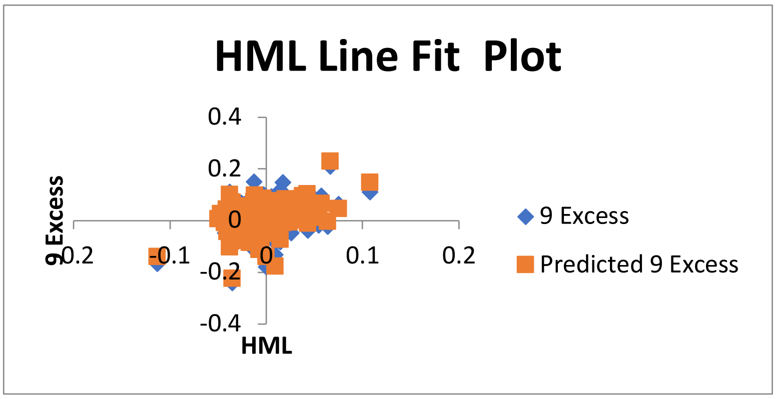
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.97376**	**3.779**	**3.052**	**0.00113**

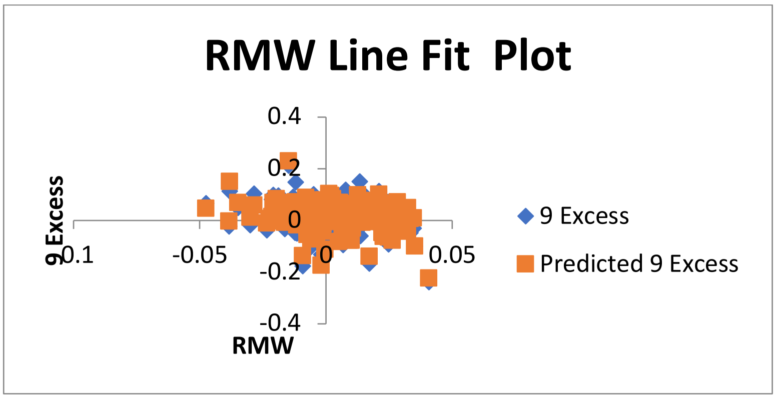
LOW ESG

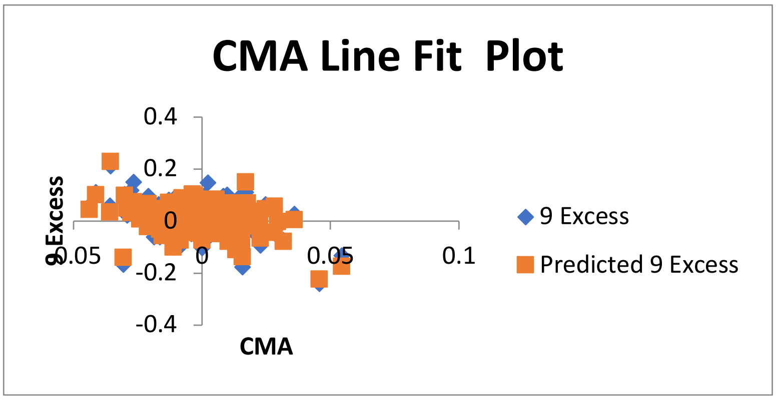
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.4
-0.2
0
0.2
0.4
Mkt-RF
9 Excess
Predicted 9 Excess

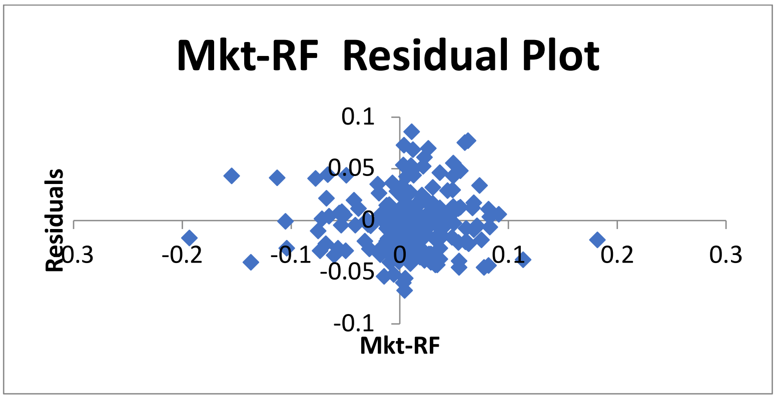

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.1
-0.05
0
0.05
0.1
SMB
9 Excess
Predicted 9 Excess

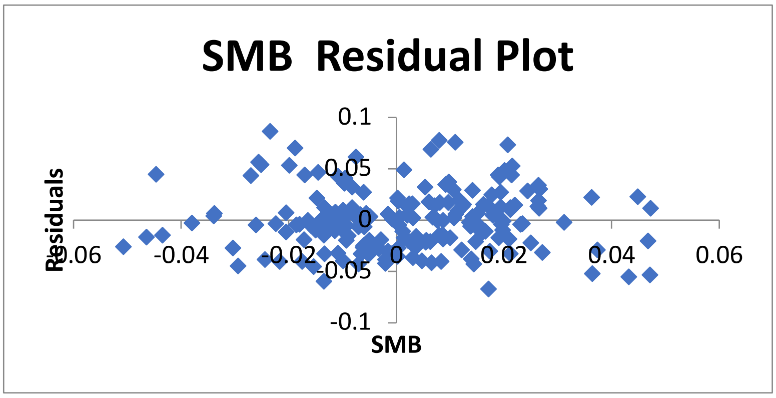

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.2
-0.1
0
0.1
0.2
HML
9 Excess
Predicted 9 Excess

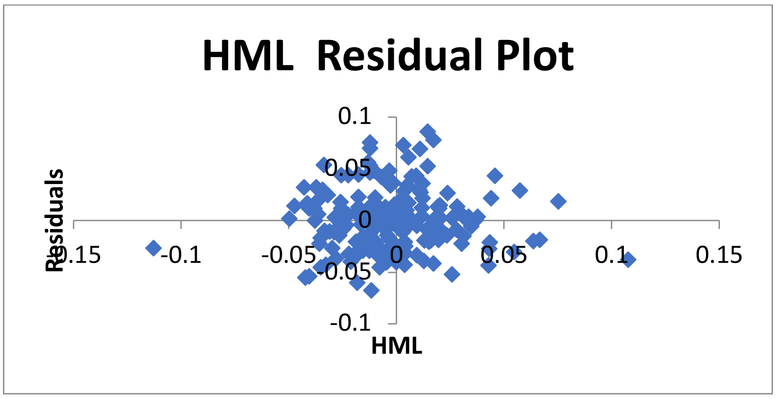


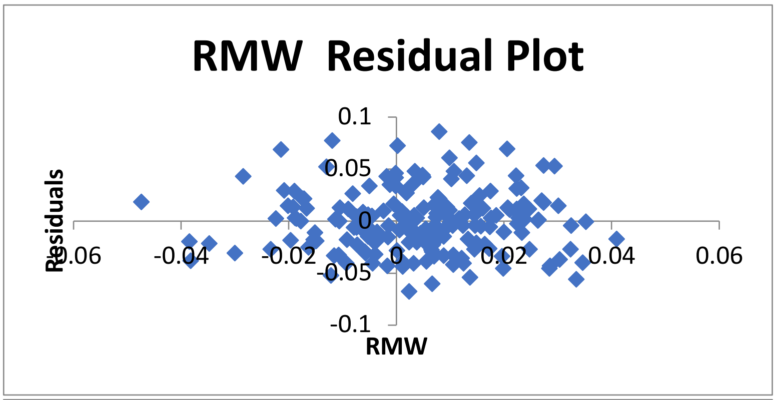


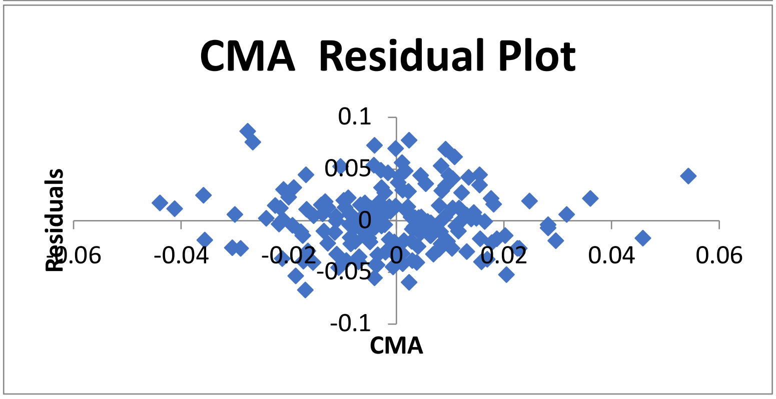
Assumption 2





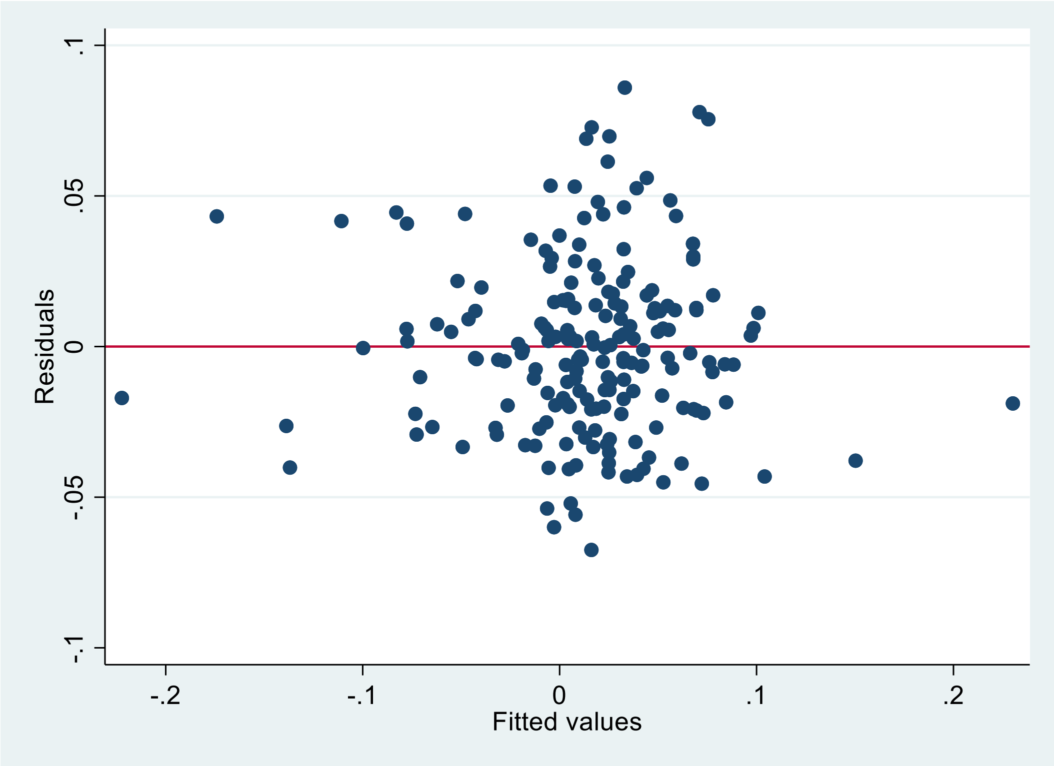






	Mean residuals
Low ESG	-2,3491E-18

Assumption 3

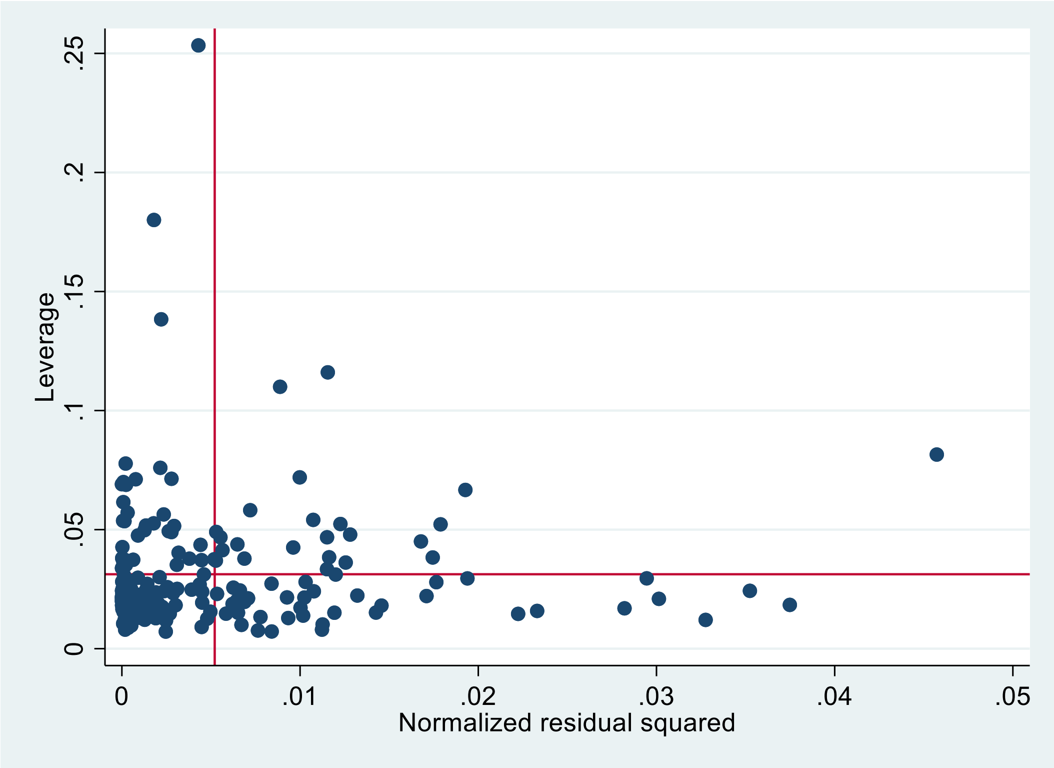


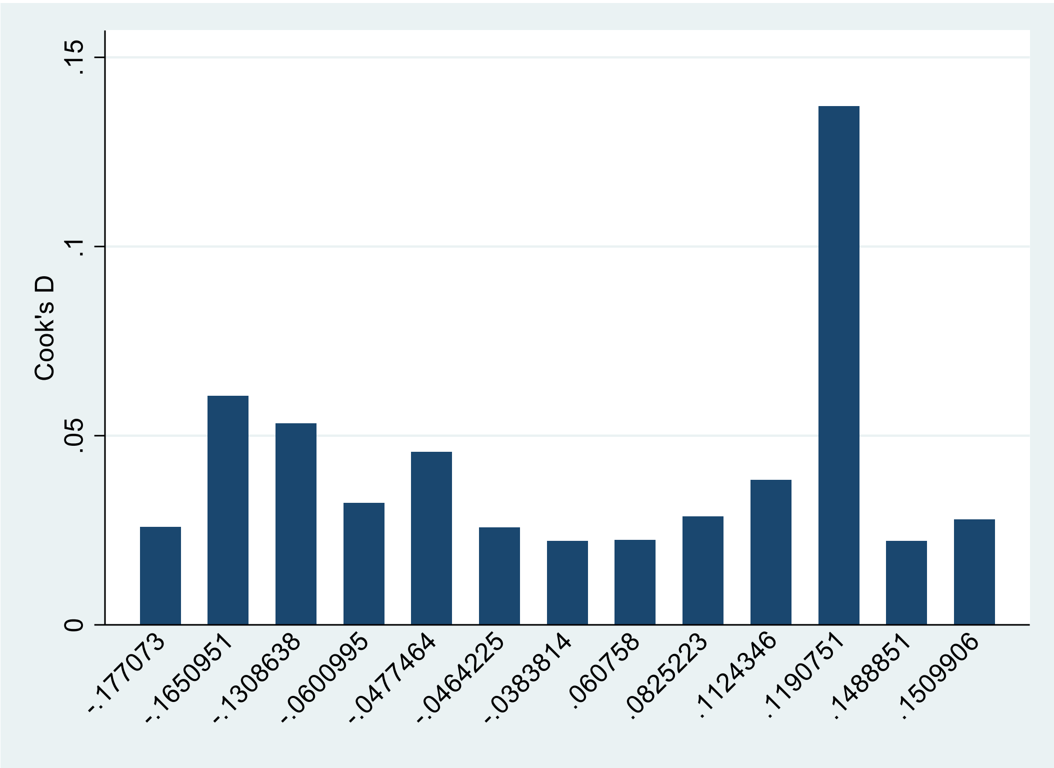

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     0.23
         Prob > chi2  =   0.6298
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     122.21
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7557
                                                Root MSE          =     .02948
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.969794	.0602374	16.10	0.000	.8509577	1.08863
smb	.1982225	.1377754	1.44	0.152	-.0735808	.4700258
hml	.4587841	.162134	2.83	0.005	.1389261	.7786422
rmw	.2170632	.2214431	0.98	0.328	-.2197998	.6539261
cma	-.5045735	.2229997	-2.26	0.025	-.9445074	-.0646397
_cons	.0047635	.0022711	2.10	0.037	.000283	.0092439

Assumption 4





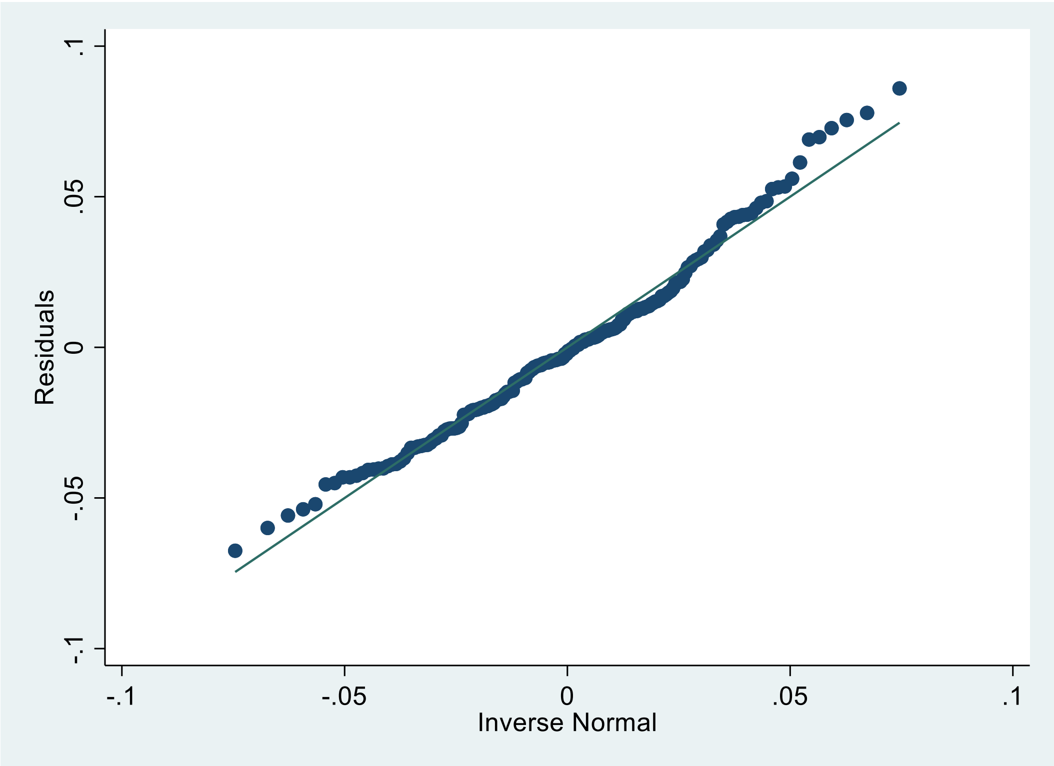
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.001**	**1**	**0.9821**

H0: no serial correlation

Assumption 7

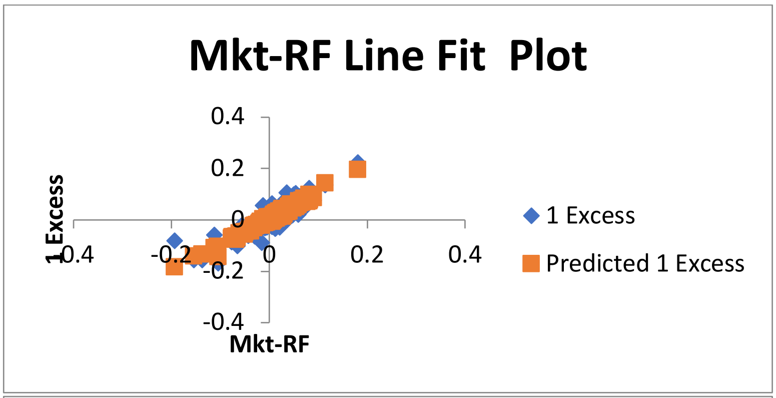


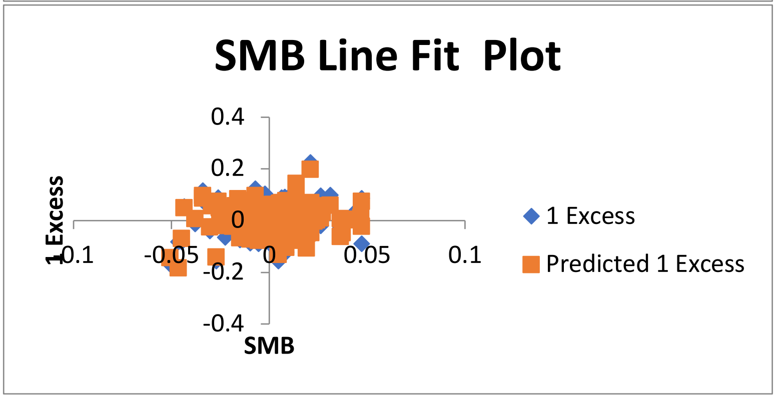
Shapiro-Wilk W test for normal data

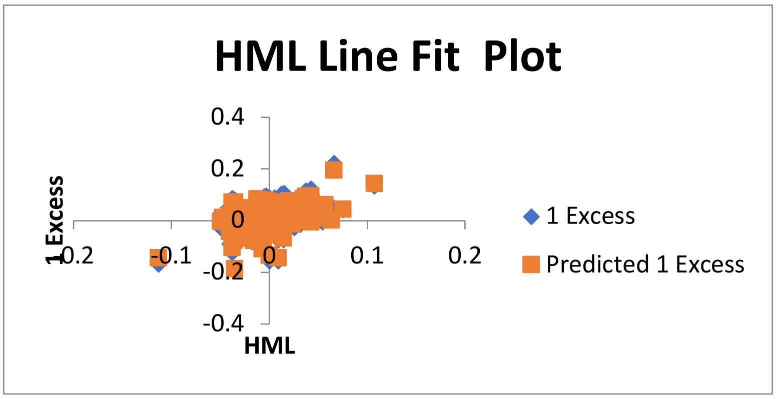
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.98251**	**2.518**	**2.120**	**0.01700**

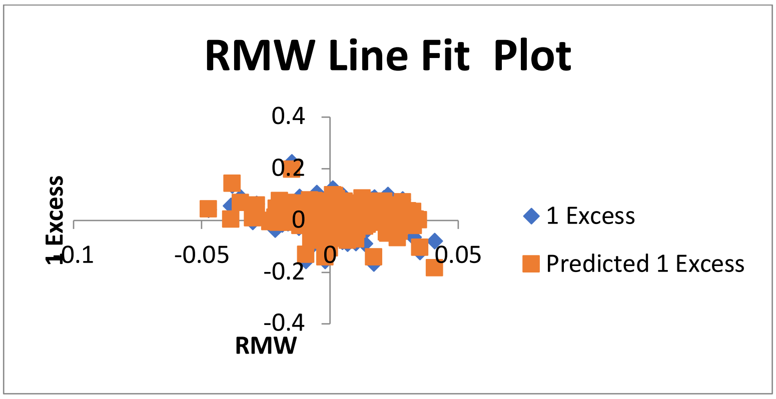
HIGH E

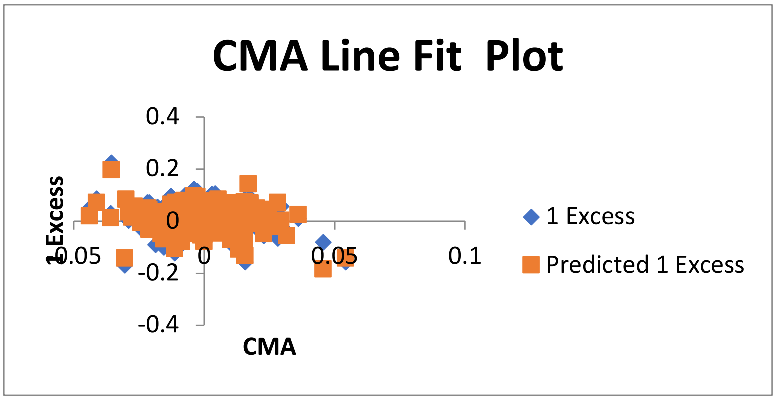
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

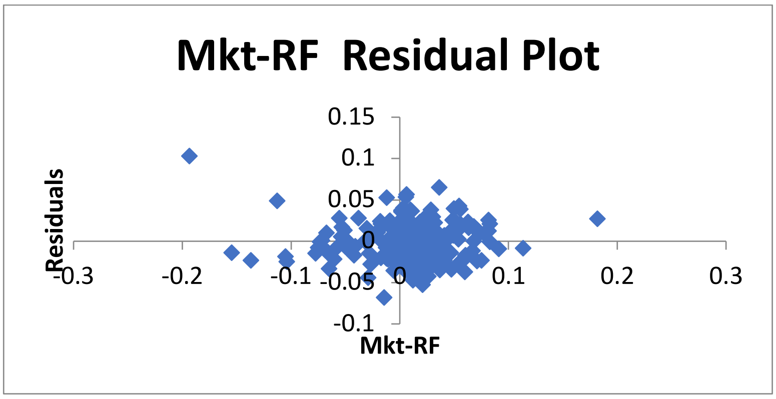

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

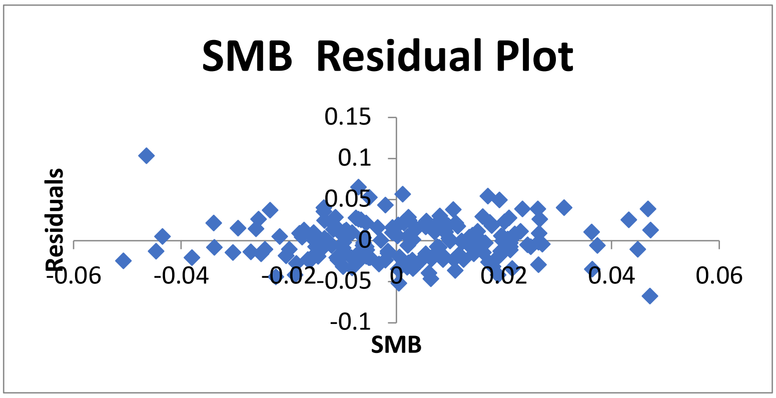

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

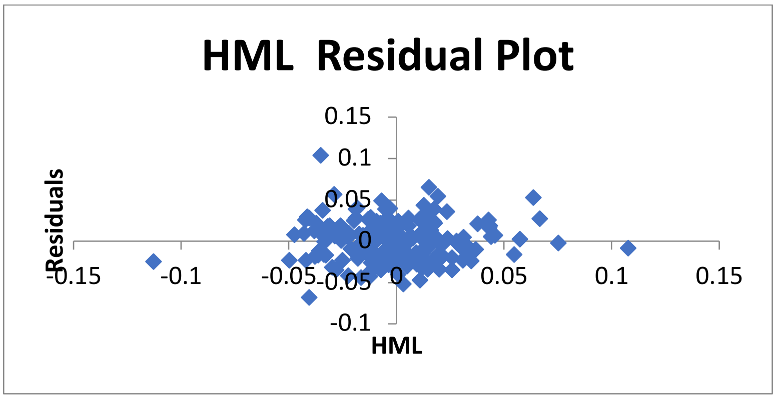


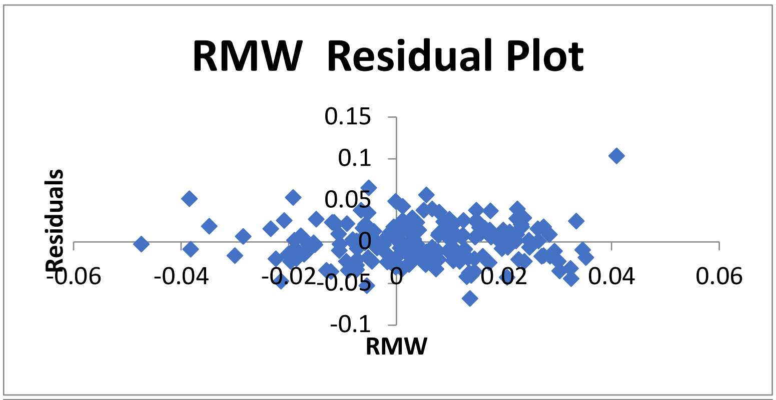


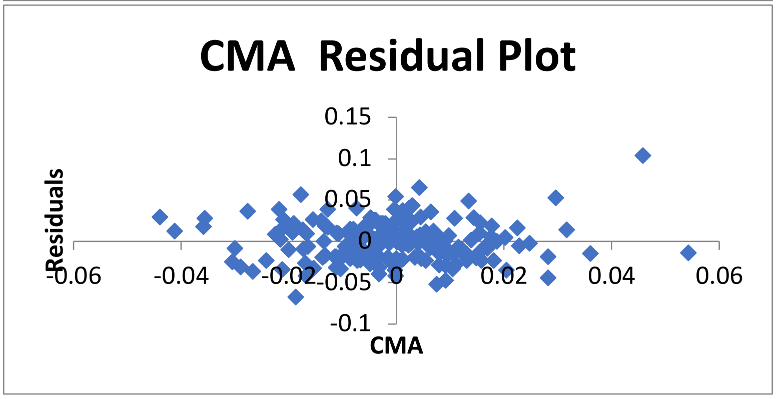
Assumption 2





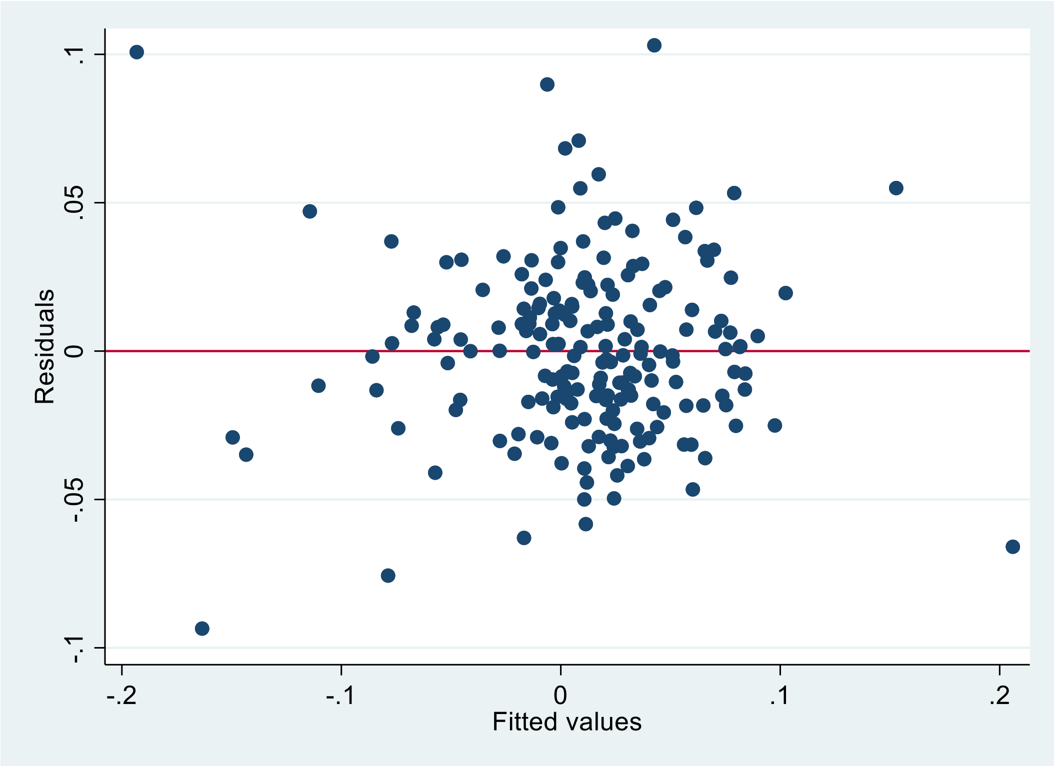






	Mean residuals
High E	-2,71051E-19

Assumption 3

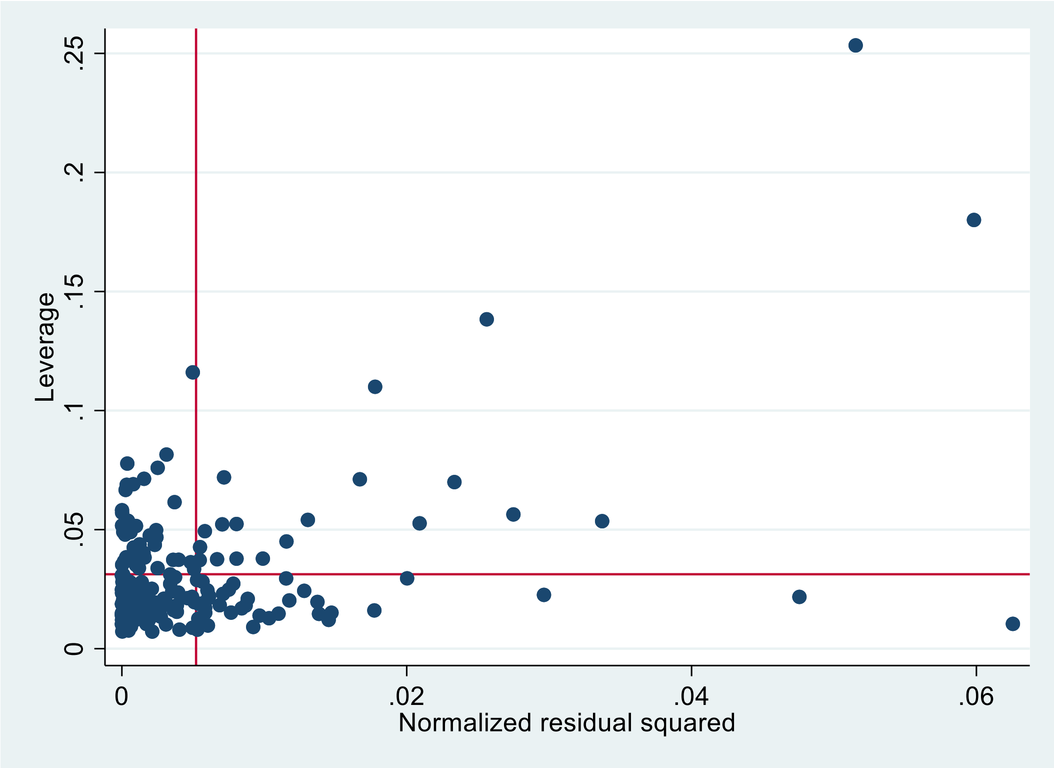


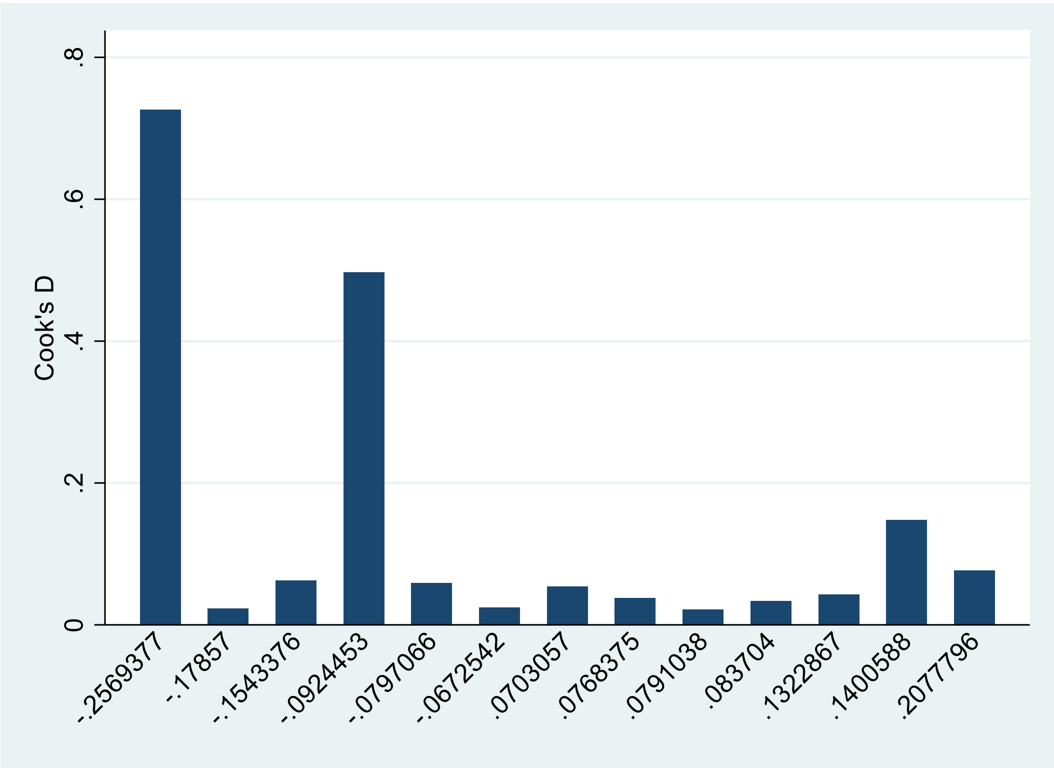

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     9.38
         Prob > chi2  =   0.0022
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      59.41
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7418
                                                Root MSE          =     .03021
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.061536	.0677081	15.68	0.000	.9279612	1.19511
smb	.1776741	.1470243	1.21	0.228	-.1123754	.4677236
hml	.3949329	.2196841	1.80	0.074	-.0384599	.8283256
rmw	.4873709	.3290303	1.48	0.140	-.1617401	1.136482
cma	.2893134	.2460711	1.18	0.241	-.1961358	.7747625
_cons	.0009267	.0027255	0.34	0.734	-.0044501	.0063035

Assumption 4





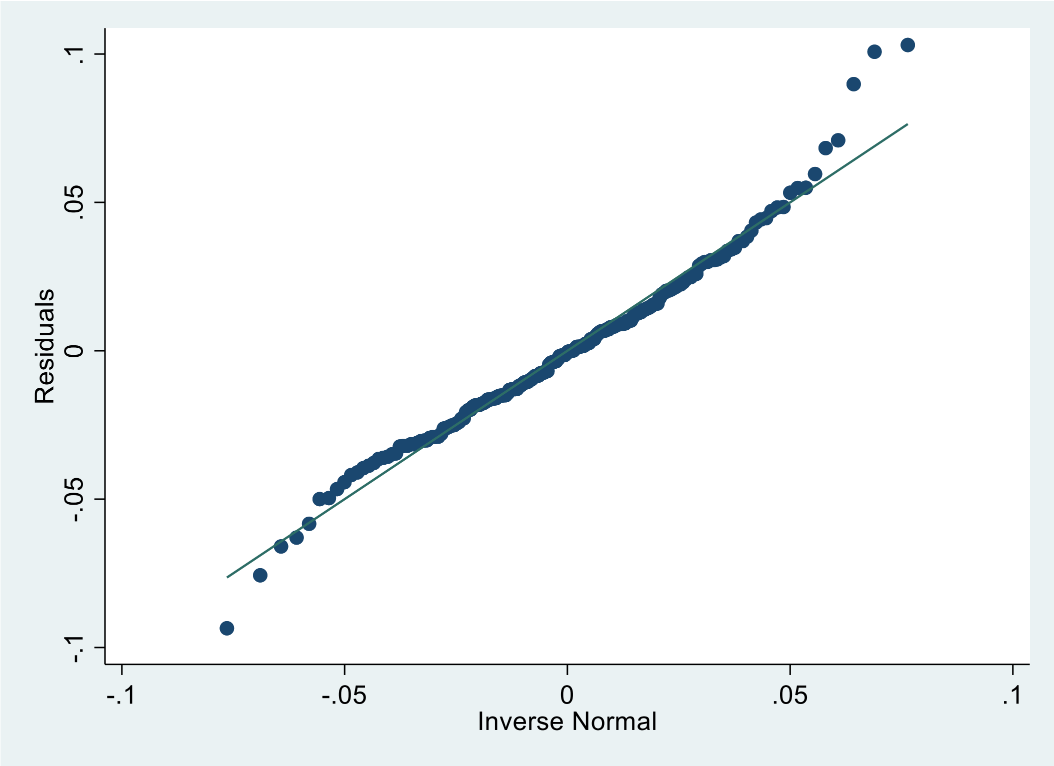
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.026**	**1**	**0.8717**

H0: no serial correlation

Assumption 7

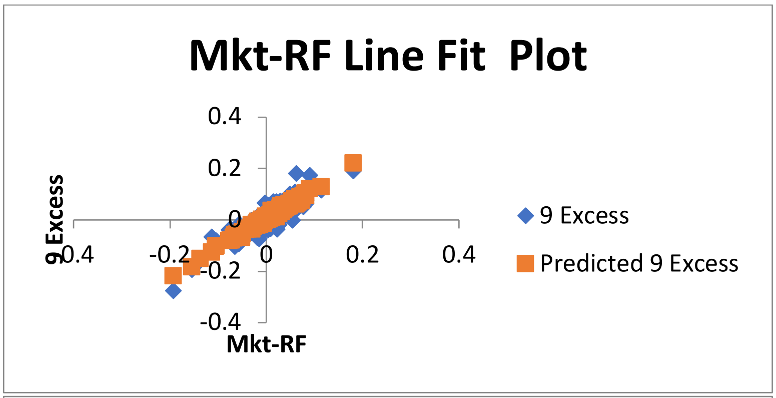


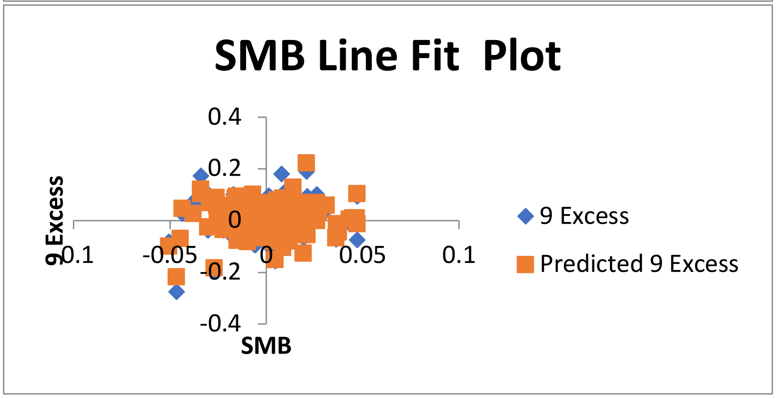
Shapiro-Wilk W test for normal data

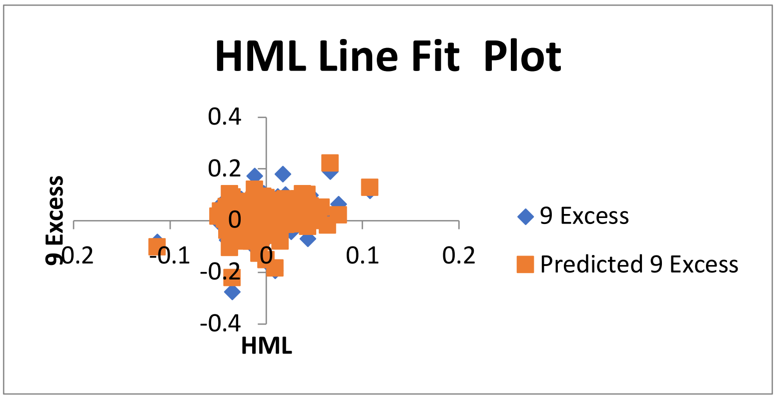
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.98166**	**2.641**	**2.230**	**0.01287**

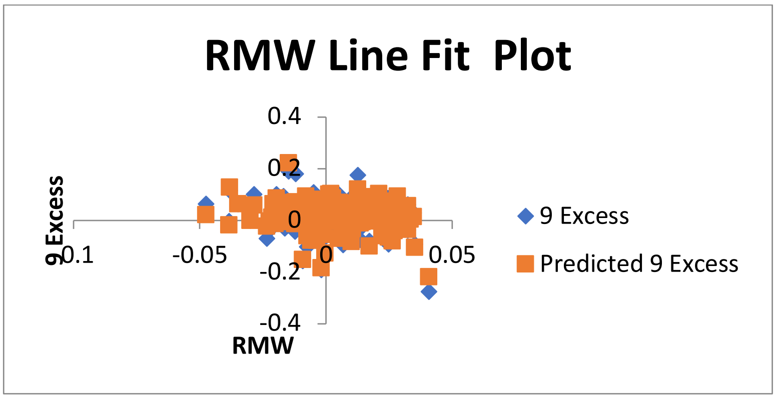
LOW E

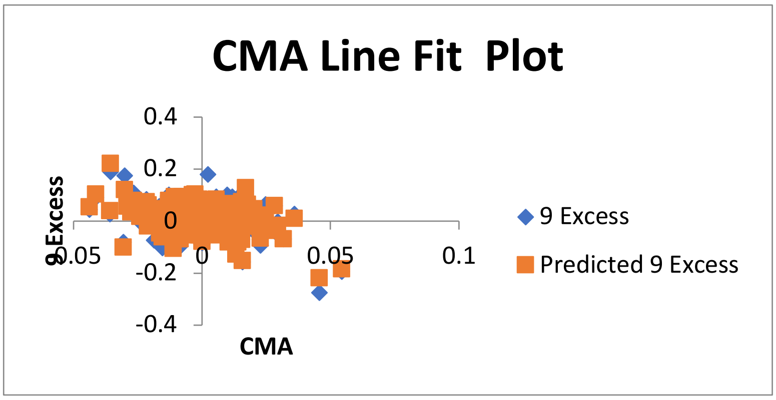
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

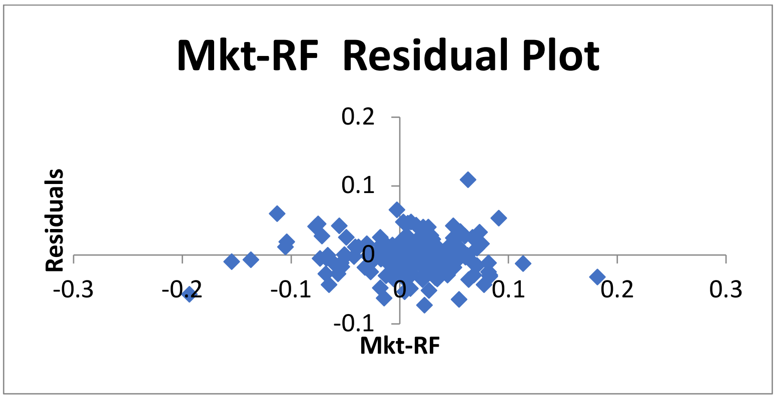

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

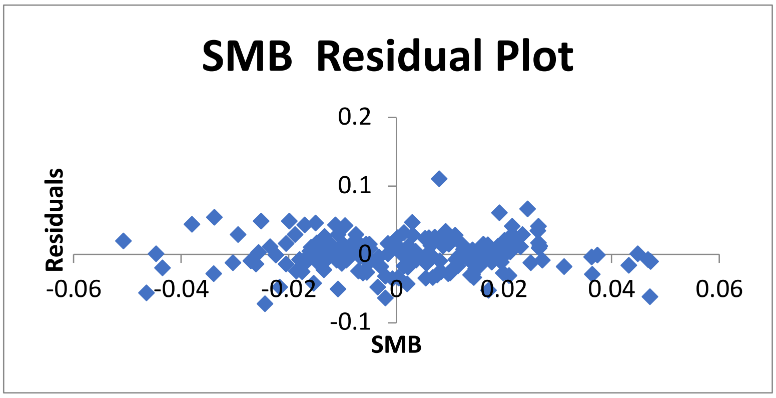

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

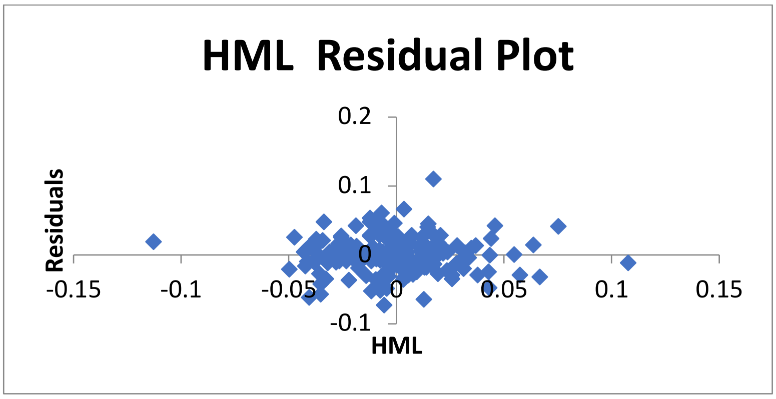


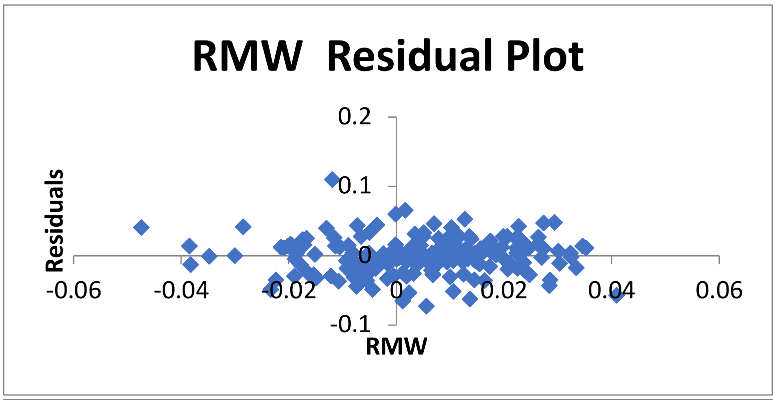


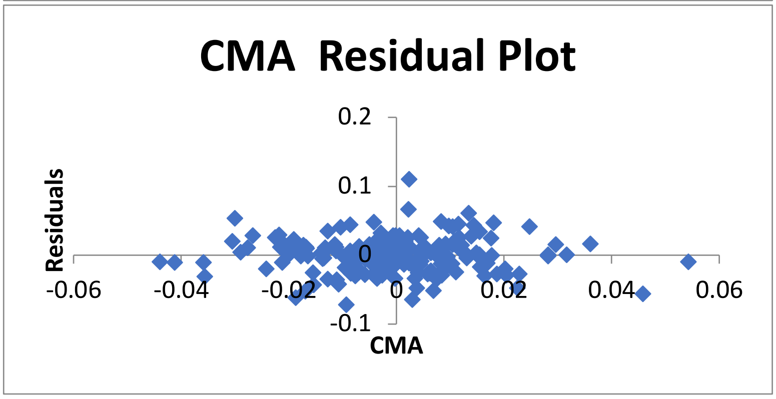
Assumption 2





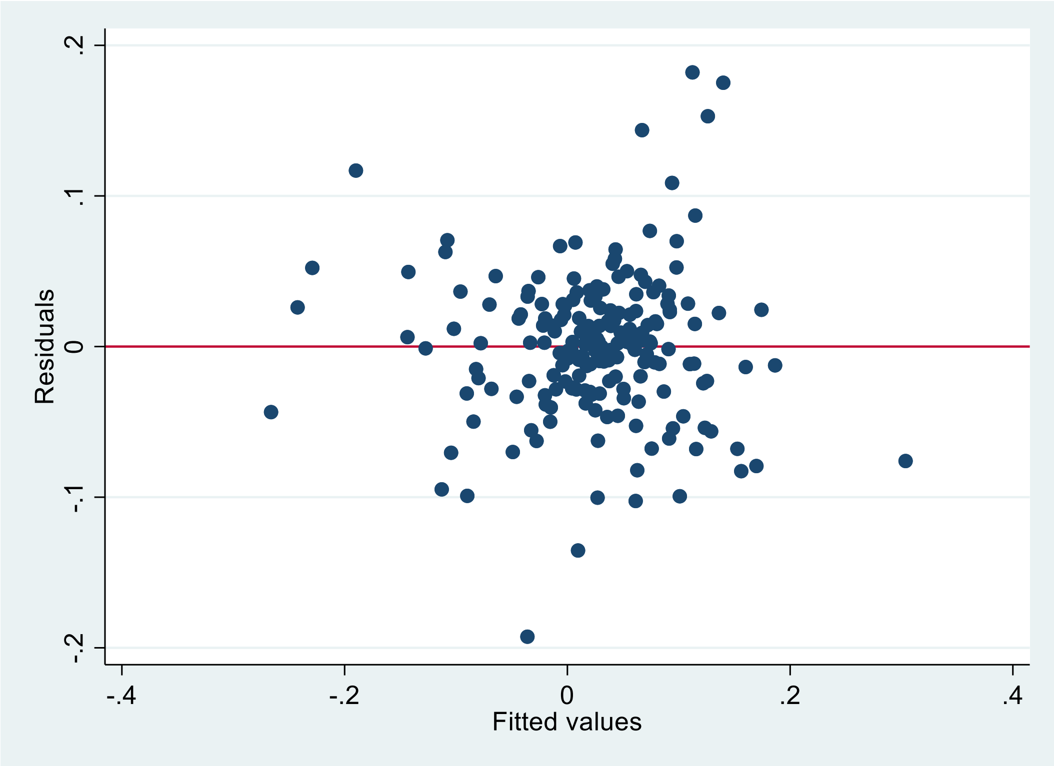






	Mean residuals
Low E	-3,31585E-18

Assumption 3

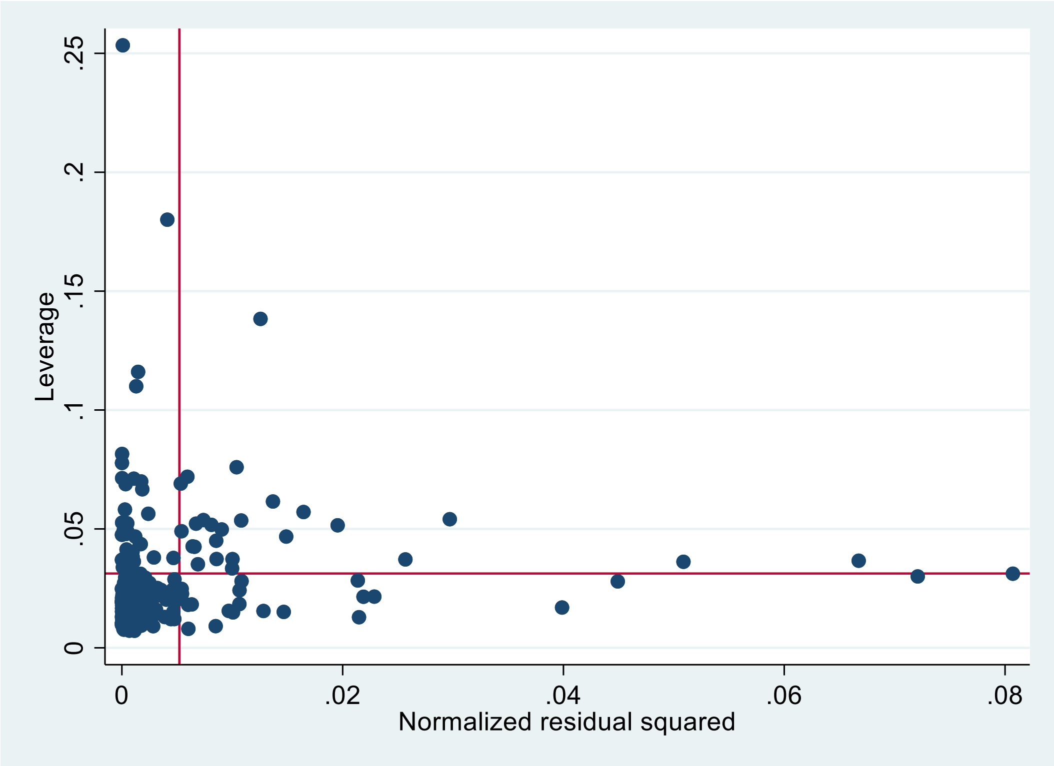


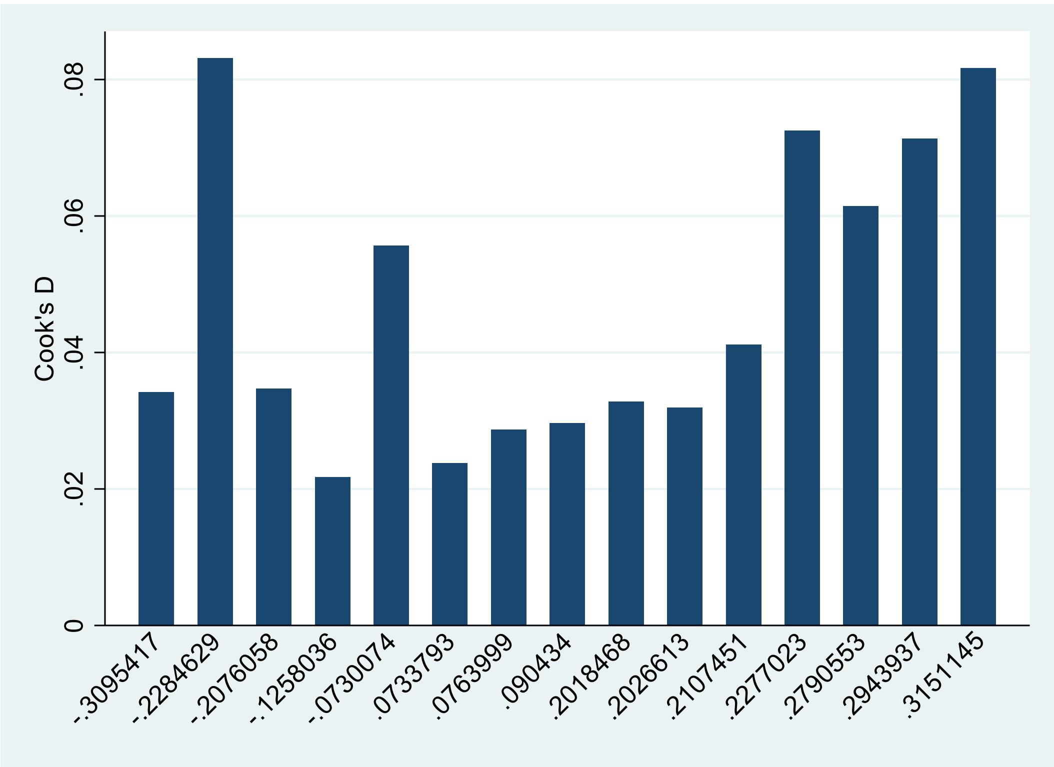

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     3.53
         Prob > chi2  =   0.0604
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      61.44
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7028
                                                Root MSE          =     .04971
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.6253	.1131793	14.36	0.000	1.402019	1.84858
smb	-.4757745	.202615	-2.35	0.020	-.8754933	-.0760556
hml	.255771	.2585273	0.99	0.324	-.2542517	.7657938
rmw	.9194443	.4011155	2.29	0.023	.1281235	1.710765
cma	-.2216346	.2905479	-0.76	0.447	-.7948275	.3515584
_cons	.0074771	.003893	1.92	0.056	-.0002031	.0151573

Assumption 4





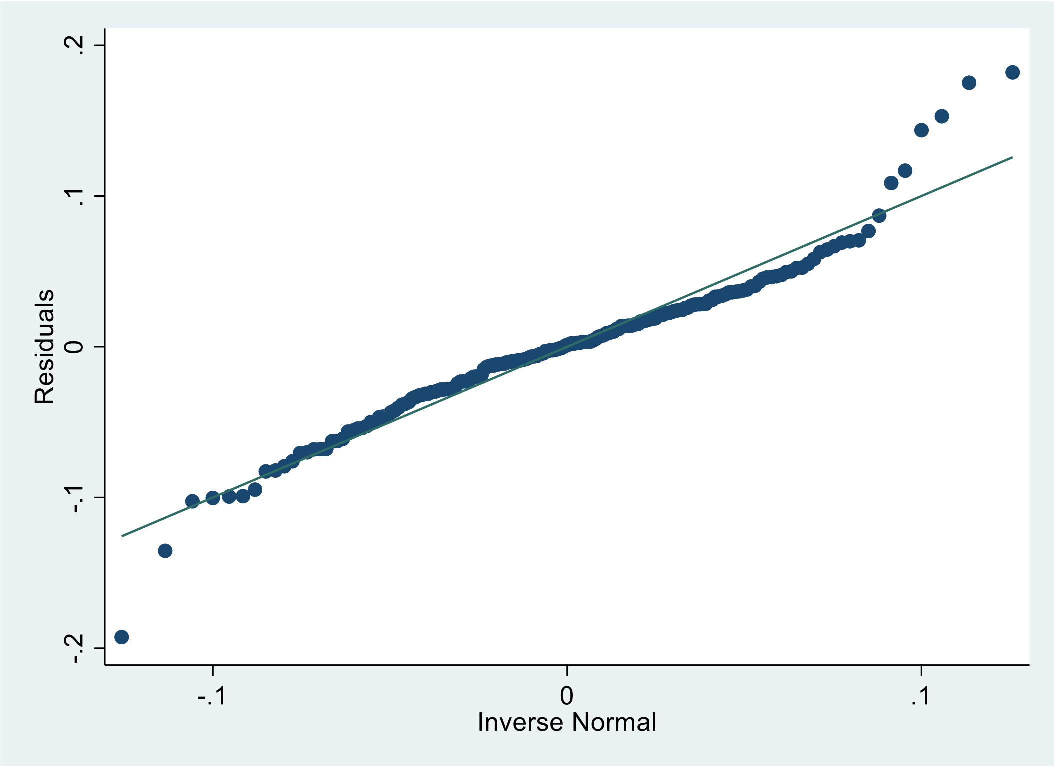
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**0.178**	**1**	**0.6729**

H0: no serial correlation

Assumption 7

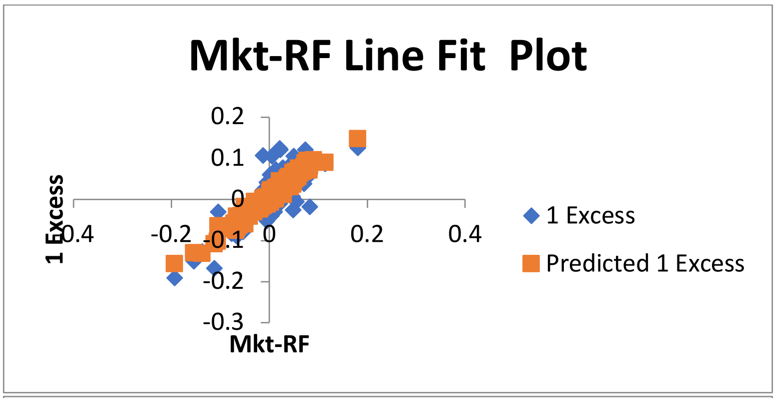


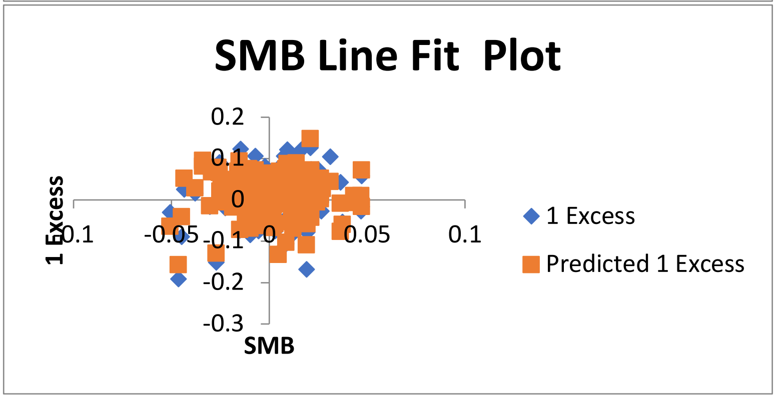
Shapiro-Wilk W test for normal data

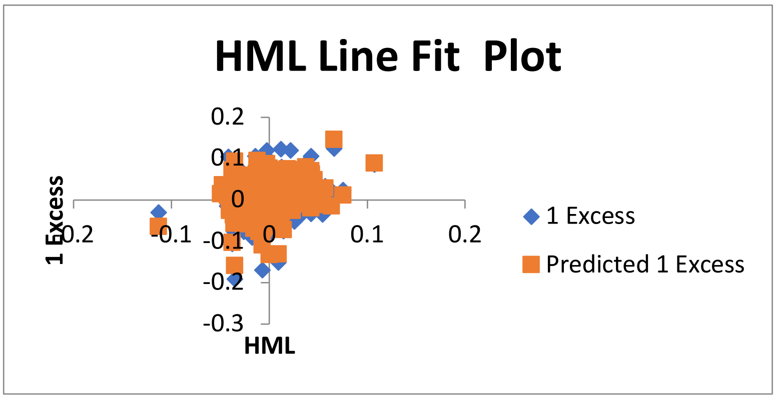
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.95593**	**6.345**	**4.242**	**0.00001**

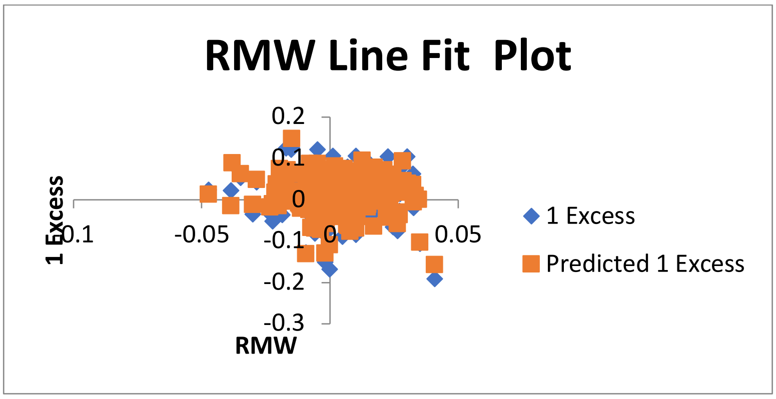
HIGH S

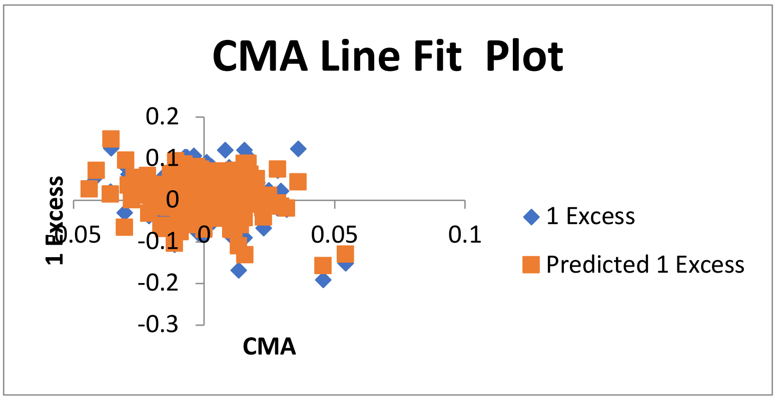
Assumption 1


Mkt-RF Line Fit Plot
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

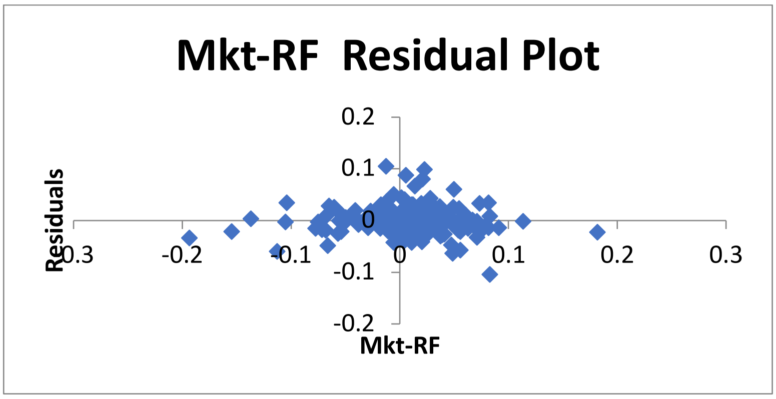

SMB Line Fit Plot
0.2
0.1
0
-0.1
-0.2
-0.3
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

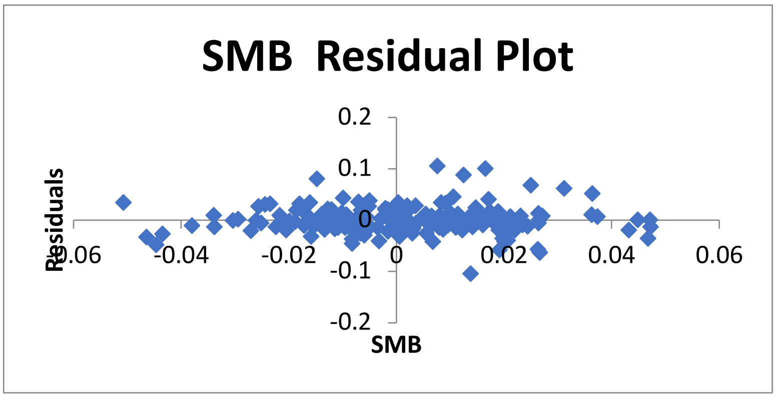

HML Line Fit Plot
0.2
0.1
0
-0.1
-0.2
-0.3
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

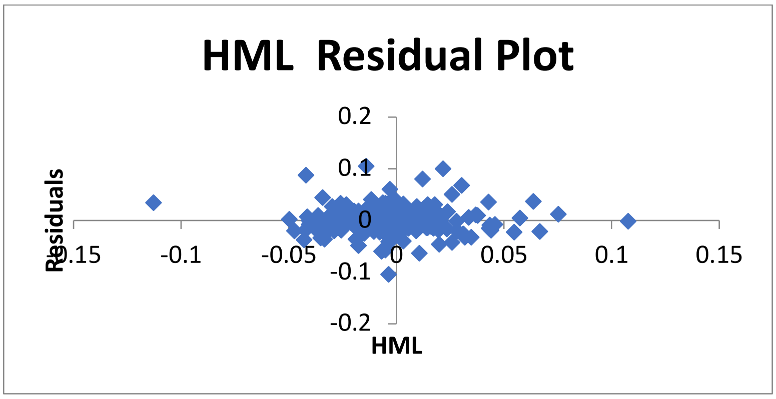


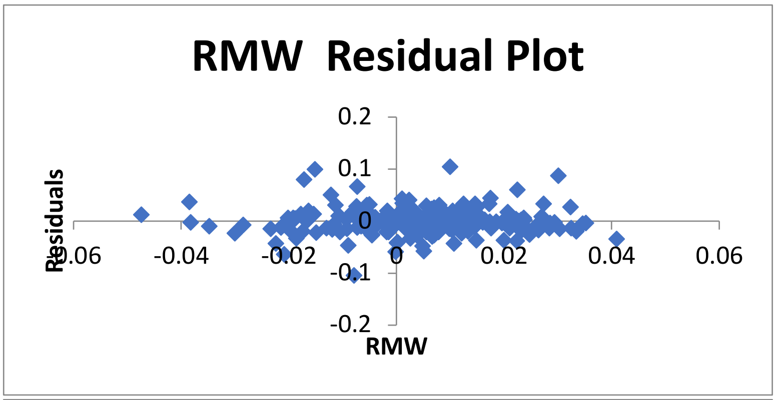


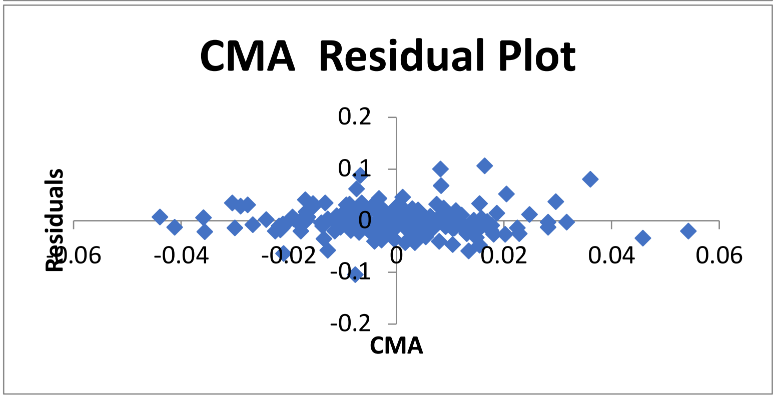
Assumption 2





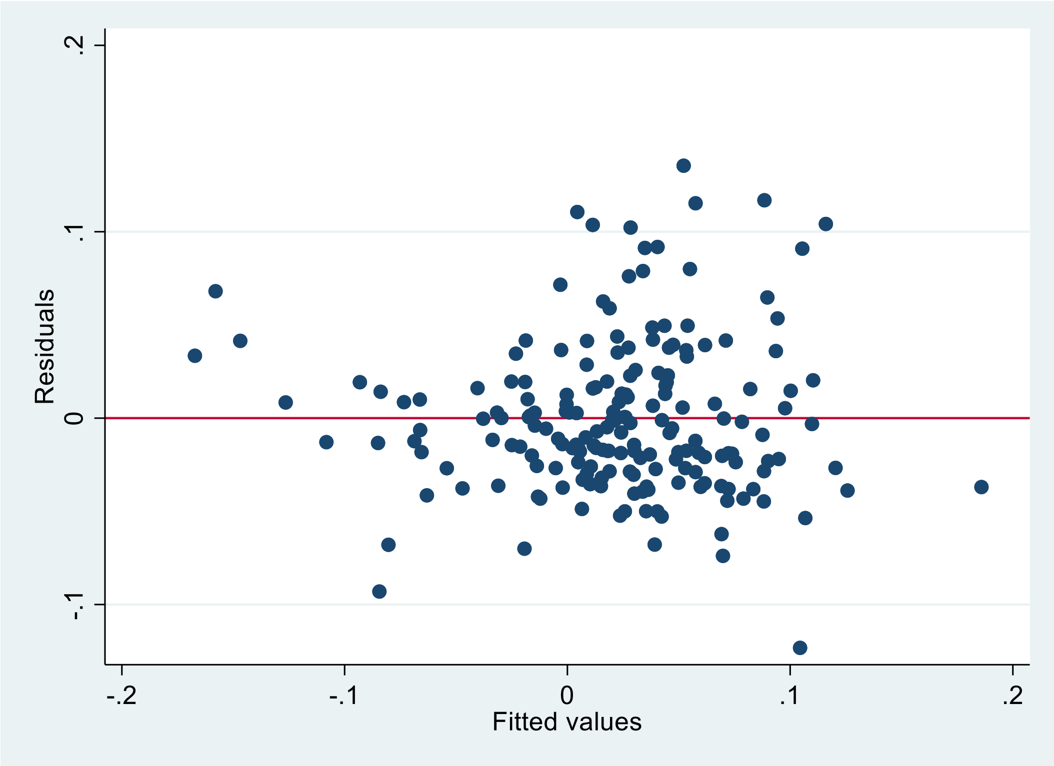






	Mean residuals
High S	-5,27645E-18

Assumption 3

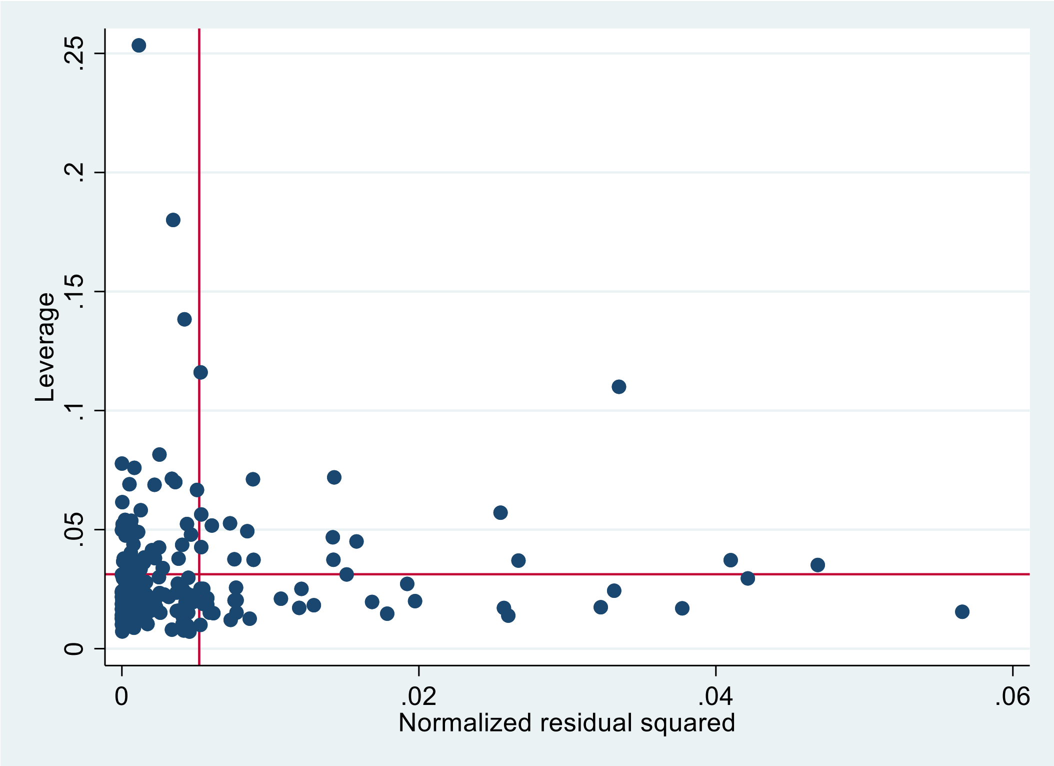


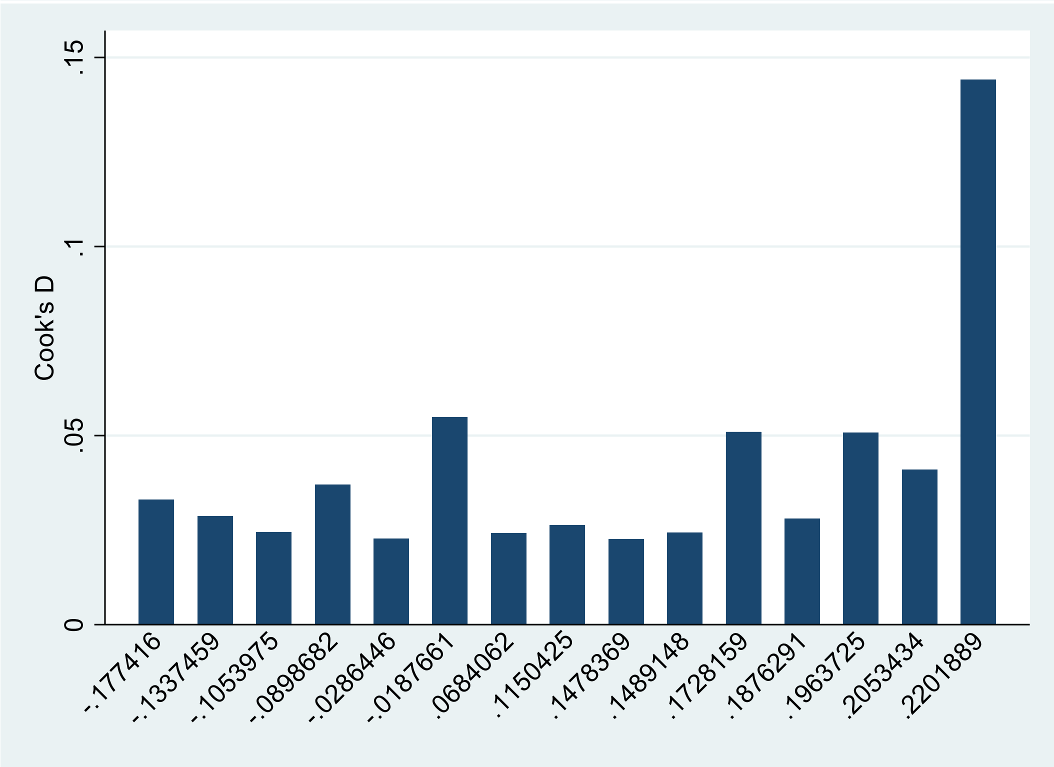

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     6.70
         Prob > chi2  =   0.0097
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      52.35
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6200
                                                Root MSE          =     .04174
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.270091	.0862721	14.72	0.000	1.099893	1.440289
smb	-.2110851	.1637959	-1.29	0.199	-.5342217	.1120516
hml	-.2856791	.2102401	-1.36	0.176	-.7004408	.1290826
rmw	.417951	.2859236	1.46	0.145	-.1461191	.9820211
cma	.6894463	.2832669	2.43	0.016	.1306174	1.248275
_cons	.0096387	.0030796	3.13	0.002	.0035633	.015714

Assumption 4





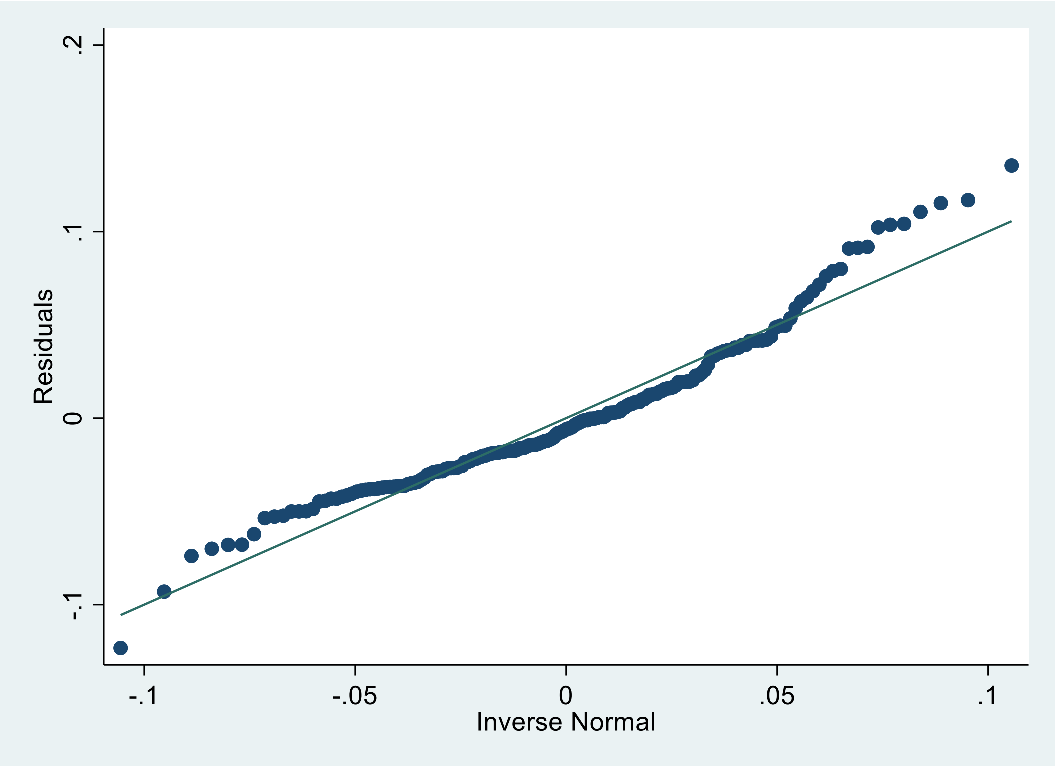
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.830**	**1**	**0.3624**

H0: no serial correlation

Assumption 7

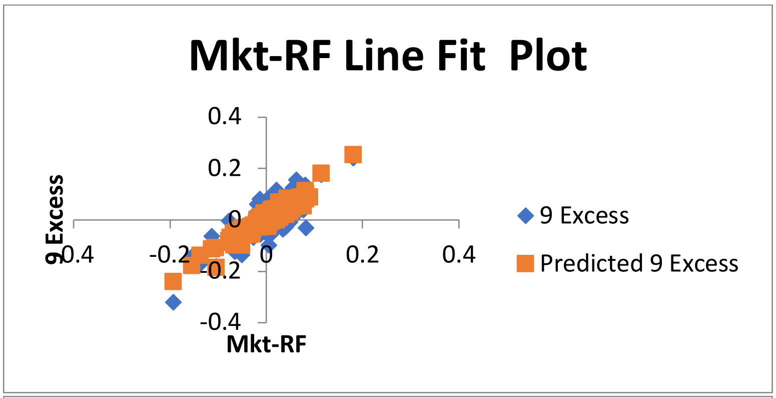


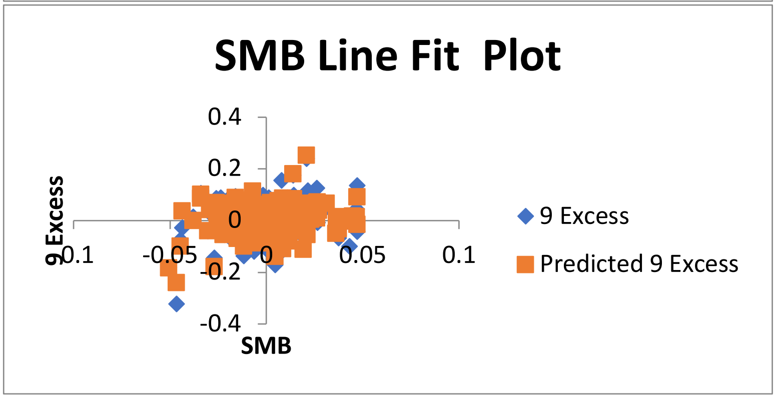
Shapiro-Wilk W test for normal data

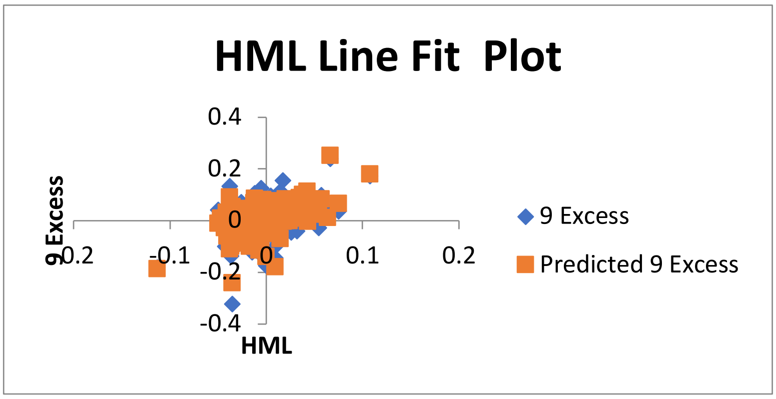
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.95432**	**6.577**	**4.325**	**0.00001**

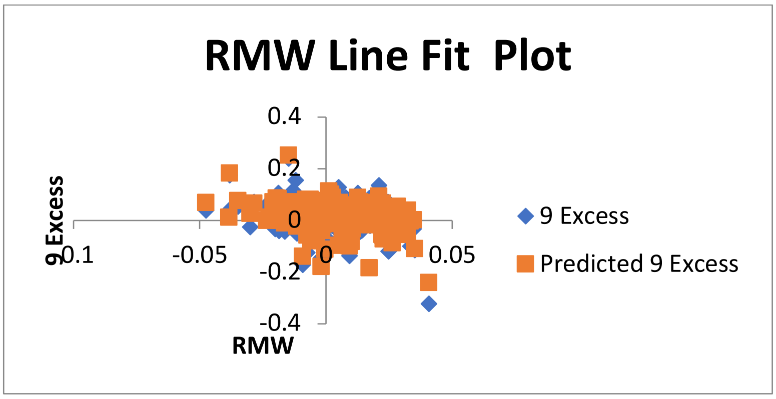
LOW S

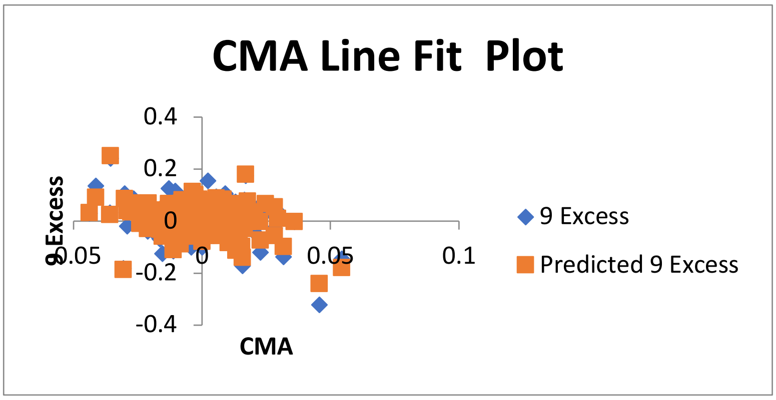
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

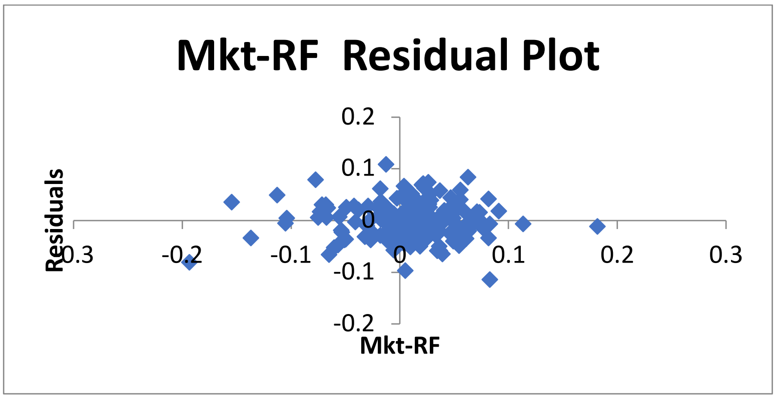

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

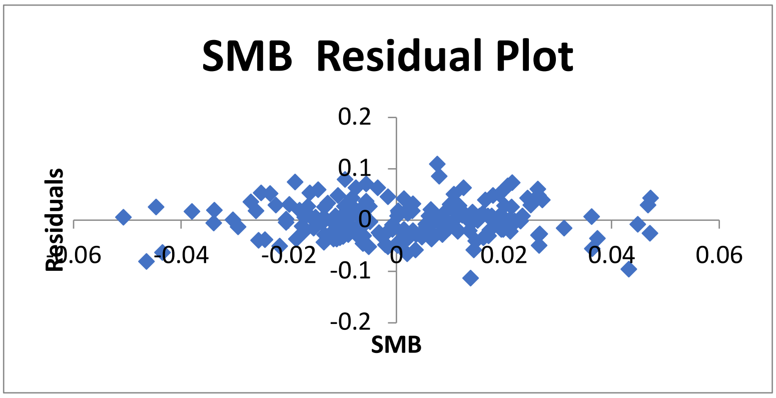

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

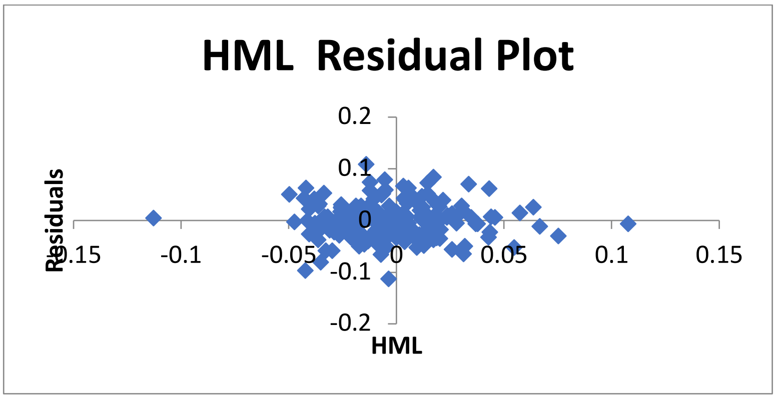


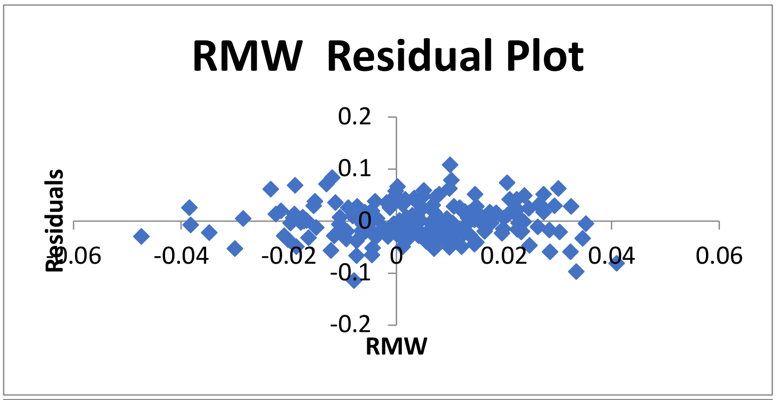


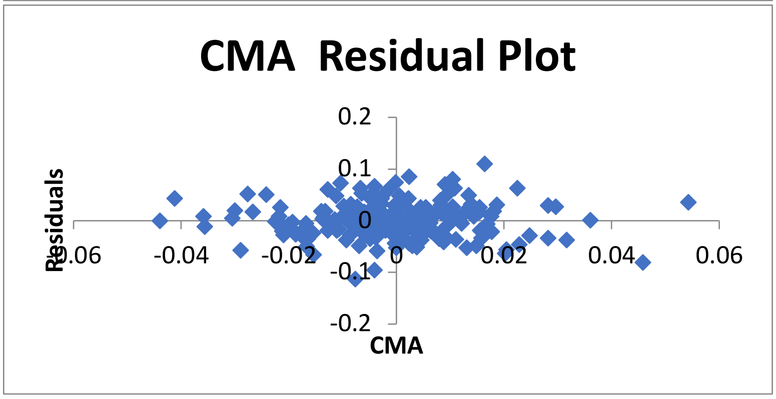
Assumption 2





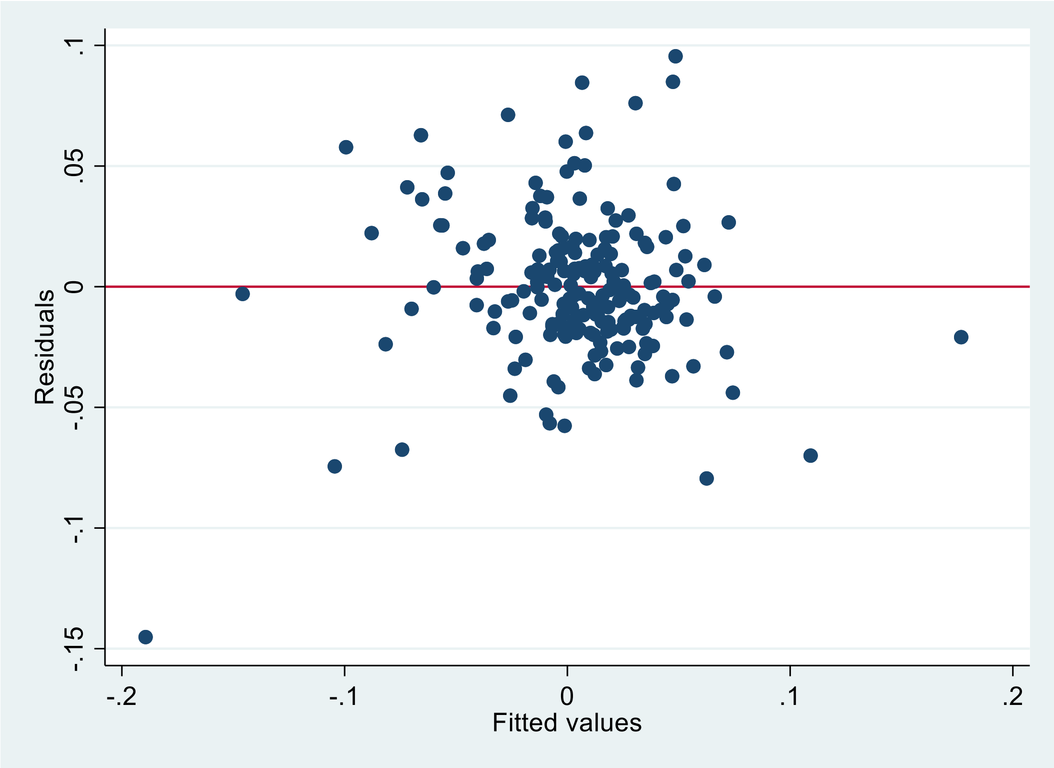






	Mean residuals
Low S	-1,4456E-18

Assumption 3

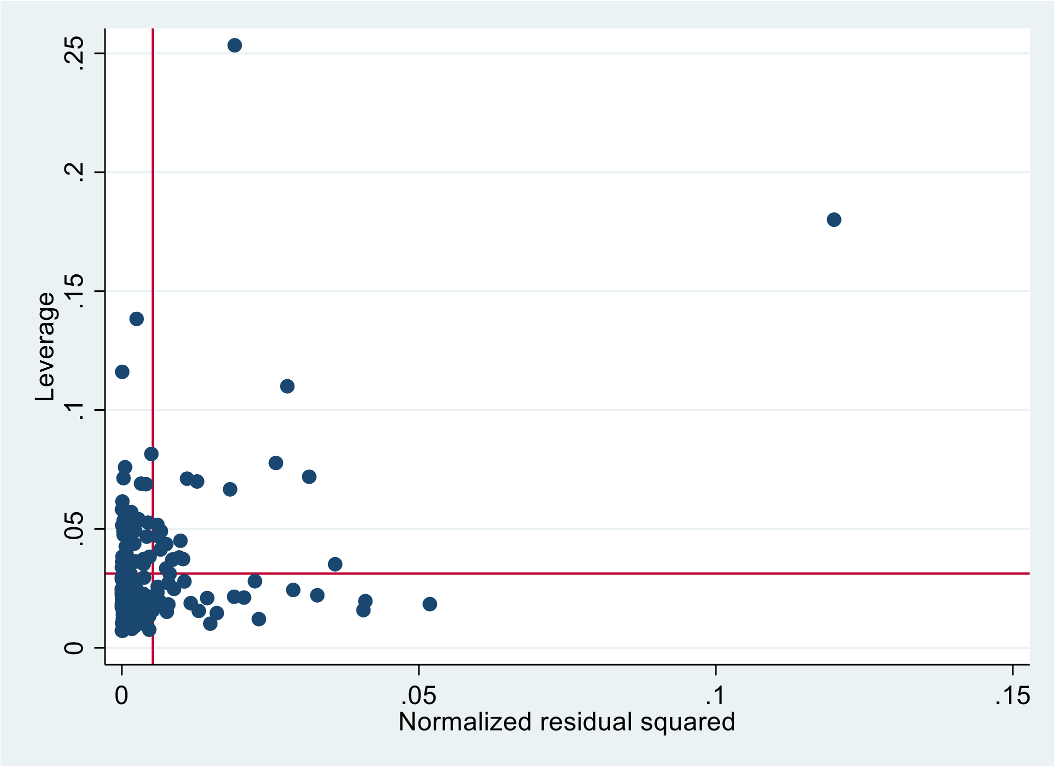


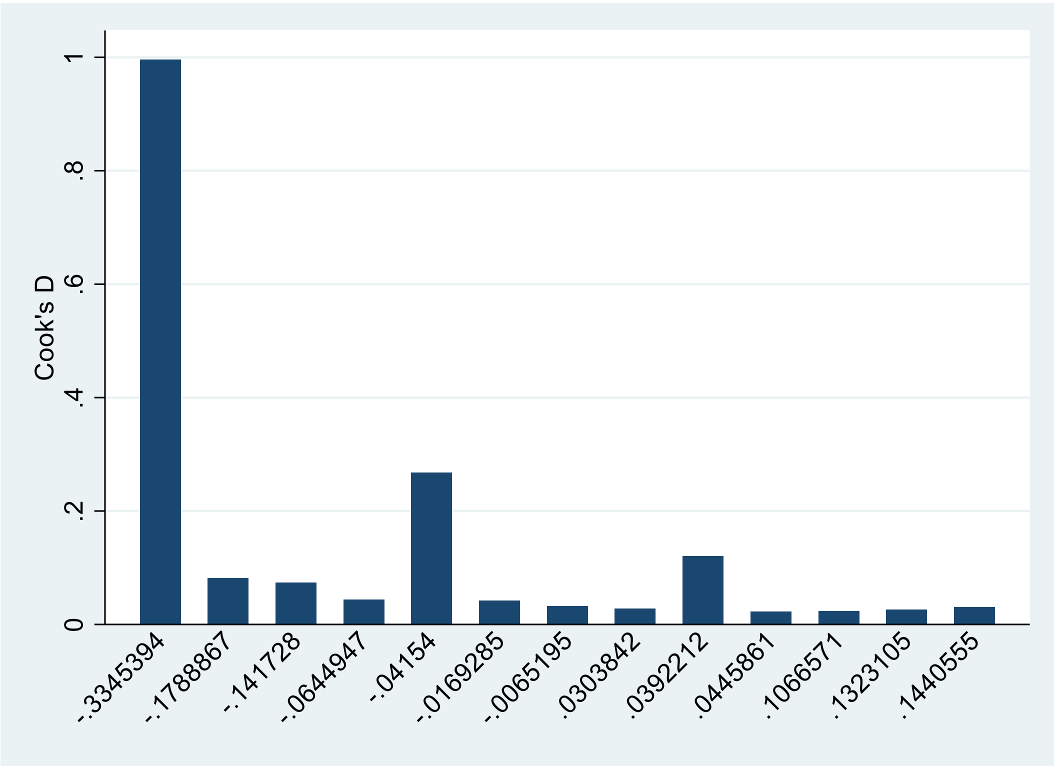

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =    36.86
         Prob > chi2  =   0.0000
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      21.76
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6281
                                                Root MSE          =     .03075
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.6853694	.0831988	8.24	0.000	.5212349	.849504
smb	.1302436	.1440386	0.90	0.367	-.1539157	.4144029
hml	.356786	.1873093	1.90	0.058	-.0127377	.7263098
rmw	-.1105228	.30806	-0.36	0.720	-.7182636	.497218
cma	-.7131382	.2500048	-2.85	0.005	-1.206348	-.2199287
_cons	-.0010762	.0024458	-0.44	0.660	-.0059014	.0037489

Assumption 4





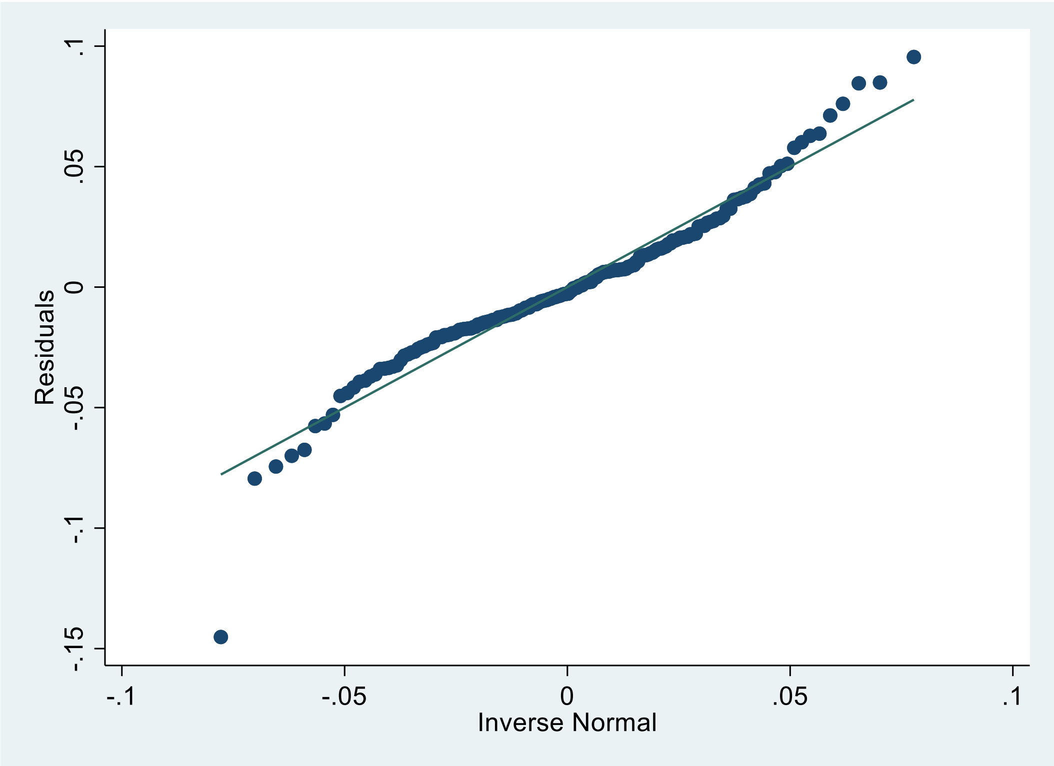
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**0.549**	**1**	**0.4586**

H0: no serial correlation

Assumption 7

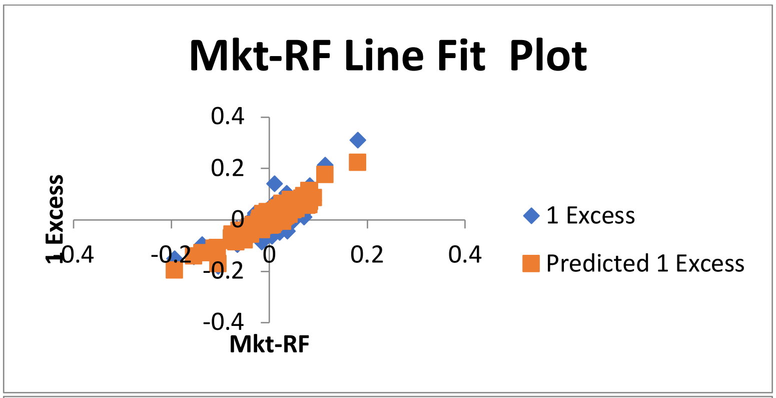


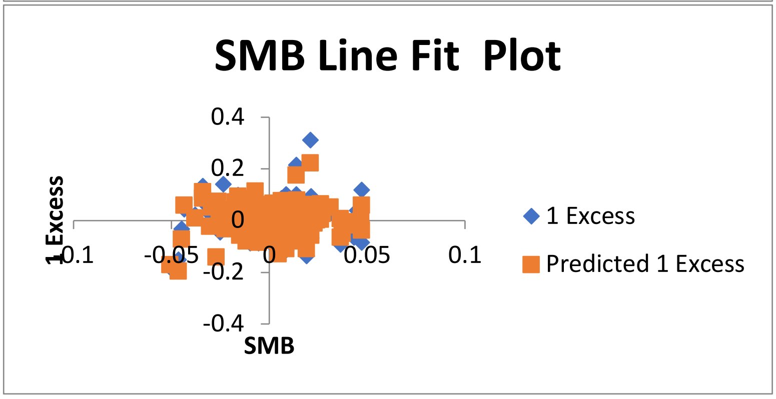
Shapiro-Wilk W test for normal data

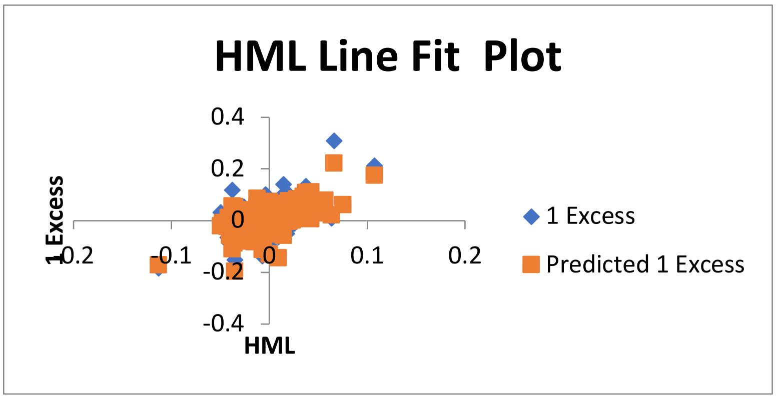
Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.95541**	**6.420**	**4.269**	**0.00001**

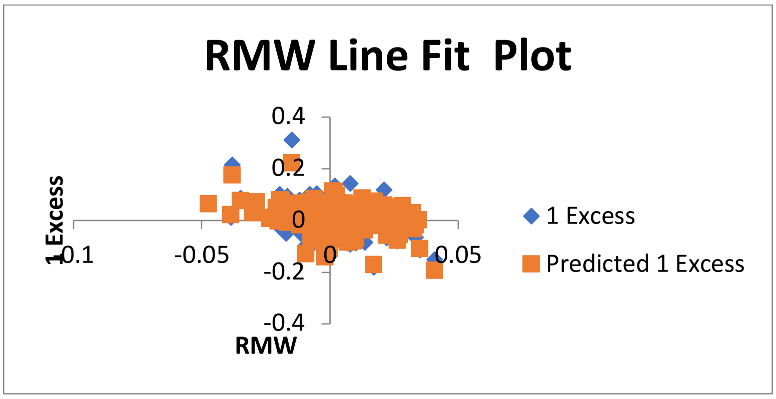
HIGH G

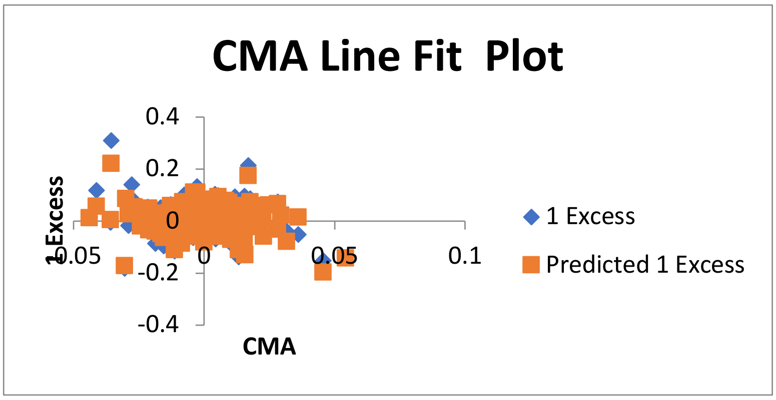
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
1 Excess
Mkt-RF
1 Excess
Predicted 1 Excess

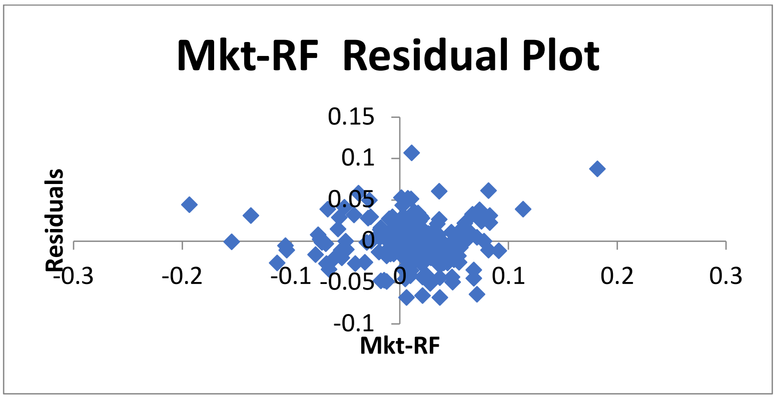

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
1 Excess
SMB
1 Excess
Predicted 1 Excess

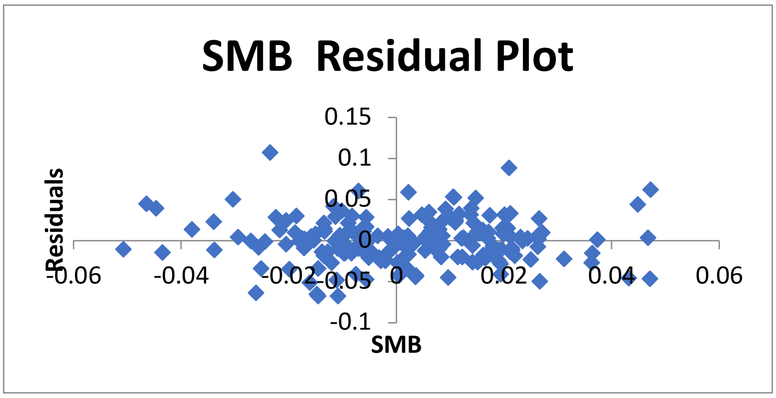

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
1 Excess
HML
1 Excess
Predicted 1 Excess

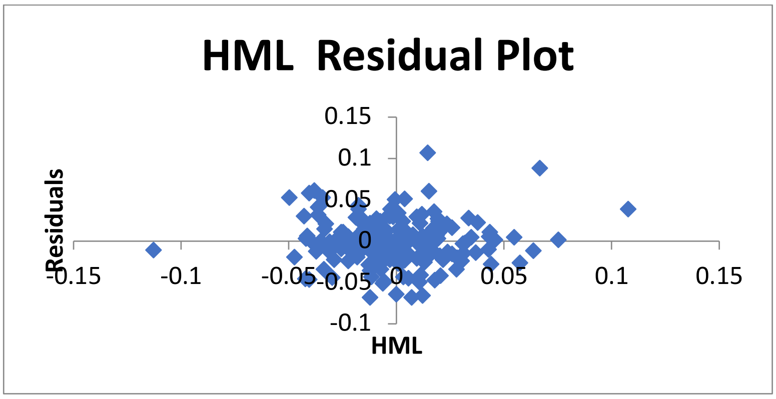


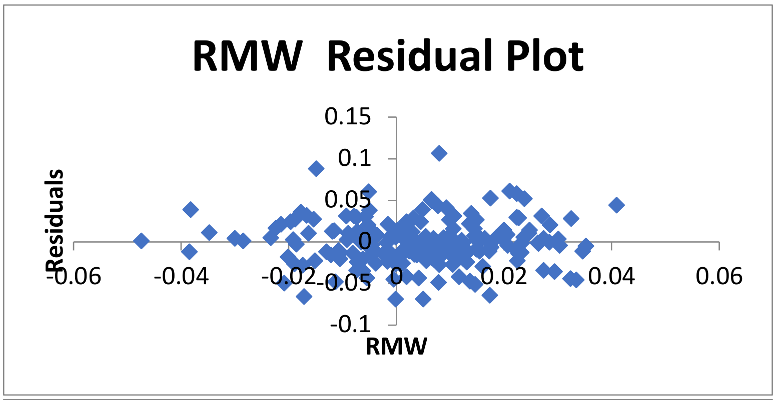


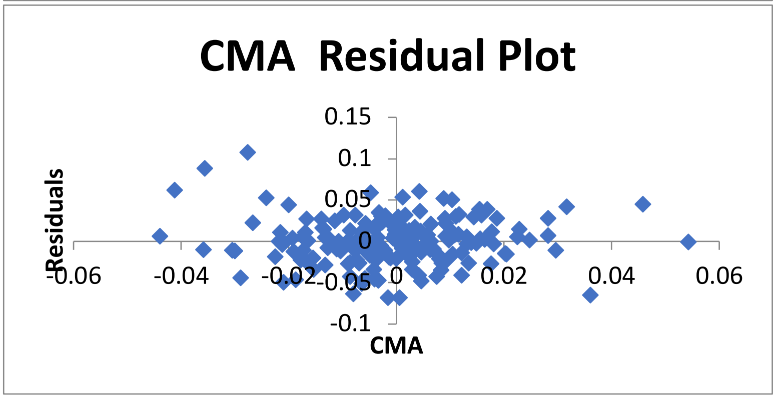
Assumption 2





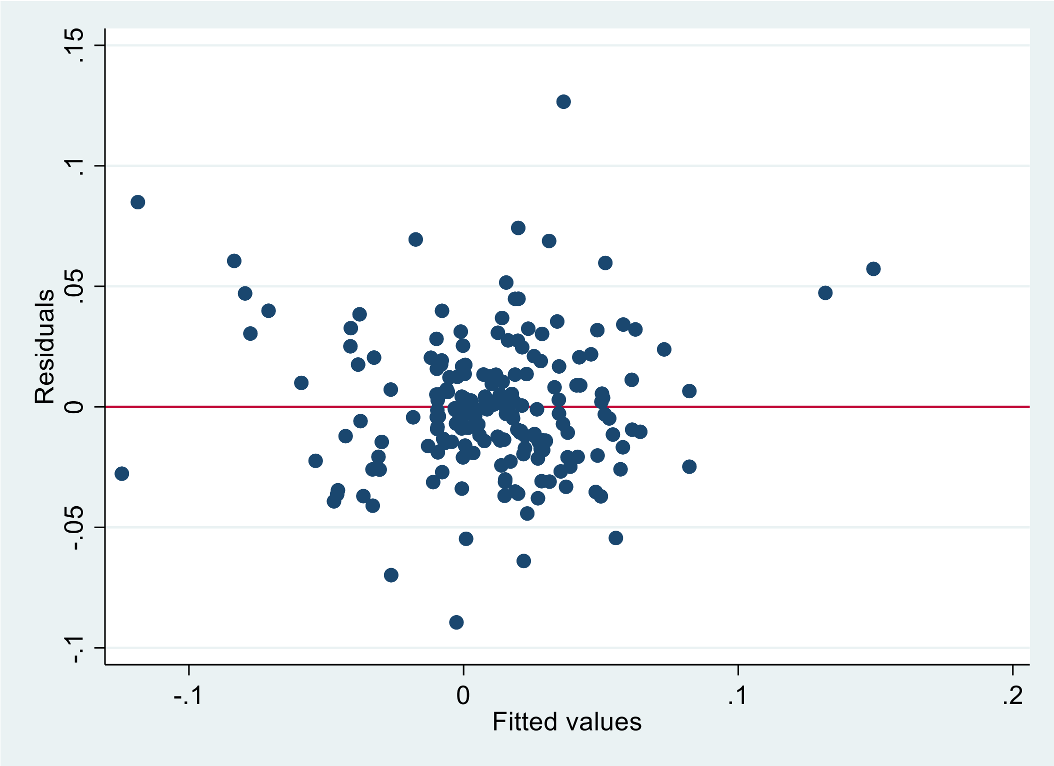






	Mean residuals
High G	4,69821E-19

Assumption 3

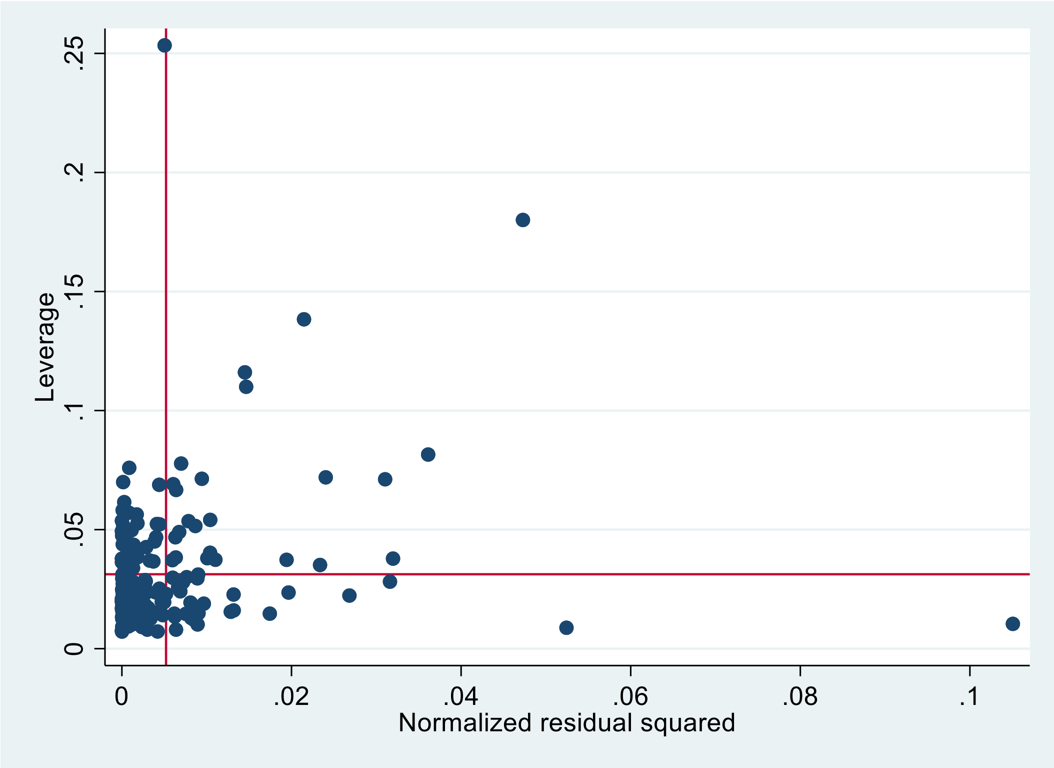


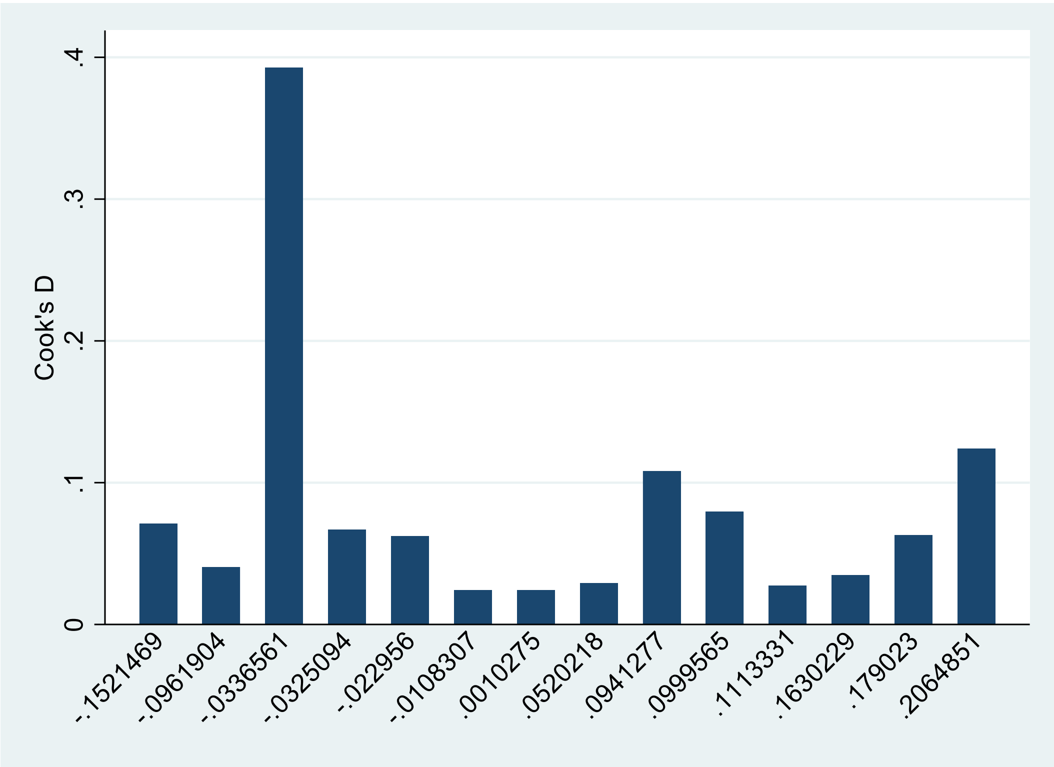

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     1.14
         Prob > chi2  =   0.2848
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      34.76
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6079
                                                Root MSE          =     .02864
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.6420241	.0740553	8.67	0.000	.4959278	.7881205
smb	-.0669902	.1218502	-0.55	0.583	-.3073763	.173396
hml	.583833	.1743309	3.35	0.001	.2399129	.927753
rmw	.2743665	.2253854	1.22	0.225	-.1702739	.7190069
cma	.1521836	.2354703	0.65	0.519	-.3123523	.6167194
_cons	.0047766	.0023109	2.07	0.040	.0002177	.0093355

Assumption 4





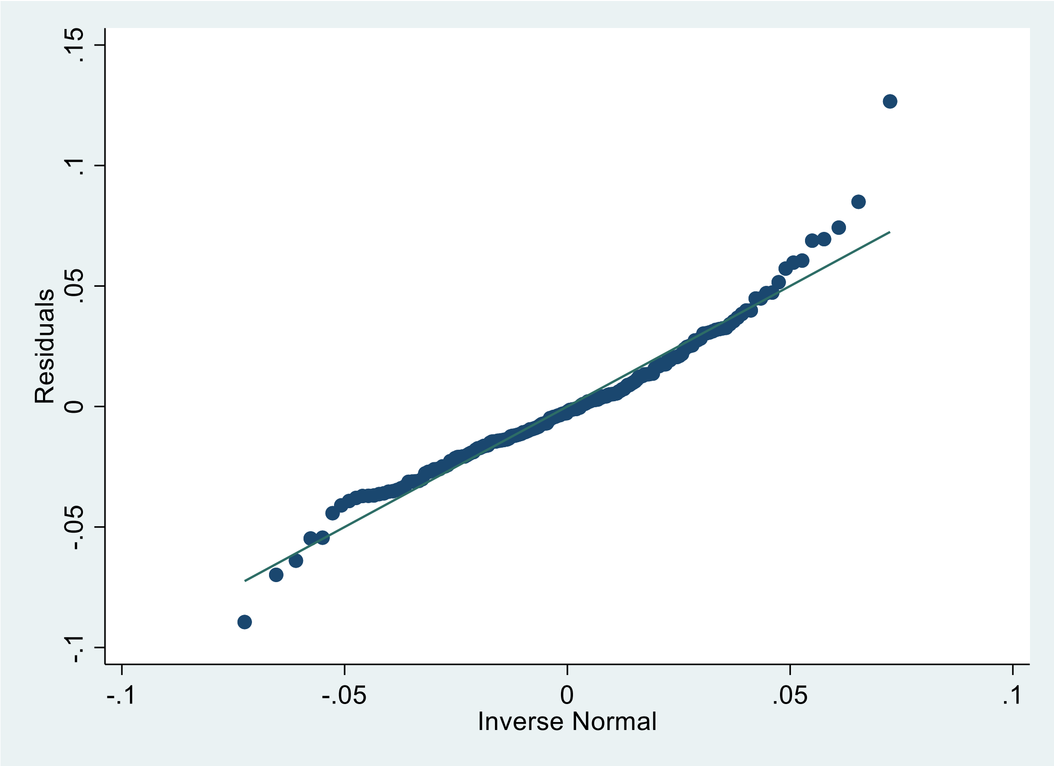
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**11.837**	**1**	**0.0006**

H0: no serial correlation

Assumption 7

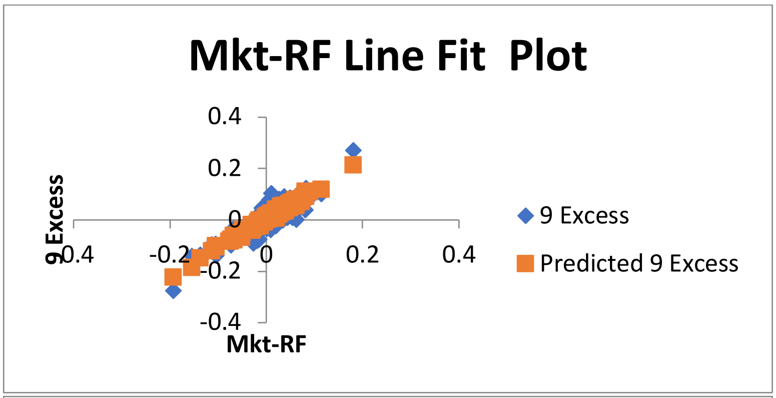


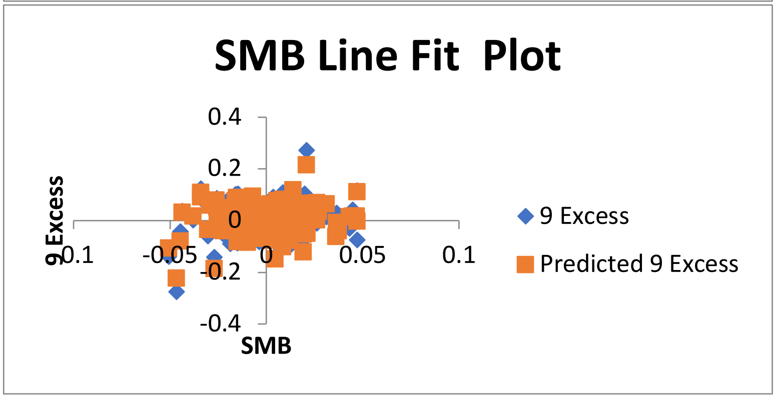
Shapiro-Wilk W test for normal data

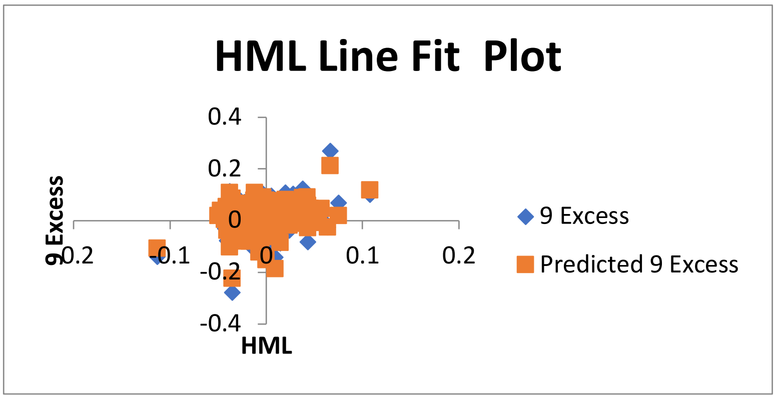
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.96651**	**4.822**	**3.612**	**0.00015**

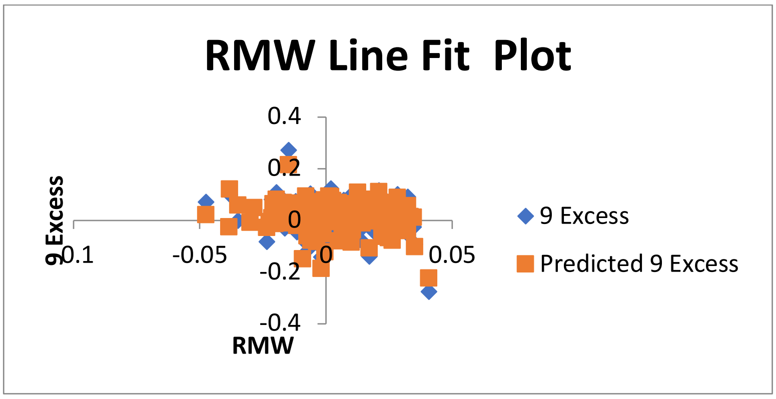
LOW G

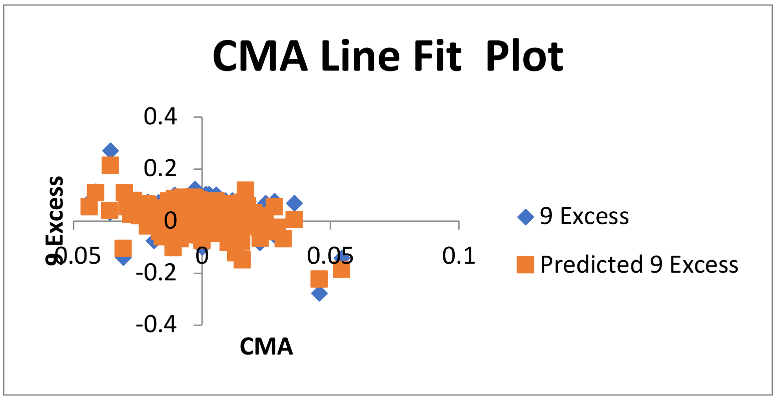
Assumption 1


Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess

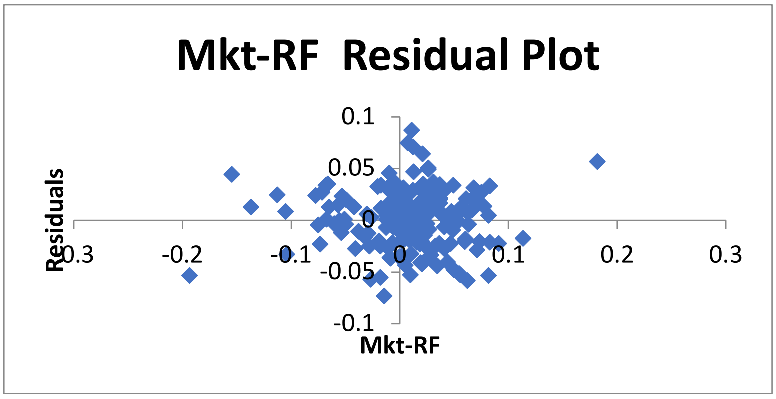

SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

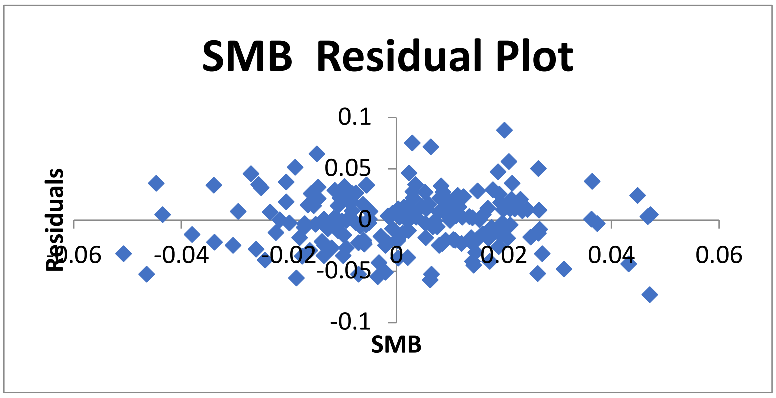

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

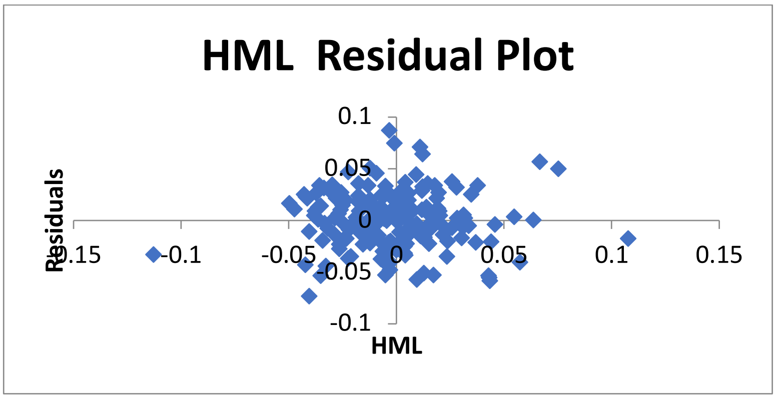


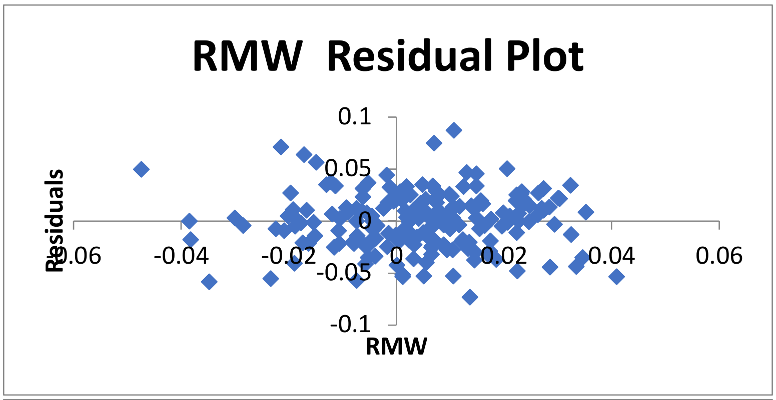


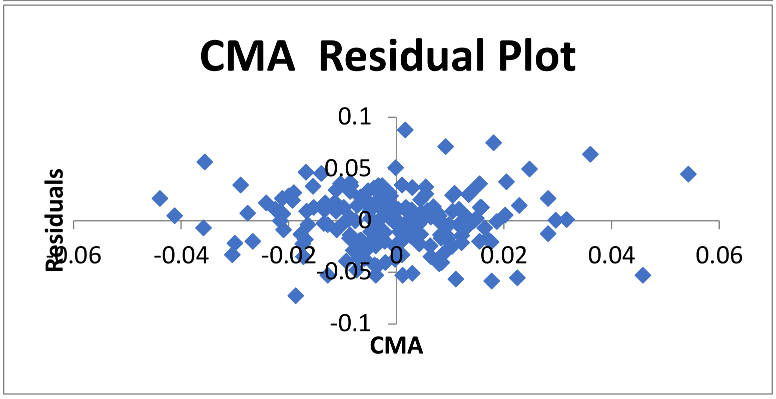
Assumption 2





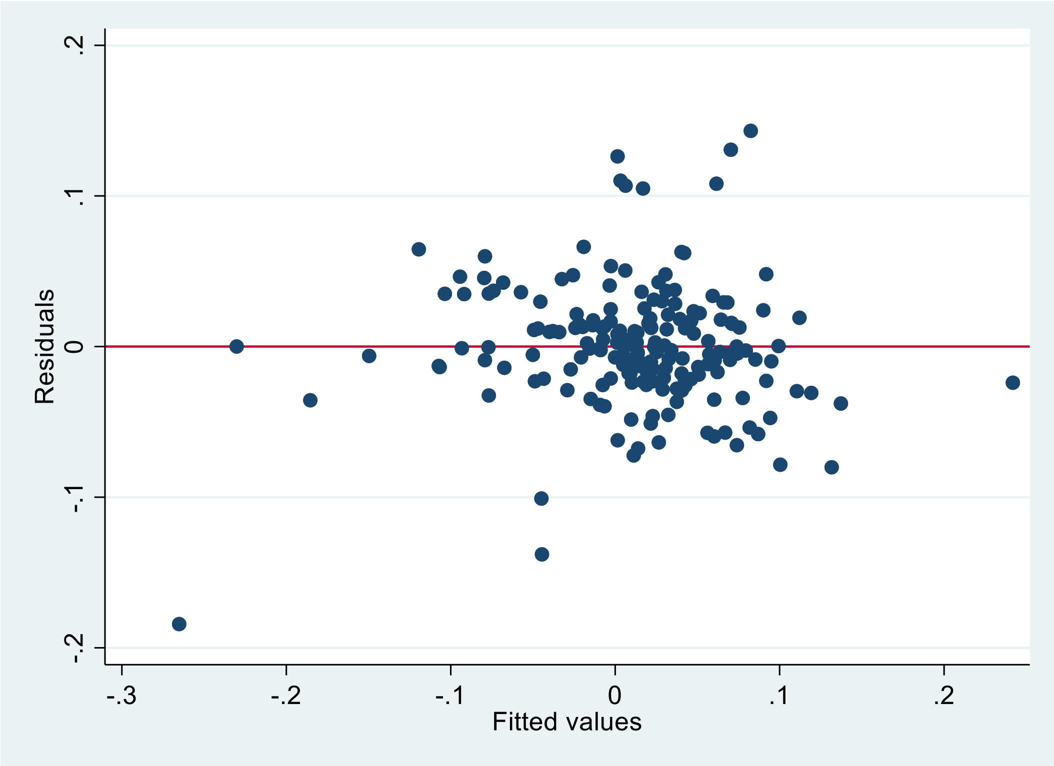






	Mean residuals
Low G	8,05924E-18

Assumption 3

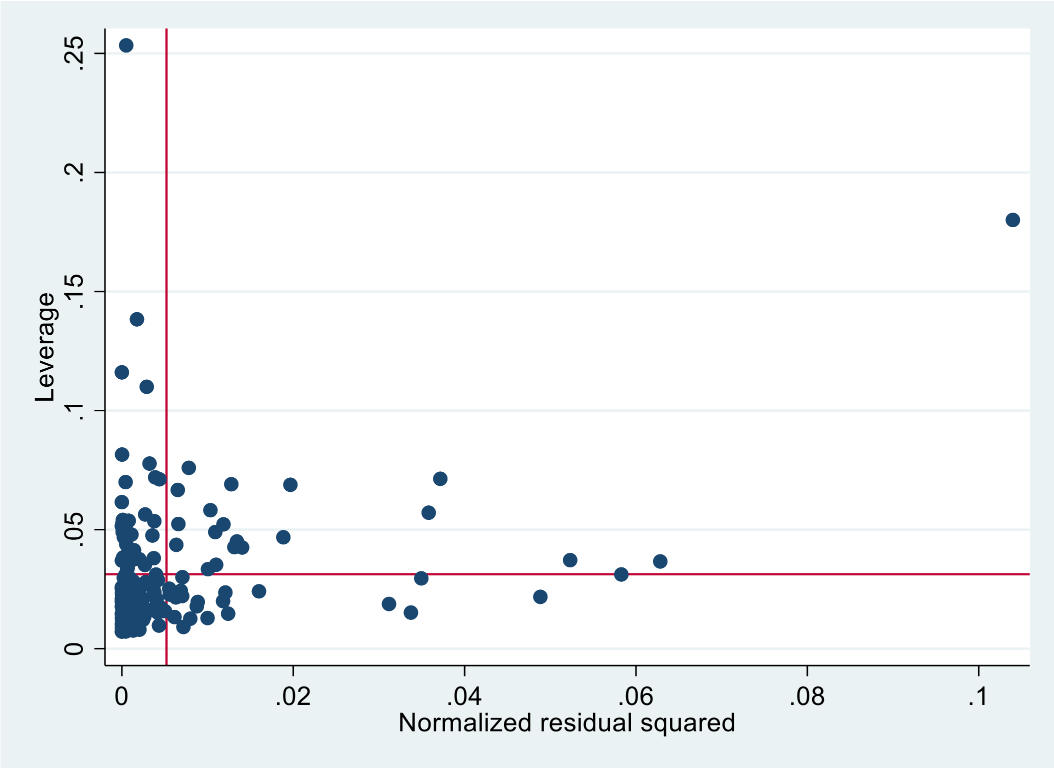


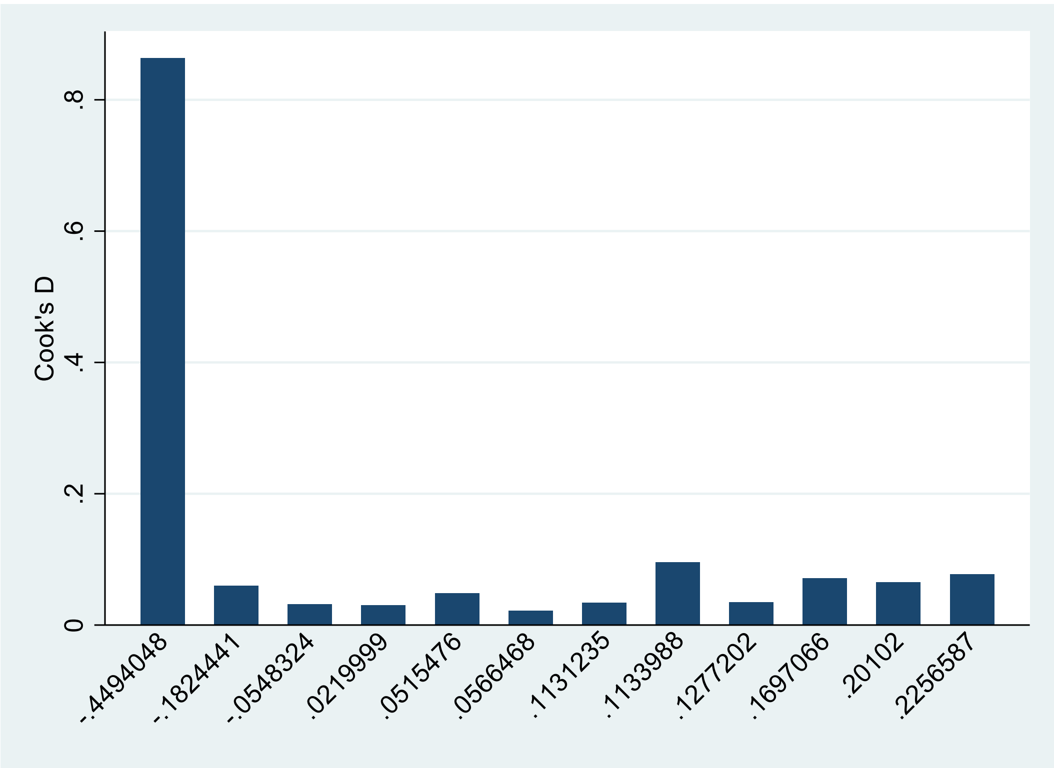

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =    12.00
         Prob > chi2  =   0.0005
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      40.27
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6856
                                                Root MSE          =     .04189
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.288469	.1076933	11.96	0.000	1.076012	1.500927
smb	.0960417	.1749929	0.55	0.584	-.2491844	.4412678
hml	-.1260944	.2309676	-0.55	0.586	-.5817473	.3295585
rmw	.1633804	.4212683	0.39	0.699	-.6676977	.9944584
cma	-.4882863	.3749212	-1.30	0.194	-1.227931	.2513583
_cons	-.0005025	.0031365	-0.16	0.873	-.0066902	.0056852

Assumption 4





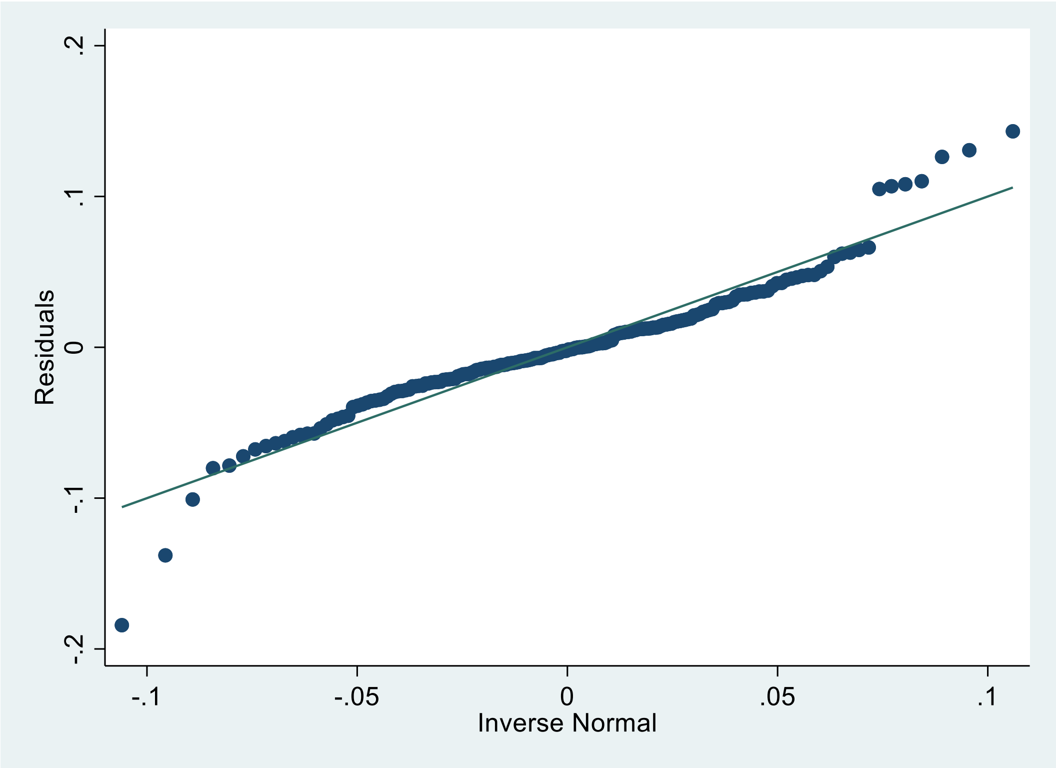
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.009**	**1**	**0.9226**

H0: no serial correlation

Assumption 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.94006**	**8.630**	**4.949**	**0.00000**

Annex 6

PART 3 – AVERAGE ALLOCATED HIGH AND LOW ESG, E, S, AND G PORTFOLIOS WITH A NEW ESG, E, S, AND G FACTOR

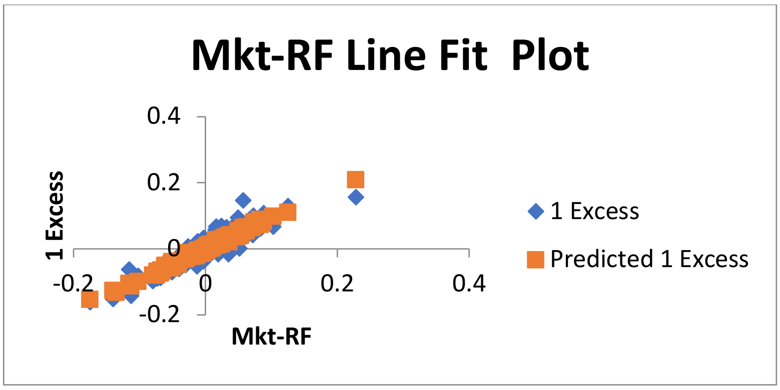
ESG - Assumption 5

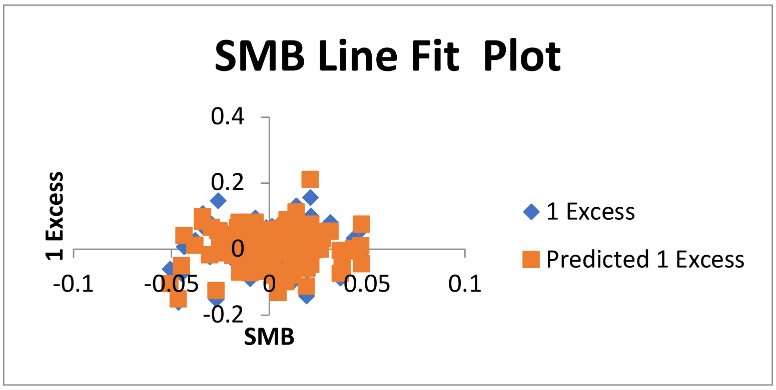
	mktrf	smb	hml	rmw	cma	gmb
mktrf	1.0000					
smb	0.1142	1.0000				
hml	0.3779	0.0113	1.0000			
rmw	-0.2136	-0.0783	-0.7764	1.0000		
cma	-0.2703	-0.2369	0.4467	-0.3659	1.0000	
gmb	-0.2366	-0.2767	-0.0504	0.0260	0.1975	1.0000

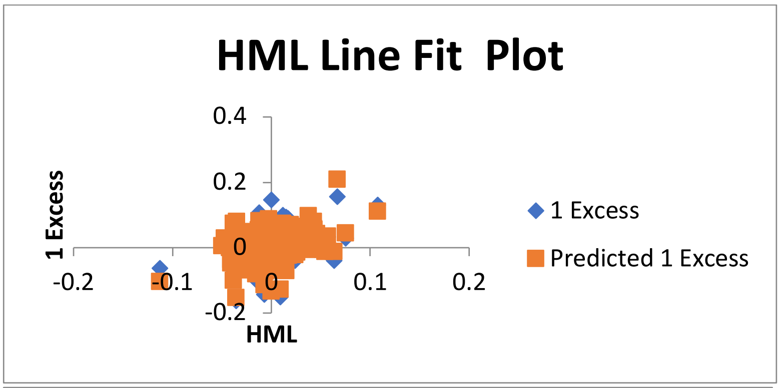
Variable	VIF	1/VIF
hml	3.68	0.271704
rmw	2.61	0.383044
cma	1.87	0.536046
mktrf	1.69	0.593296
smb	1.16	0.863221
gmb	1.15	0.872175
Mean VIF	2.02	

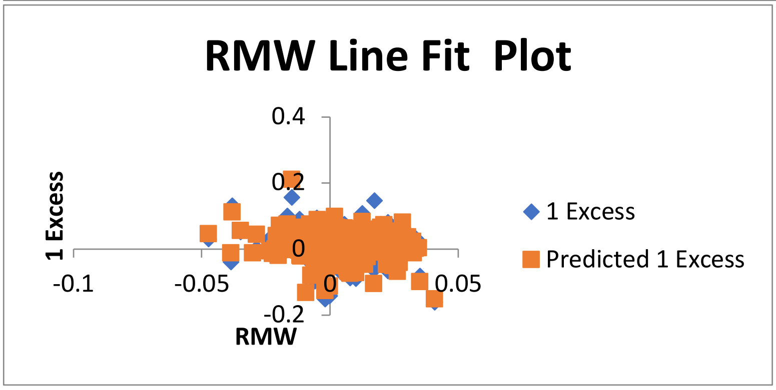
HIGH ESG

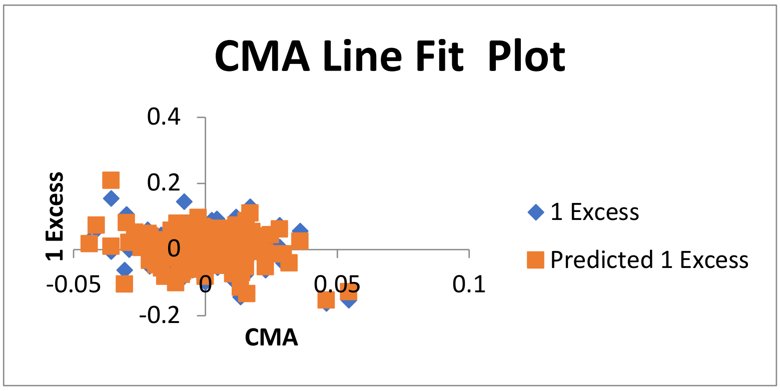
Assumption 1

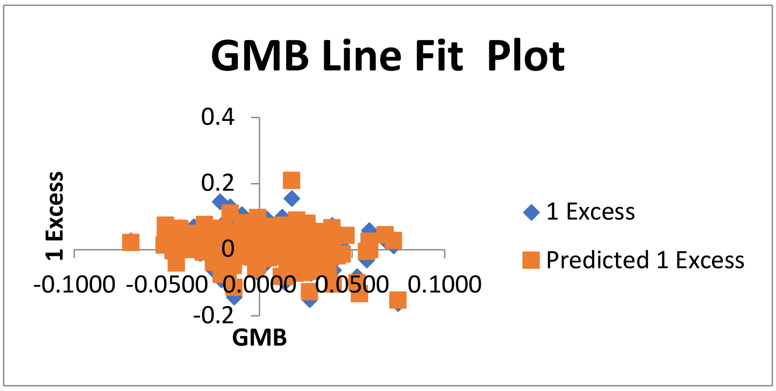




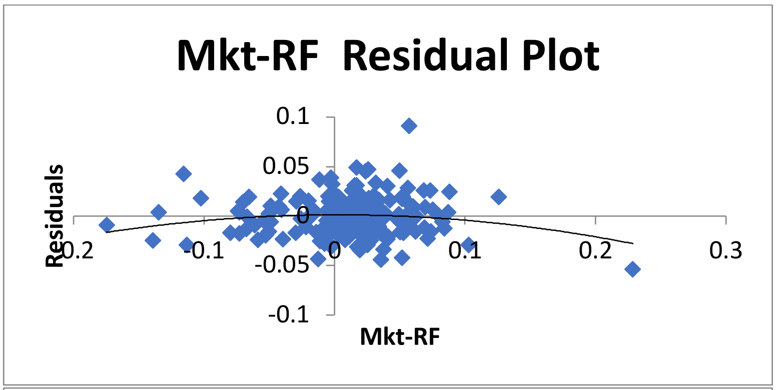


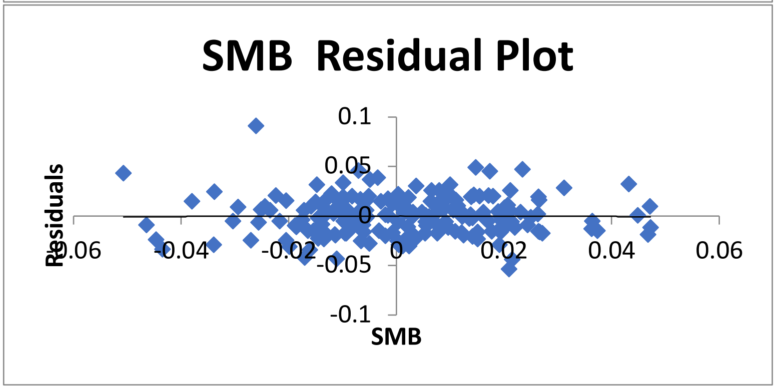


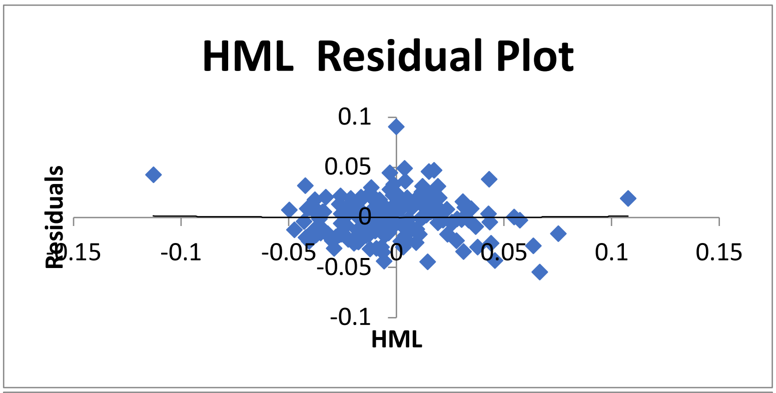


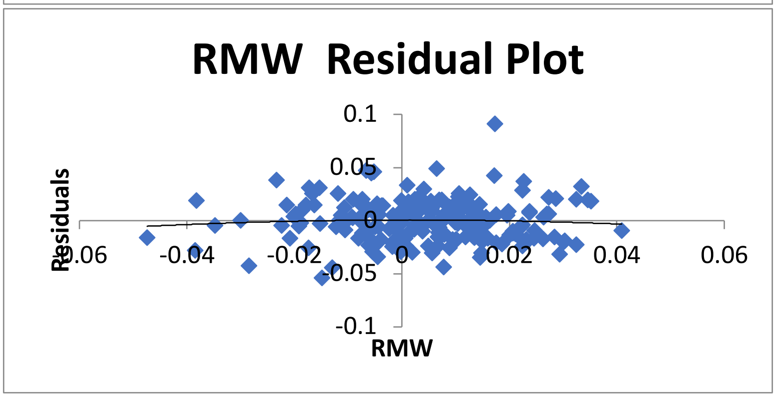


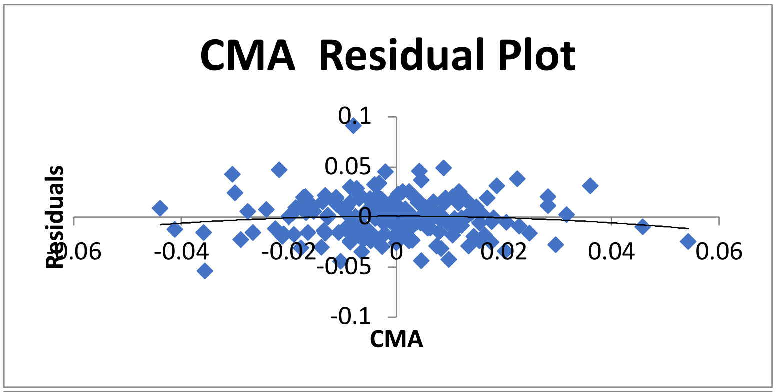
Assumption 2

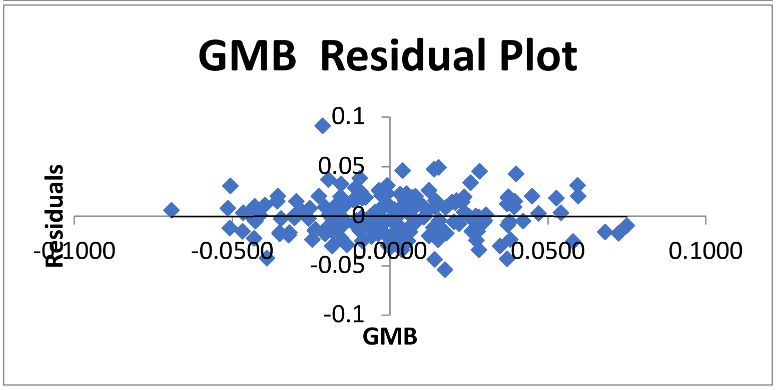

Mkt-RF Residual Plot
0.1
0.05
0
-0.05
-0.1
-0.2
-0.1
0
0.1
0.2
0.3
Residuals
Mkt-RF


SMB Residual Plot
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Residuals
SMB


HML Residual Plot
0.1
0.05
0
-0.05
-0.1
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
Residuals
HML

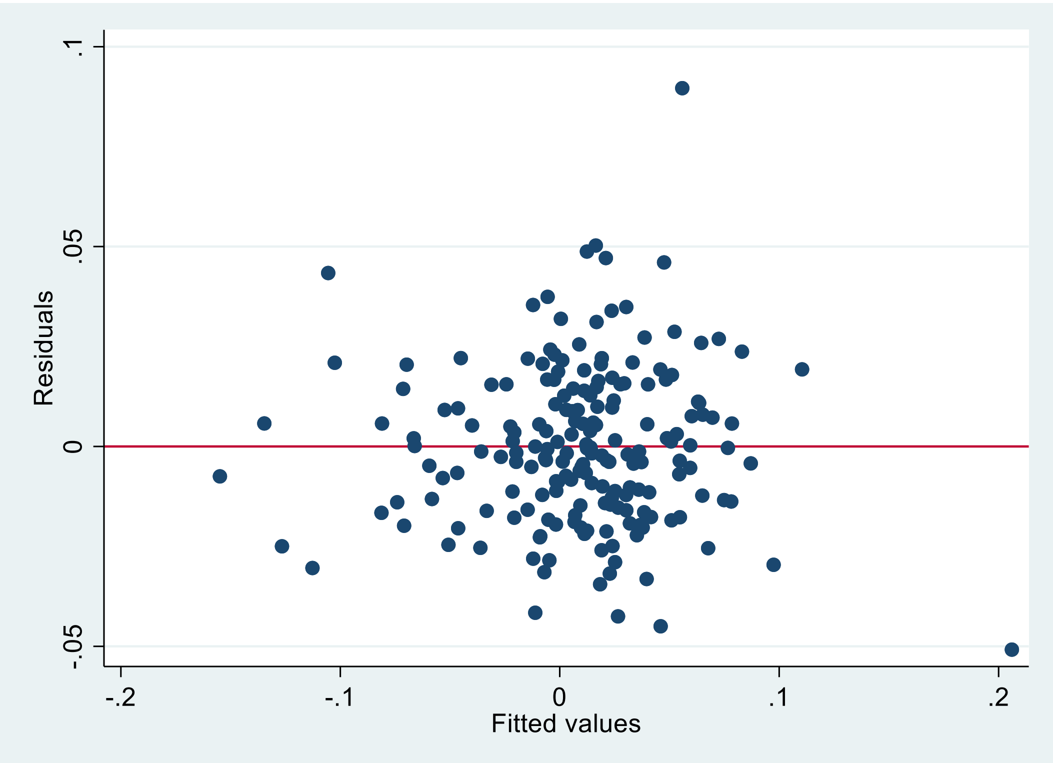

RMW Residual Plot
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Residuals
RMW





	Mean residuals
High ESG	3,07191E-18

Assumption 3

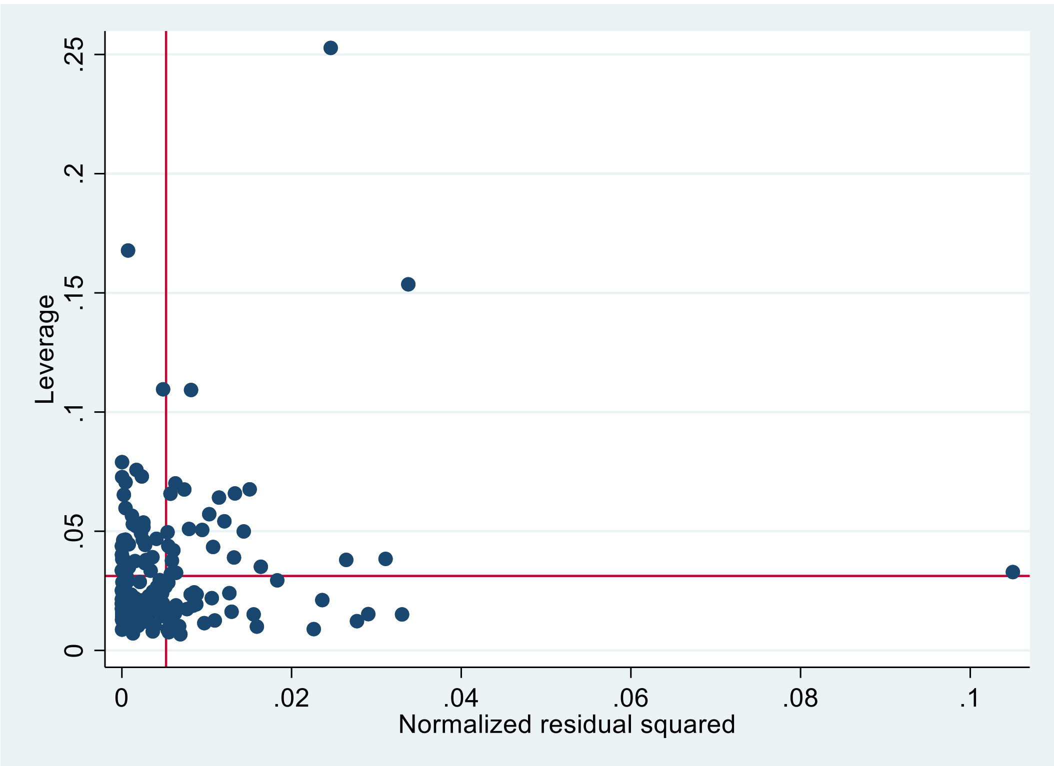


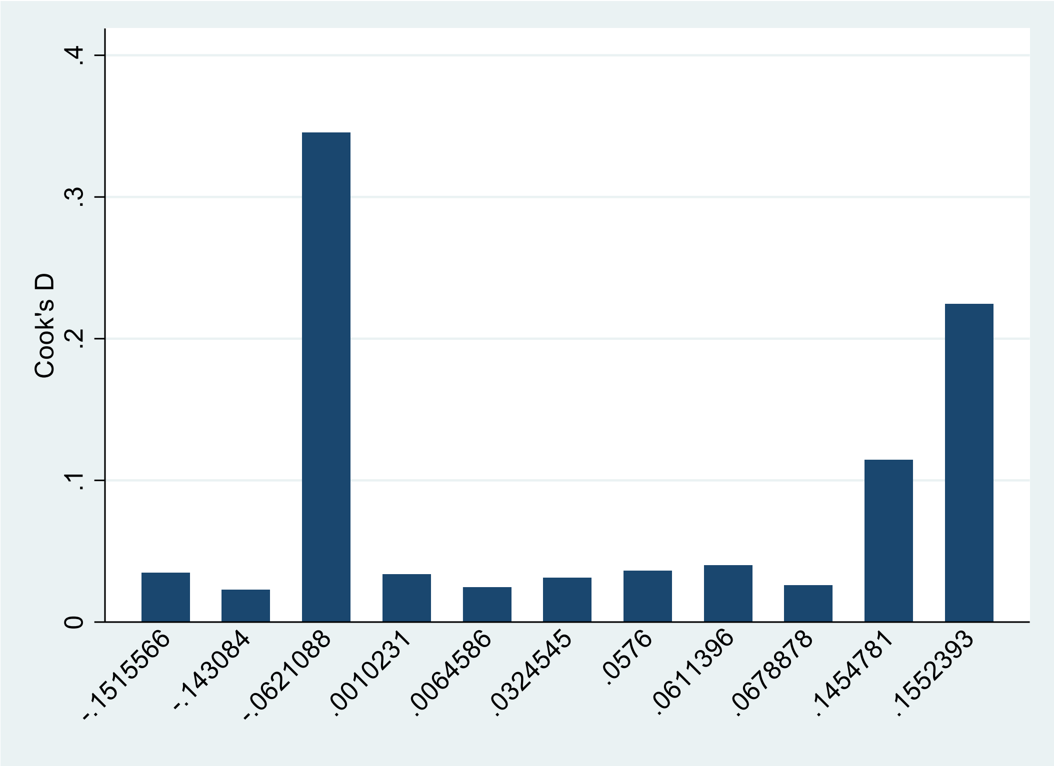
```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     6.16
         Prob > chi2  =   0.0131
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     151.78
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8348
                                                Root MSE          =     .02028
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.018605	.0379575	26.84	0.000	.9437229	1.093488
smb	-.0641058	.0996464	-0.64	0.521	-.2606883	.1324767
hml	-.1787864	.1281861	-1.39	0.165	-.431672	.0740991
rmw	.0264126	.1823109	0.14	0.885	-.3332504	.3860756
cma	.3184645	.1434826	2.22	0.028	.035402	.601527
_cons	-.0018749	.0015913	-1.18	0.240	-.0050143	.0012644

Assumption 4





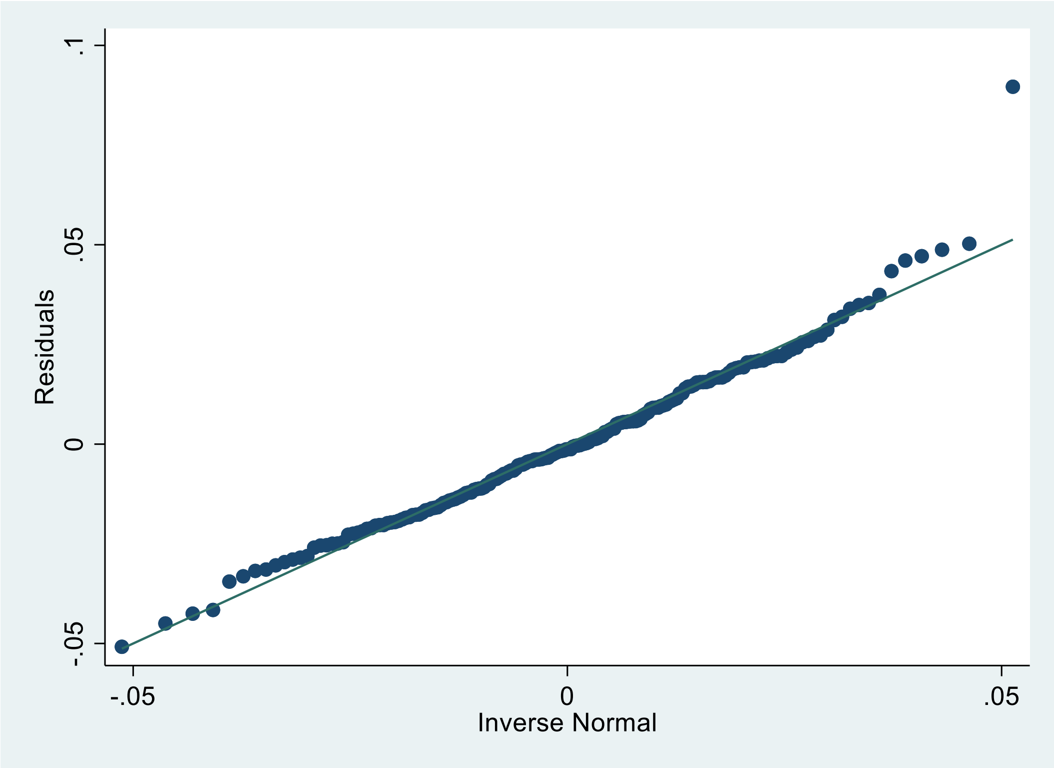
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.512**	**1**	**0.4742**

H0: no serial correlation

Assumption 7

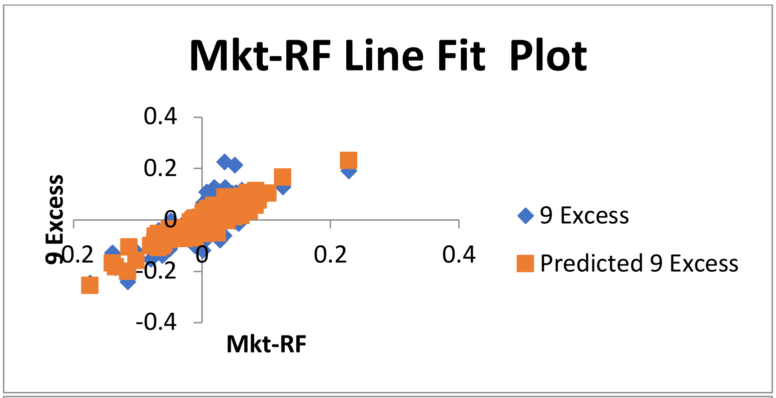


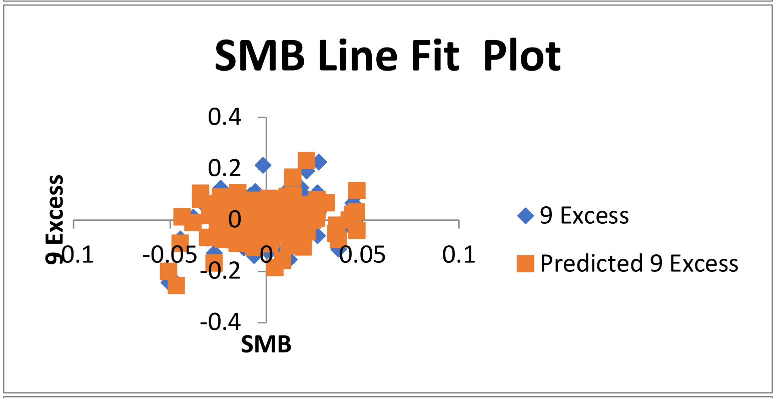
Shapiro-Wilk W test for normal data

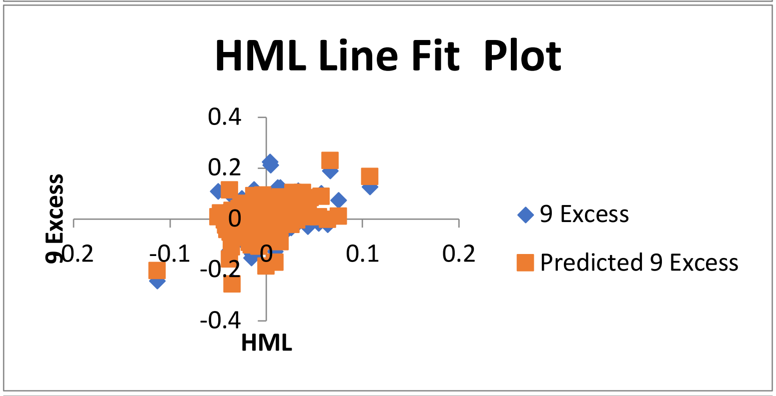
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.97977**	**2.913**	**2.455**	**0.00705**

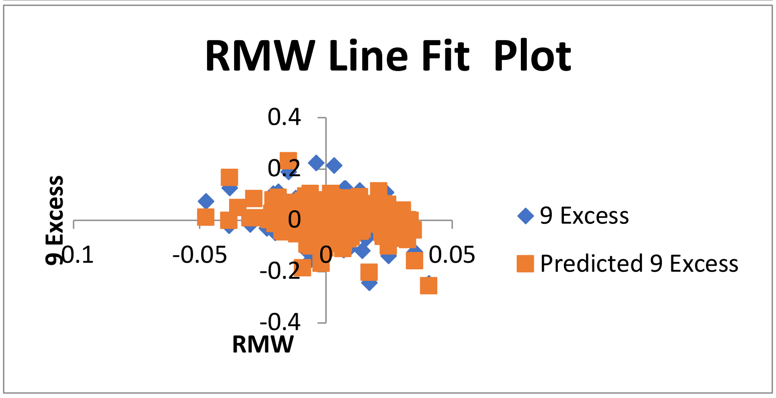
LOW ESG

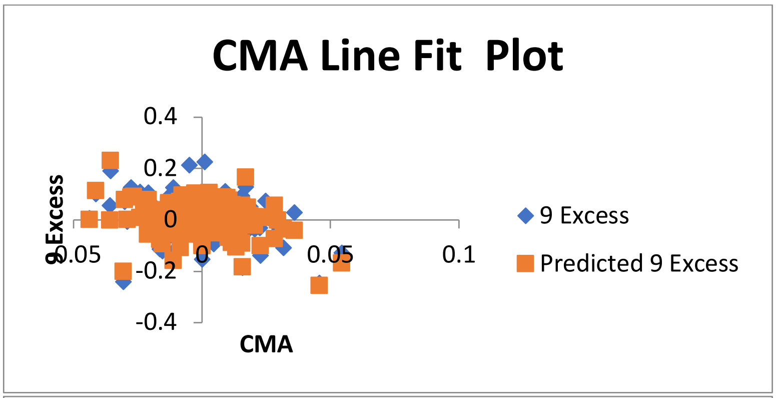
Assumption 1

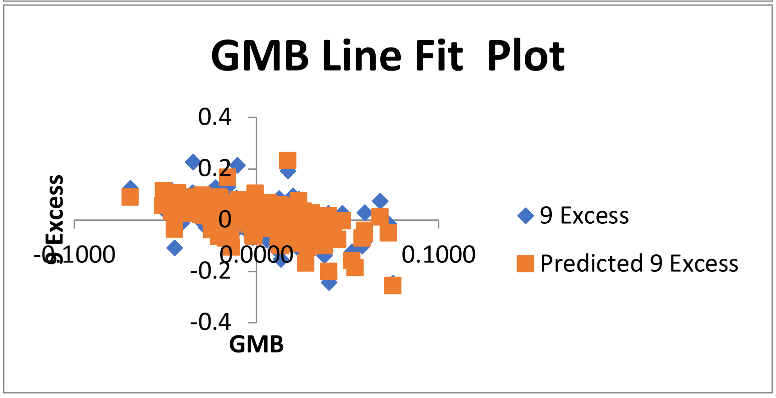

Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess


SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

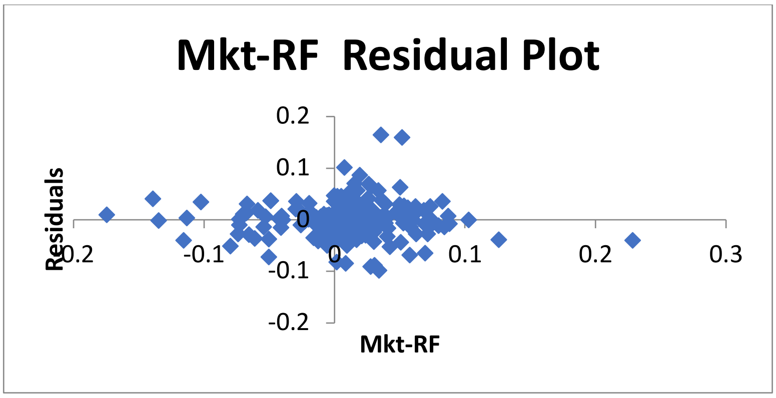

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

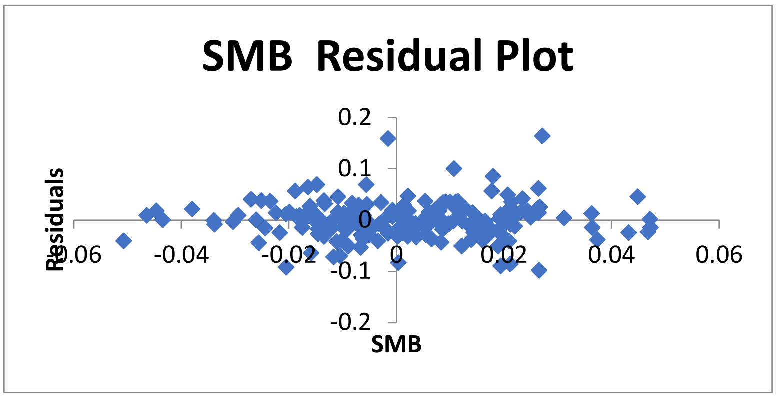

RMW Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
9 Excess
RMW
9 Excess
Predicted 9 Excess

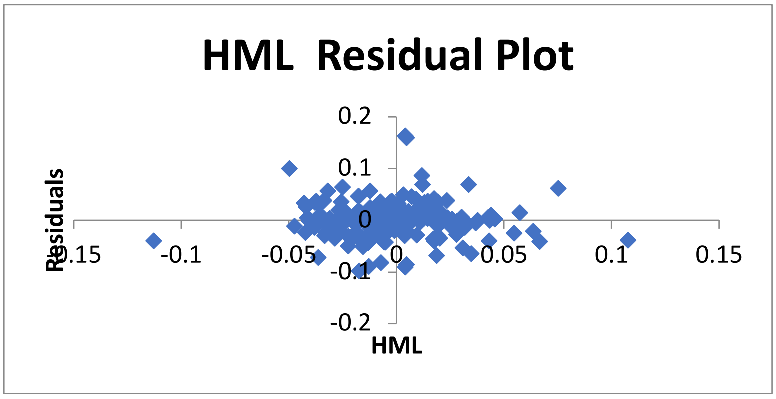


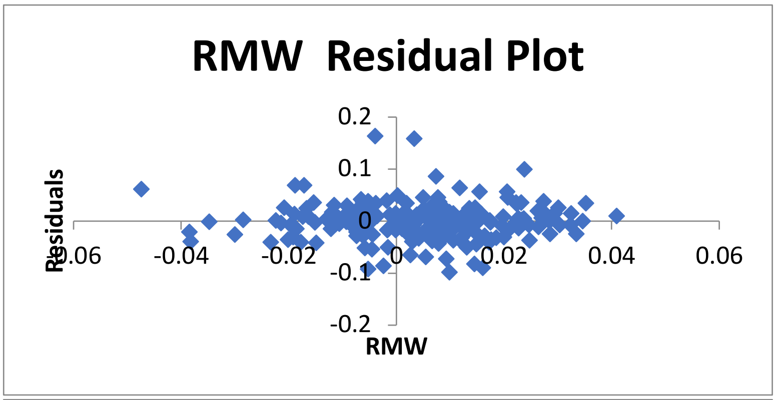


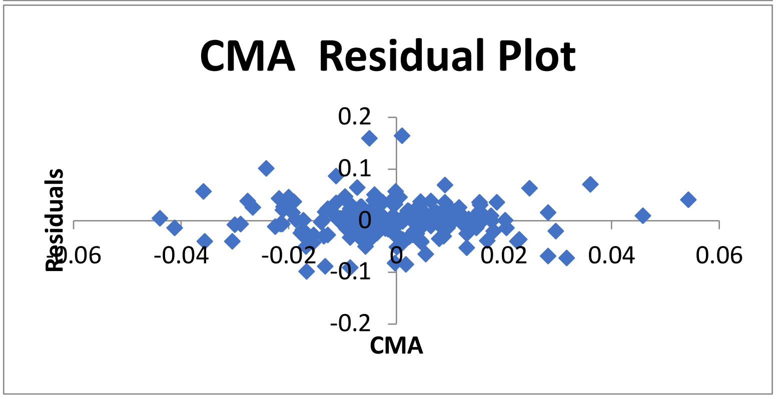
Assumption 2

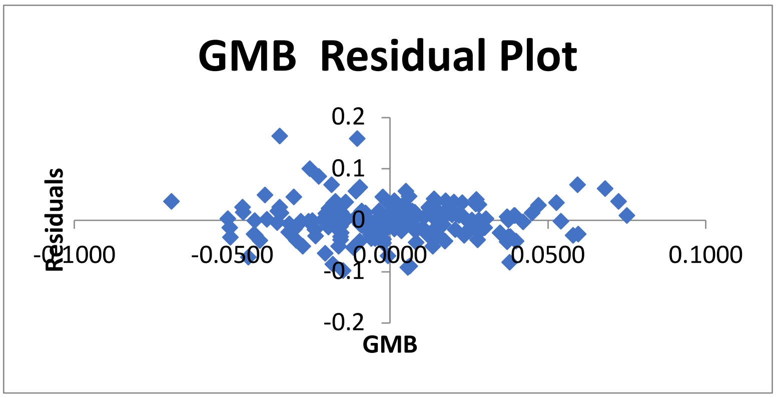






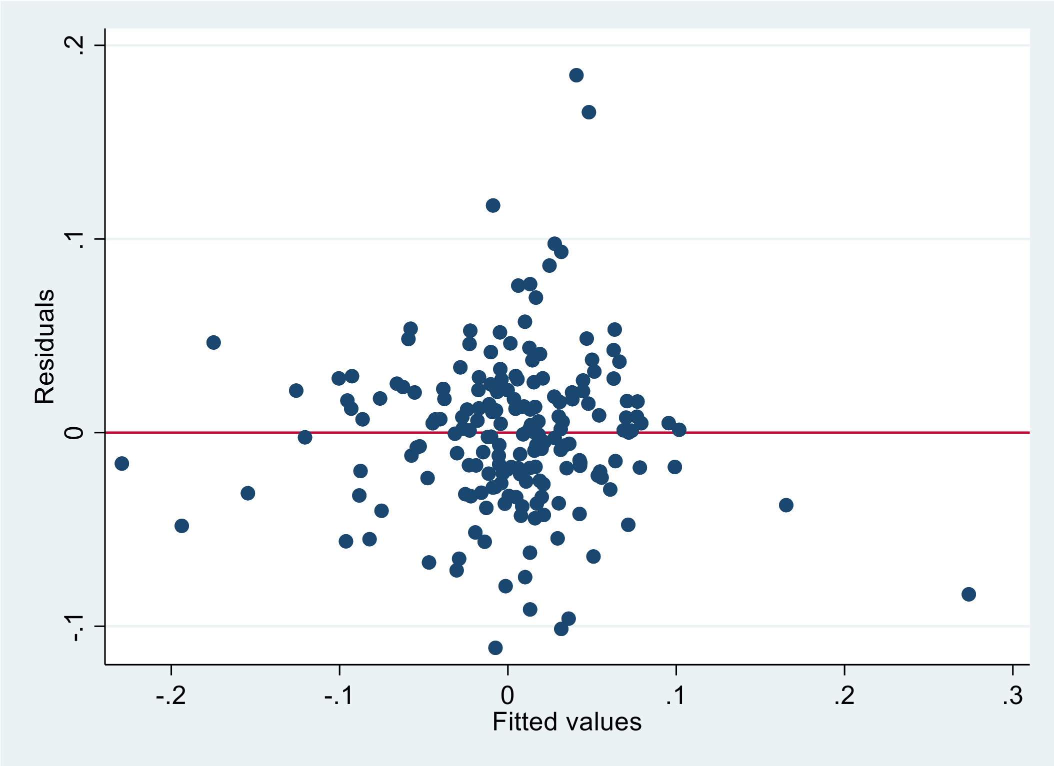






	Mean residuals
Low ESG	7,6617E-18

Assumption 3

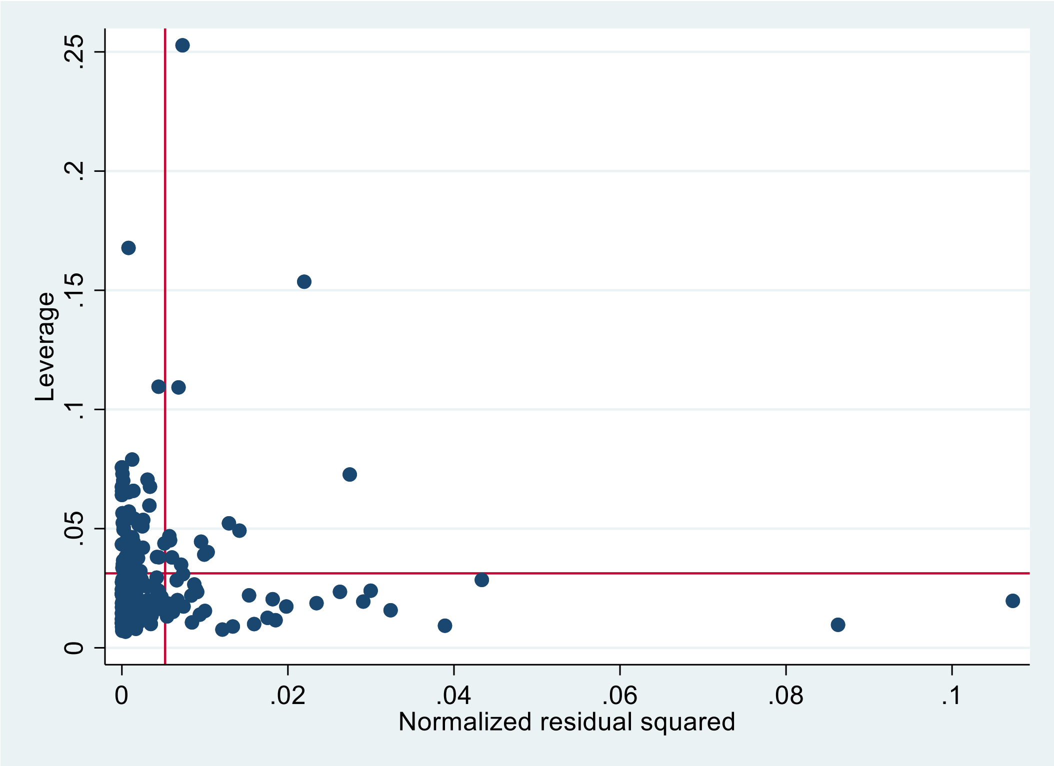


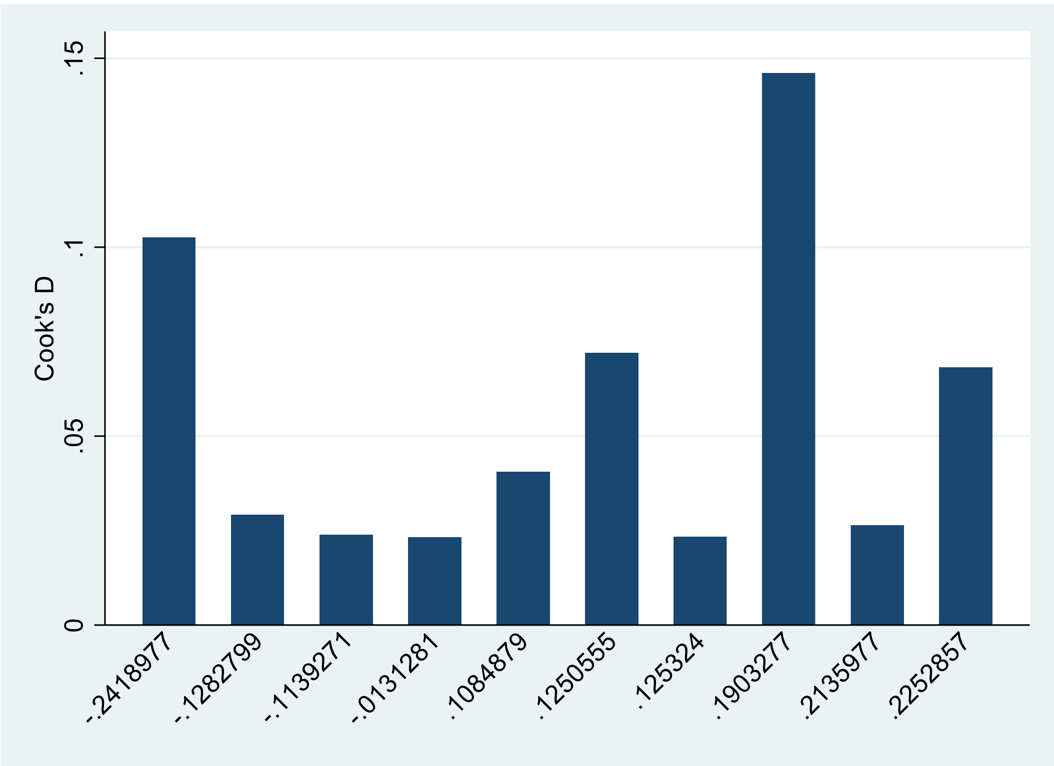

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     4.85
         Prob > chi2  =   0.0277
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      66.46
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6533
                                                Root MSE          =     .04131
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.055839	.0706414	14.95	0.000	.9164775	1.1952
smb	.4380265	.173289	2.53	0.012	.0961619	.7798911
hml	.4372758	.2128746	2.05	0.041	.0173168	.8572347
rmw	.2126268	.2581594	0.82	0.411	-.2966702	.7219237
cma	-.1851189	.2819257	-0.66	0.512	-.741302	.3710642
_cons	-.0092975	.0030375	-3.06	0.003	-.0152899	-.0033051

Assumption 4





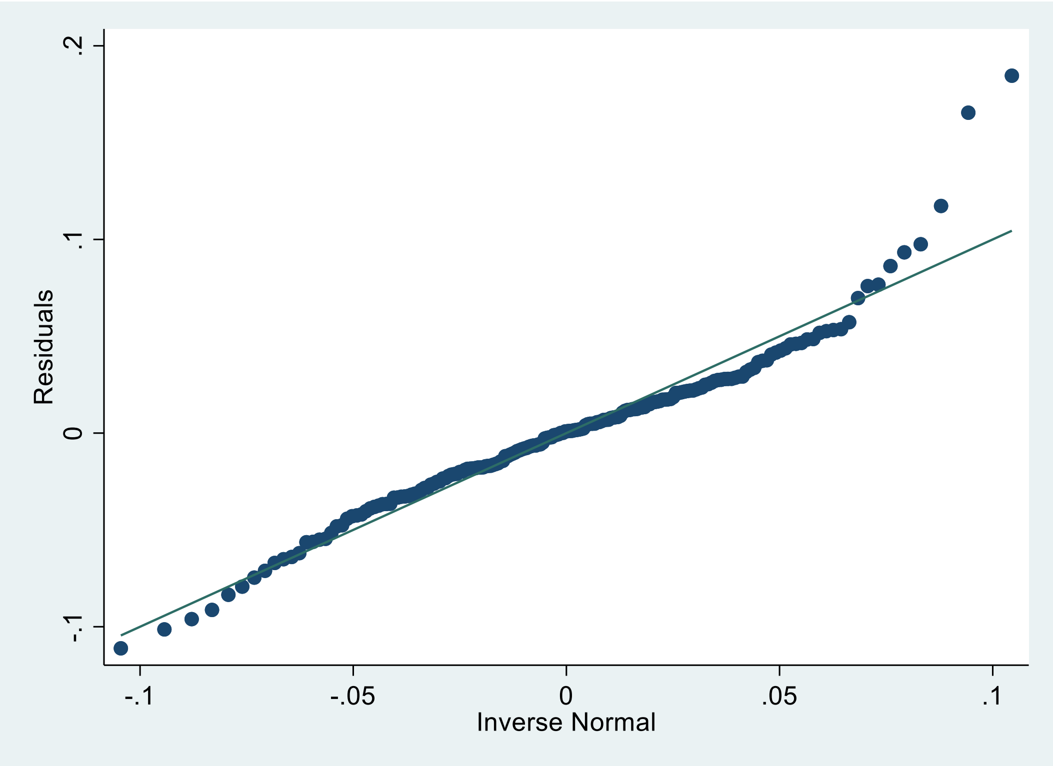
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**3.640**	**1**	**0.0564**

H0: no serial correlation

Assumption 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.95223**	**6.878**	**4.428**	**0.00000**

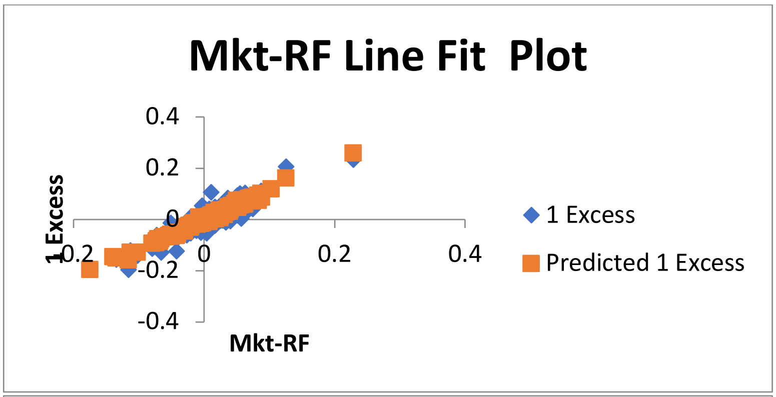
E assumption 5

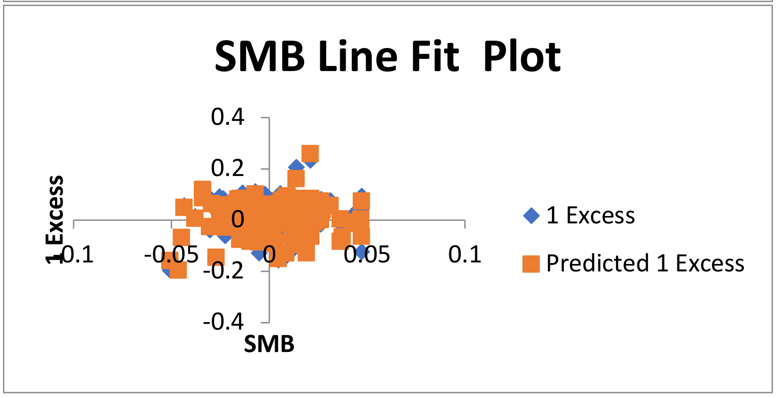
	mktrf	smb	hml	rmw	cma	gmb
mktrf	1.0000					
smb	0.3600	1.0000				
hml	0.5681	0.1099	1.0000			
rmw	-0.1344	-0.0626	-0.7449	1.0000		
cma	0.2565	-0.2889	0.7769	-0.6818	1.0000	
gmb	-0.0885	-0.0004	-0.2804	0.0550	-0.0971	1.0000

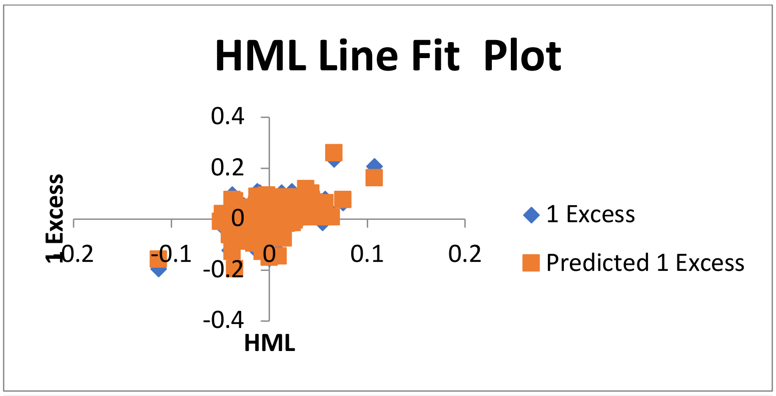
Variable	VIF	1/VIF
hml	8.82	0.113417
cma	4.54	0.220334
rmw	3.75	0.266593
mktrf	2.67	0.374228
smb	1.80	0.554501
gmb	1.32	0.758377
Mean VIF	3.82	

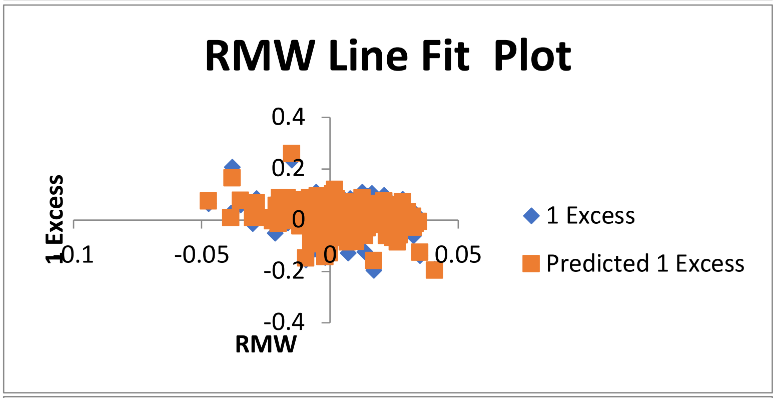
HIGH E

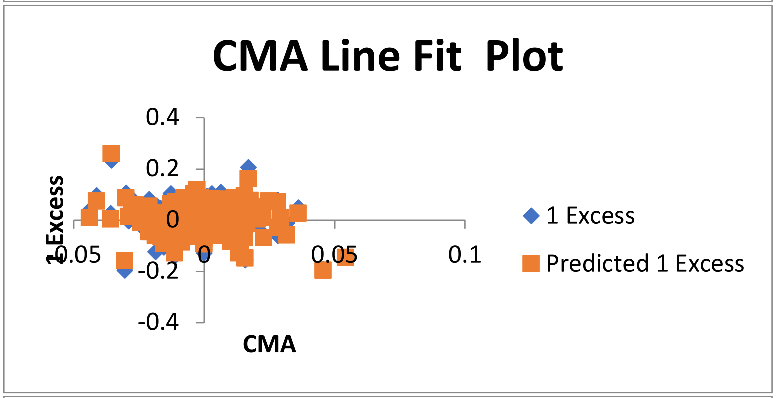
Assumption 1

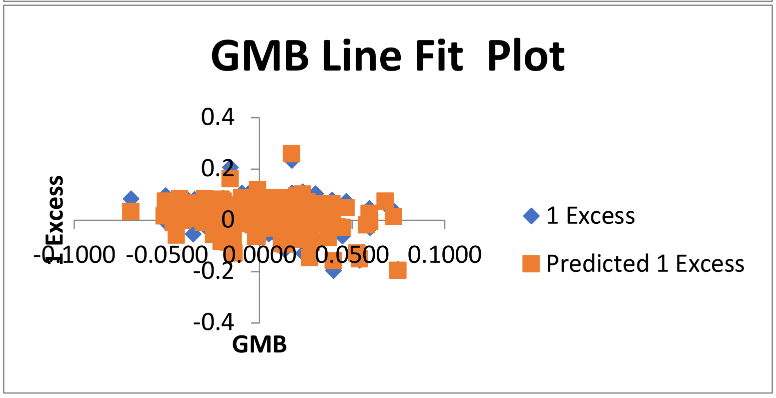




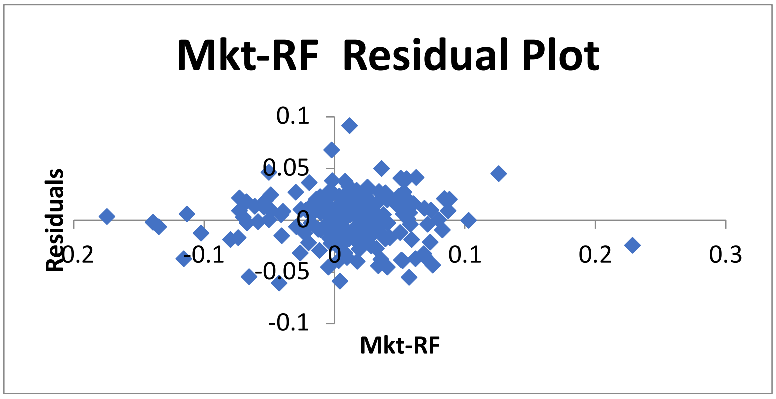


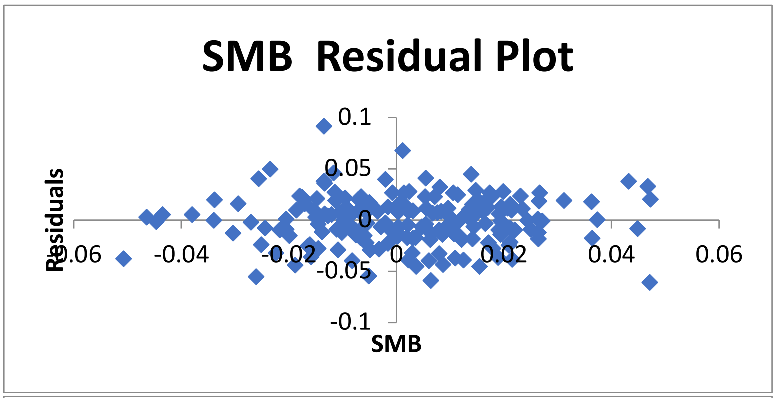


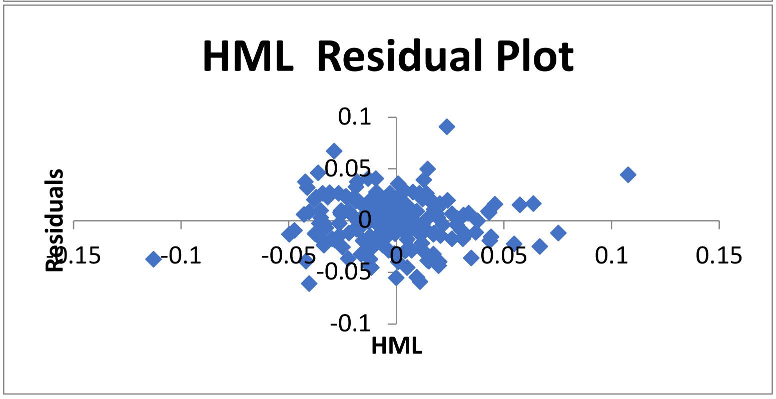


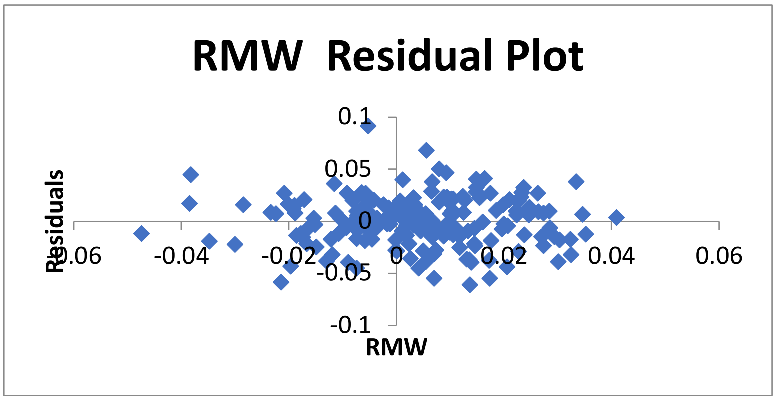


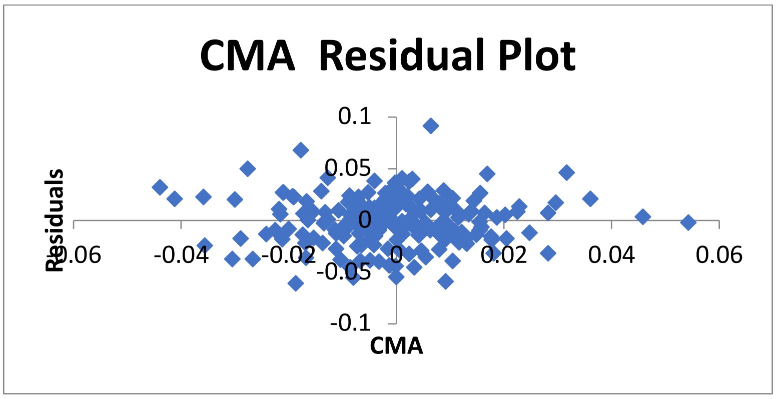
Assumption 2

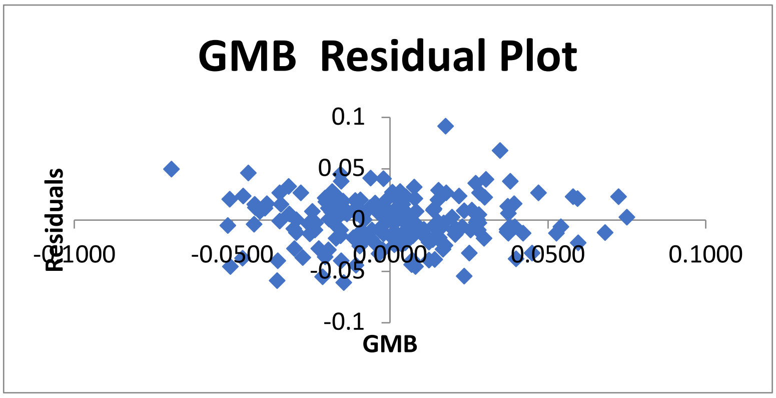

Mkt-RF Residual Plot
Residuals
0.1
0.05
0
-0.05
-0.1
-0.2
-0.1
0
0.1
0.2
0.3
Mkt-RF


SMB Residual Plot
Residuals
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
SMB


HML Residual Plot
Residuals
0.1
0.05
0
-0.05
-0.1
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
HML

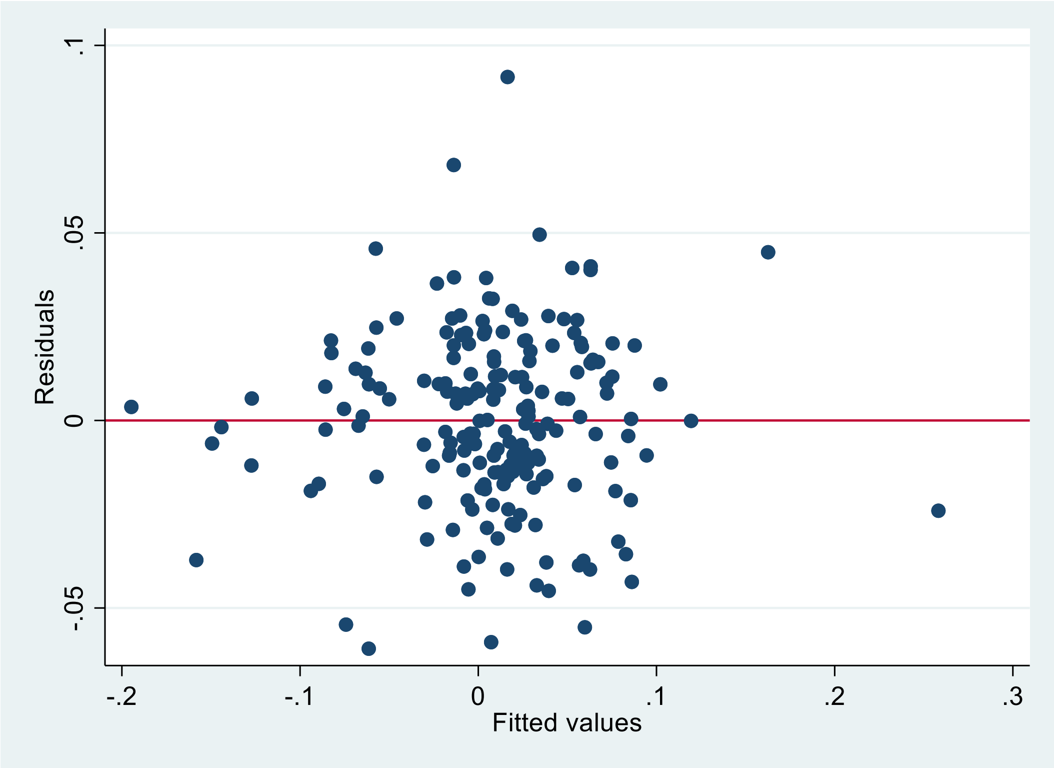

RMW Residual Plot
Residuals
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
RMW





	Mean residuals
High E	1,72027E-16

Assumption 3

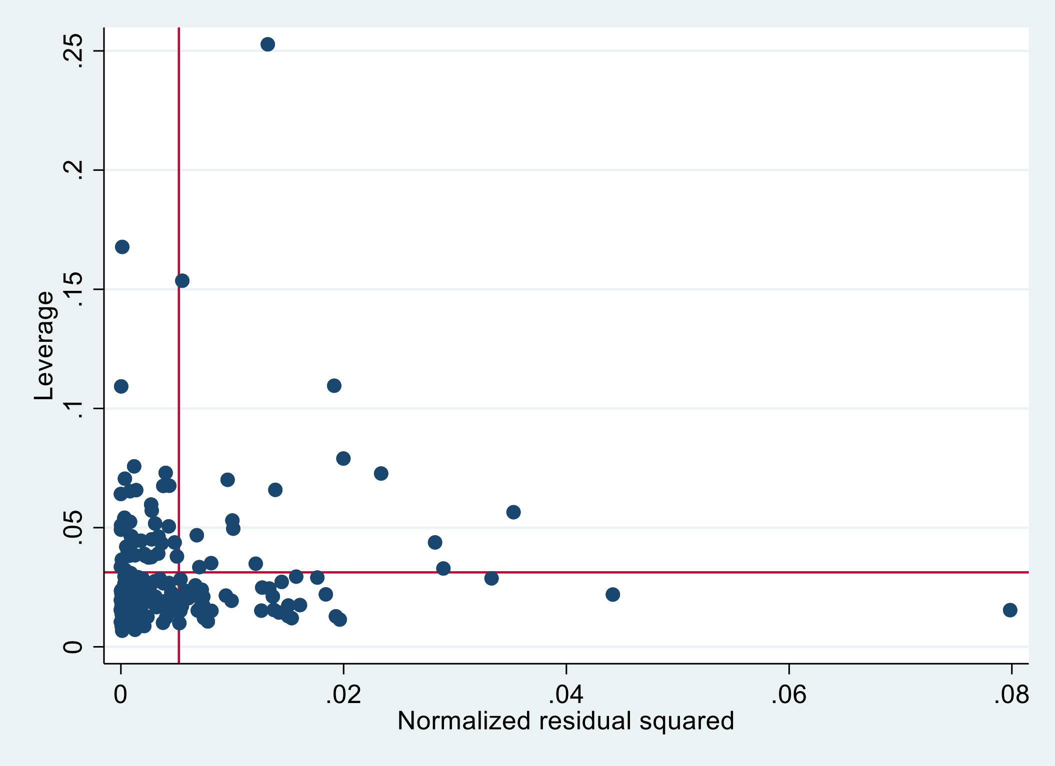


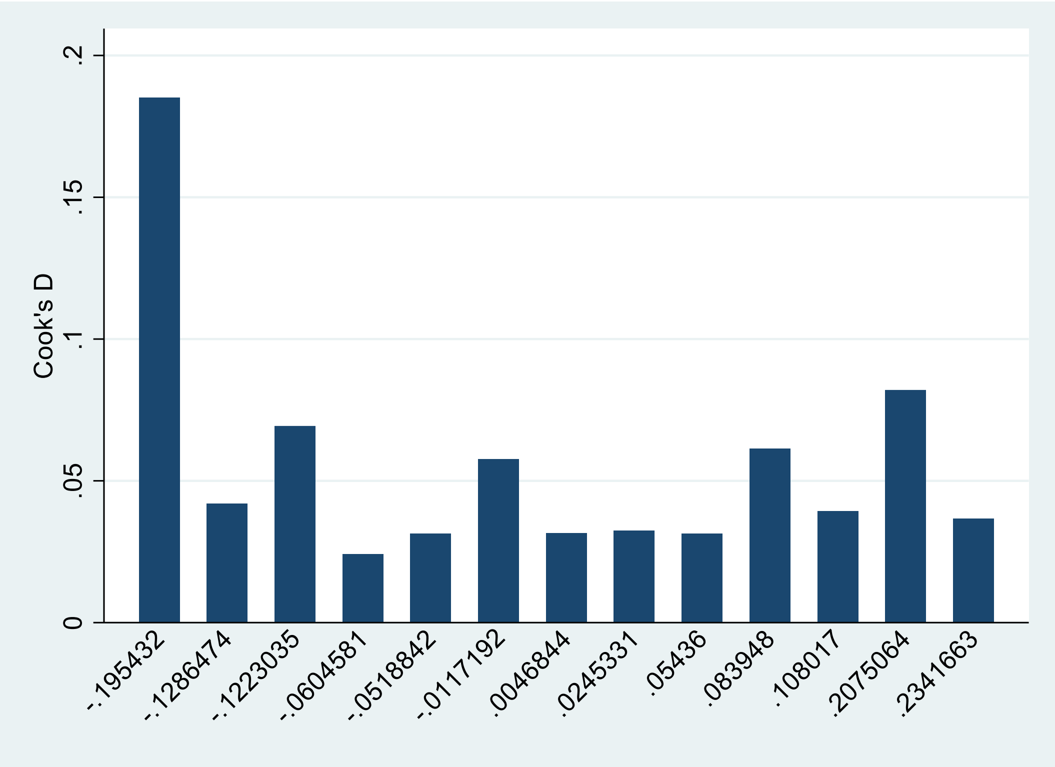

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     0.70
         Prob > chi2  =   0.4043
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     236.11
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8425
                                                Root MSE          =     .02376
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.124562	.0435289	25.83	0.000	1.038688	1.210435
smb	-.00633	.1066054	-0.06	0.953	-.2166411	.2039811
hml	.1649674	.1534143	1.08	0.284	-.1376885	.4676232
rmw	-.0394087	.194042	-0.20	0.839	-.4222148	.3433975
cma	.236783	.1771342	1.34	0.183	-.1126673	.5862333
_cons	-.0019162	.0018798	-1.02	0.309	-.0056247	.0017922

Assumption 4





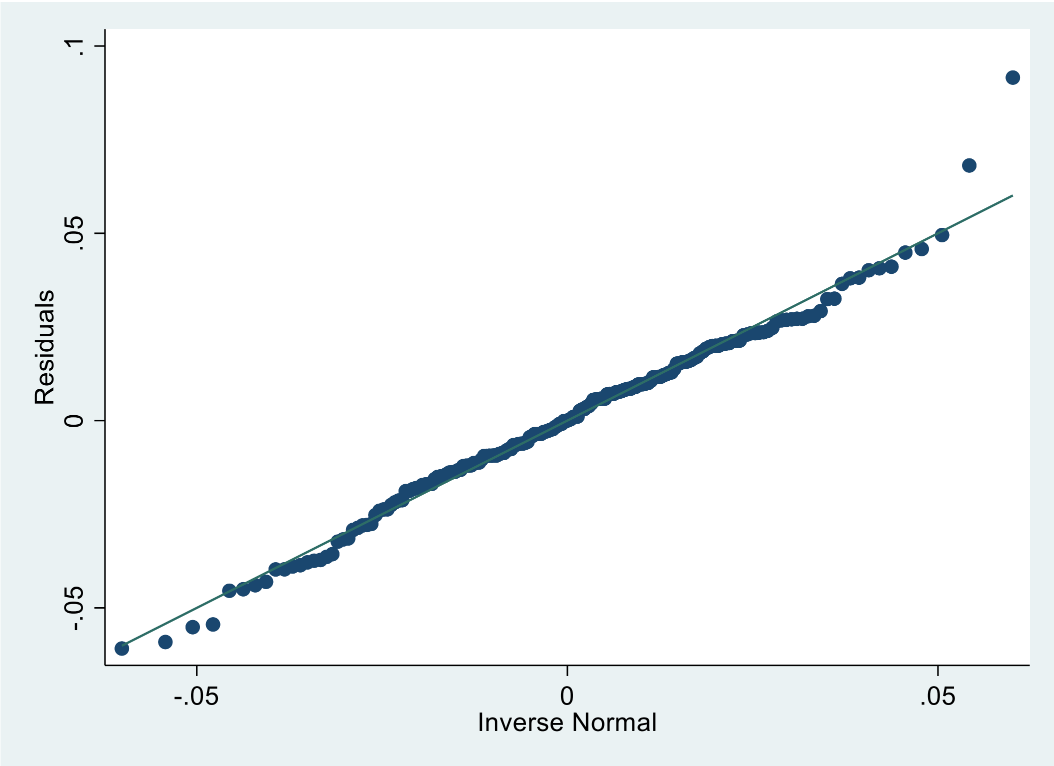
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.001**	**1**	**0.9707**

H0: no serial correlation

Assumption 7

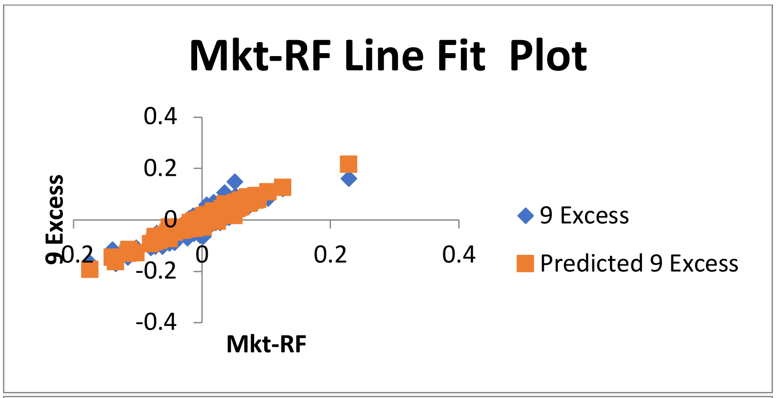


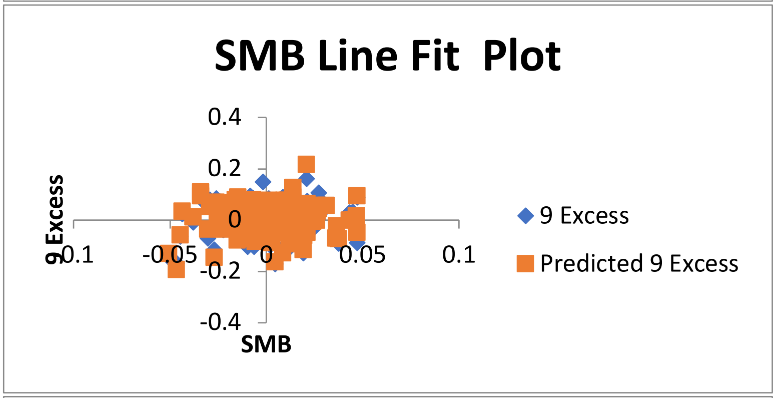
Shapiro-Wilk W test for normal data

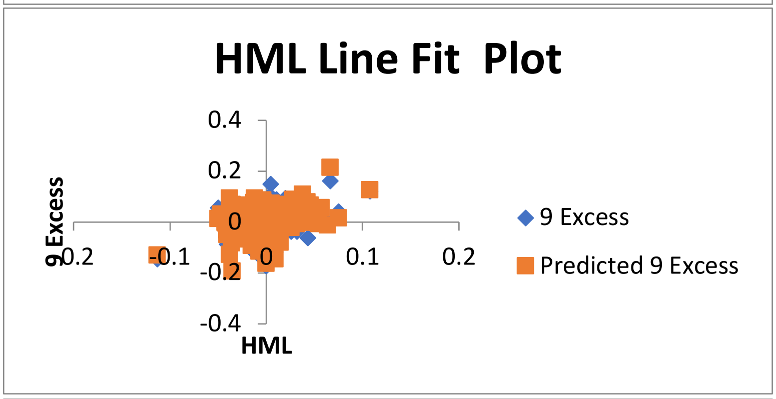
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.98799**	**1.730**	**1.258**	**0.10412**

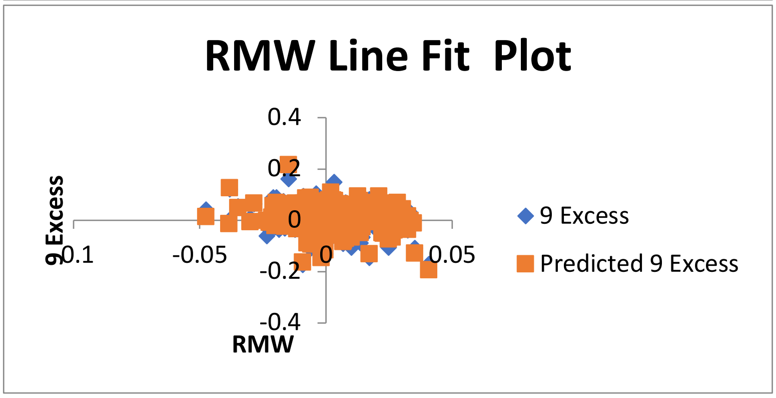
LOW E

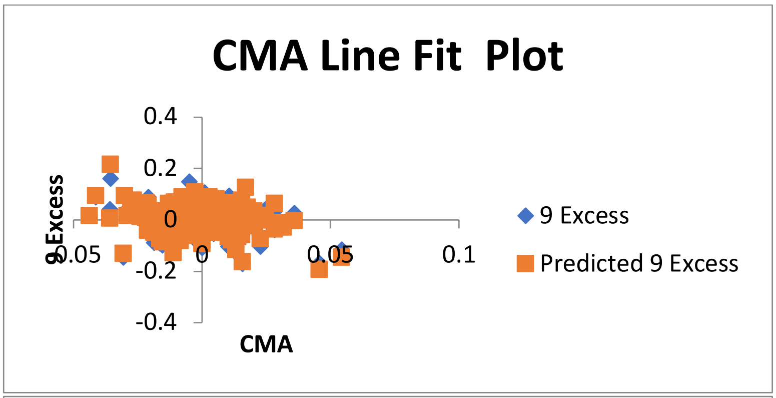
Assumption 1

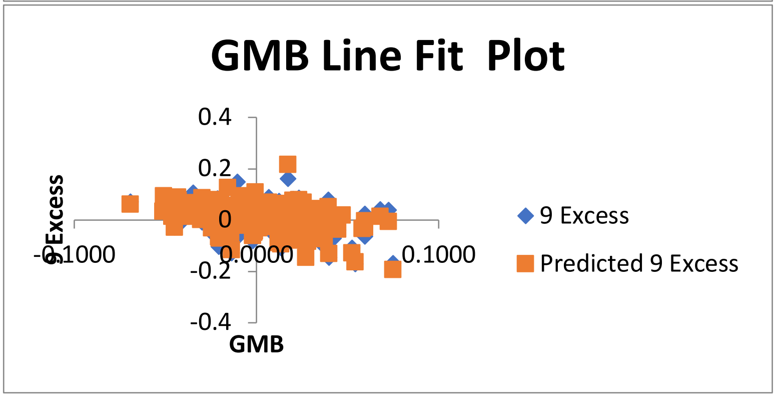

Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.2
0
0.2
0.4
Mkt-RF
9 Excess
Predicted 9 Excess


SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.1
-0.05
0
0.05
0.1
SMB
9 Excess
Predicted 9 Excess

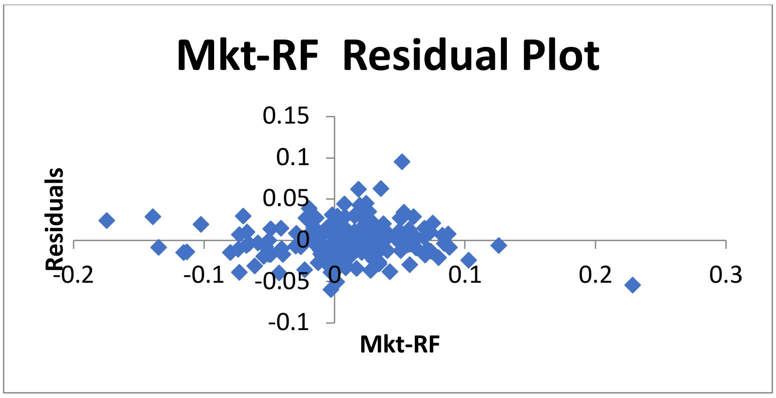

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.2
-0.1
0
0.1
0.2
HML
9 Excess
Predicted 9 Excess

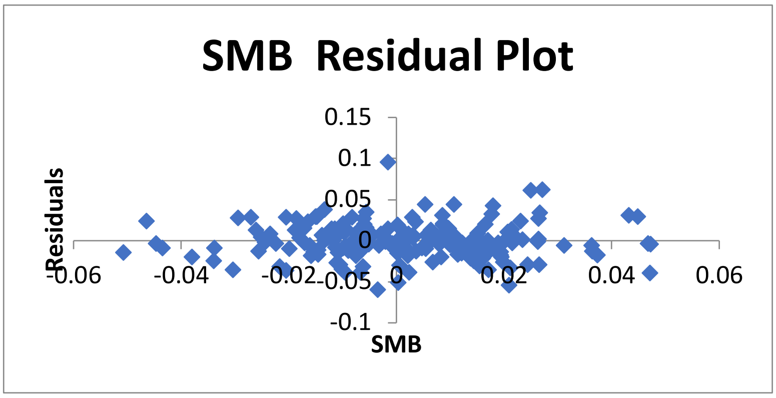

RMW Line Fit Plot
0.4
0.2
0
-0.2
-0.4
9 Excess
-0.1
-0.05
0
0.05
RMW
9 Excess
Predicted 9 Excess

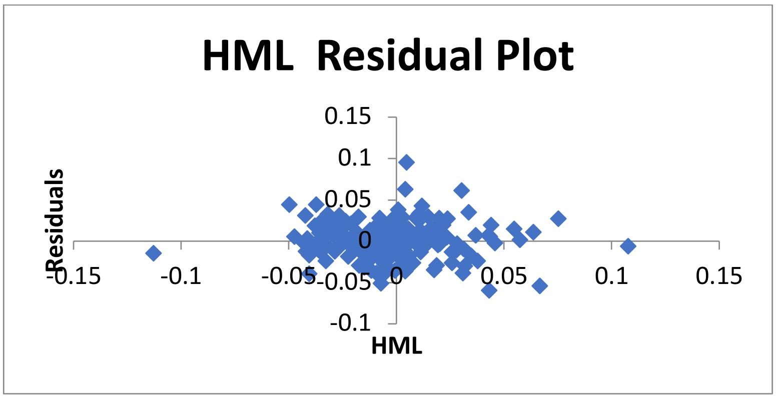


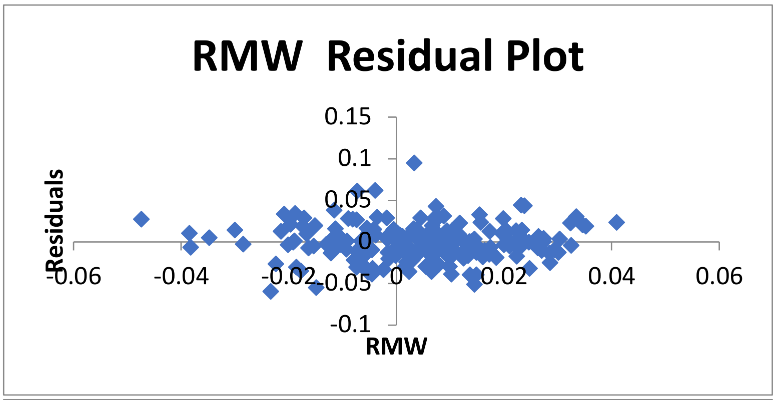


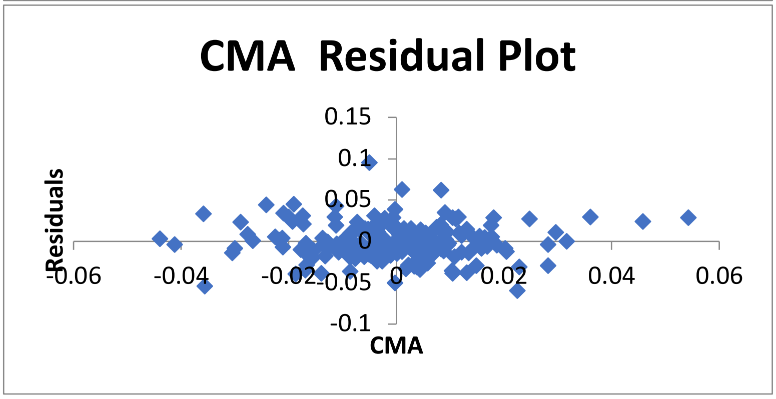
Assumption 2

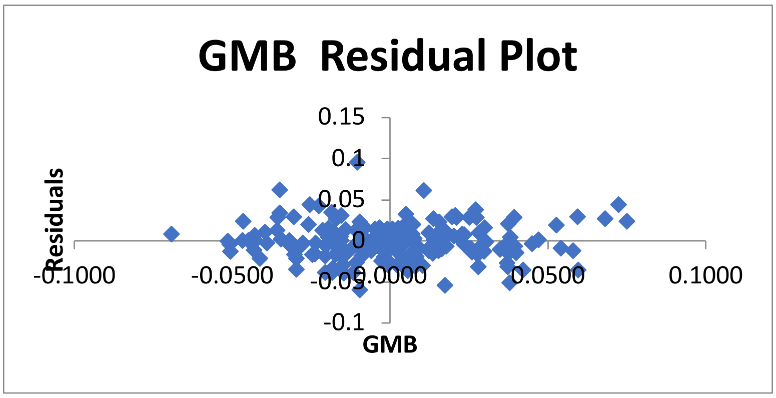






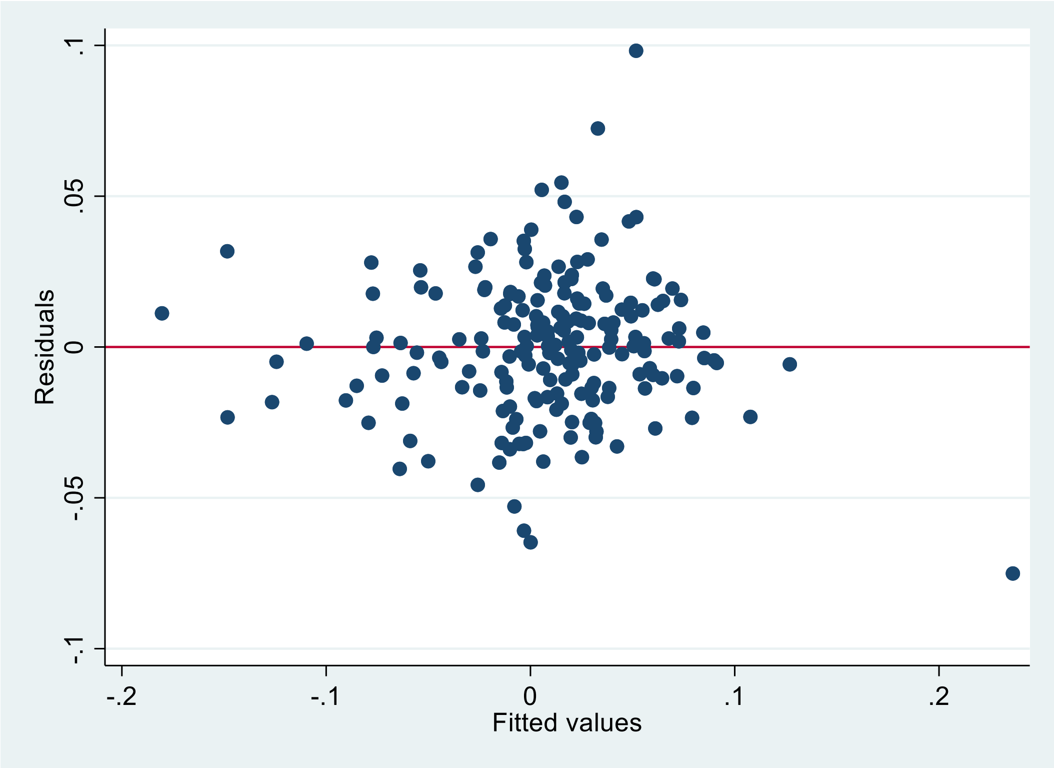






	Mean residuals
Low E	4,33681E-16

Assumption 3

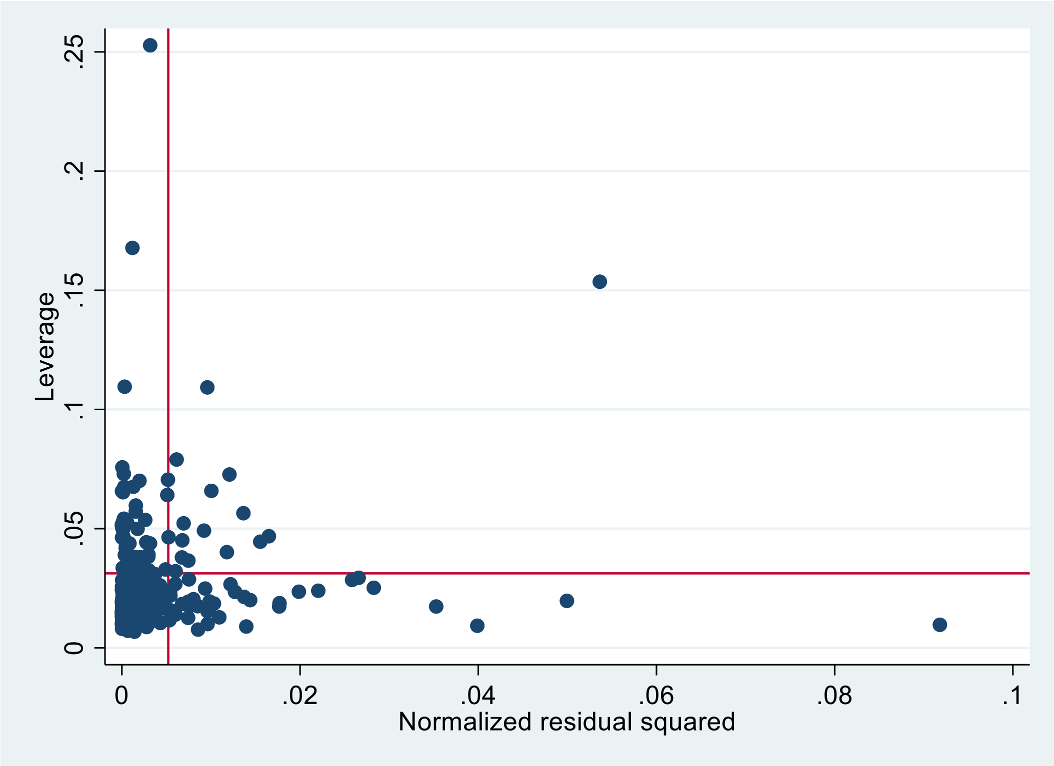


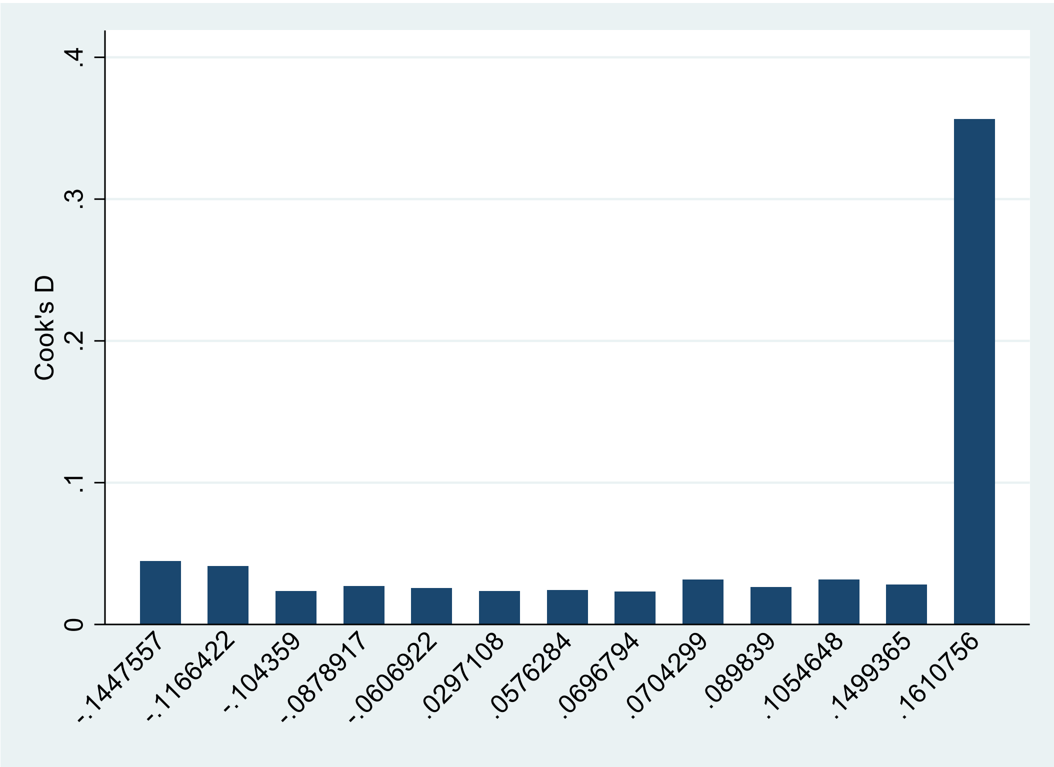

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     5.34
         Prob > chi2  =   0.0209
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     124.27
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8180
                                                Root MSE          =     .02377
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.071048	.0438043	24.45	0.000	.9846313	1.157465
smb	-.0291114	.0970771	-0.30	0.765	-.2206251	.1624024
hml	.0047906	.1212561	0.04	0.969	-.2344234	.2440046
rmw	.1418012	.1507866	0.94	0.348	-.1556706	.4392731
cma	.0750783	.1669984	0.45	0.654	-.2543762	.4045327
_cons	-.0036756	.0018493	-1.99	0.048	-.007324	-.0000273

Assumption 4





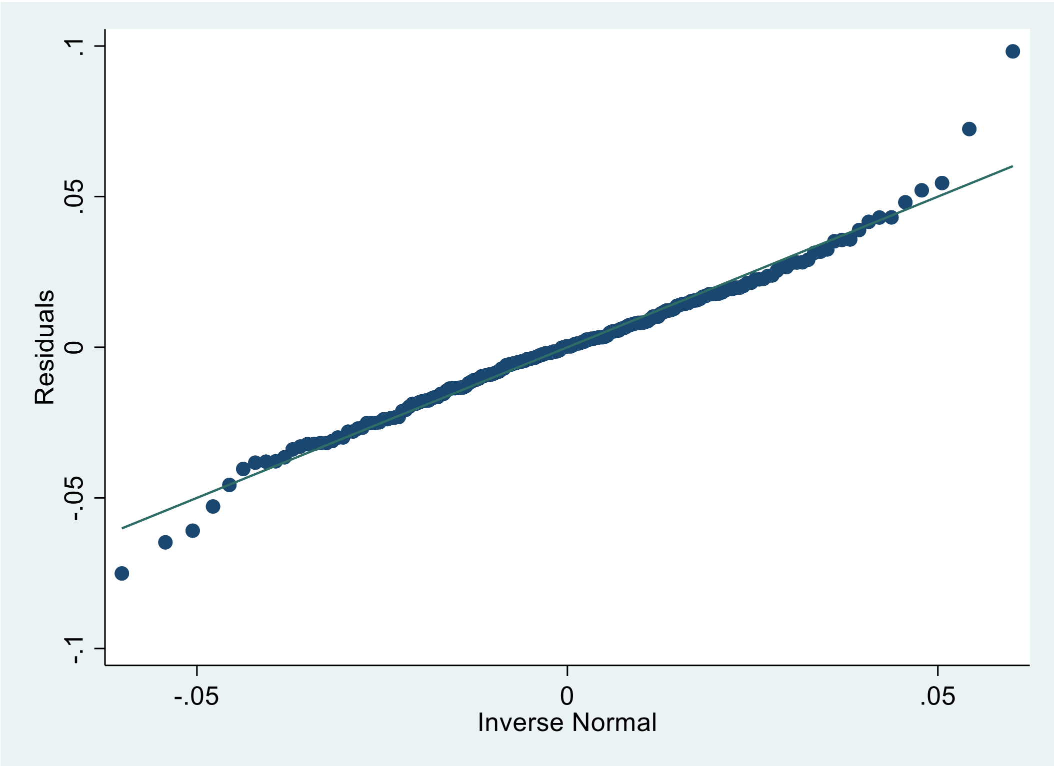
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**2.486**	**1**	**0.1148**

H0: no serial correlation

Assumption 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.98157**	**2.653**	**2.241**	**0.01252**

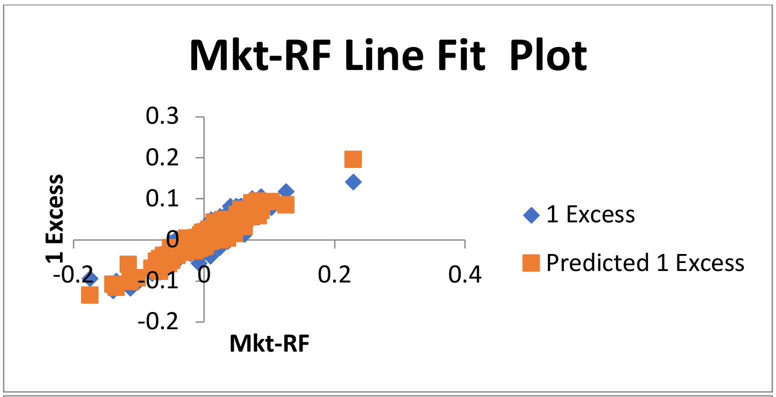
S – Assumption 5

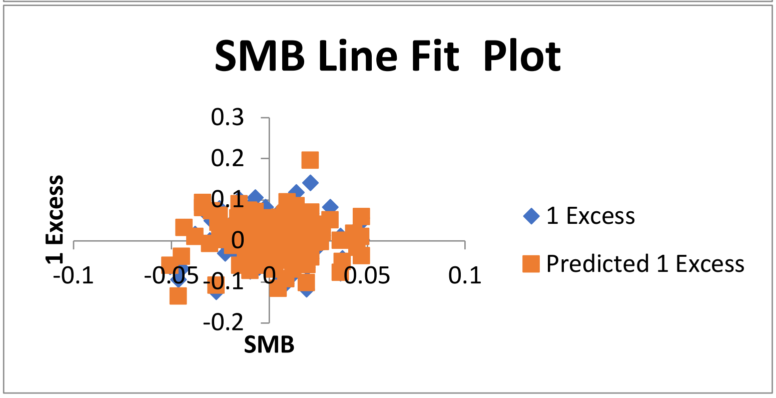
	mktrf	smb	hml	rmw	cma	gmb
mktrf	1.0000					
smb	0.3600	1.0000				
hml	0.5681	0.1099	1.0000			
rmw	-0.1344	-0.0626	-0.7449	1.0000		
cma	0.2565	-0.2889	0.7769	-0.6818	1.0000	
gmb	-0.1276	-0.0762	-0.2039	0.0541	-0.0520	1.0000

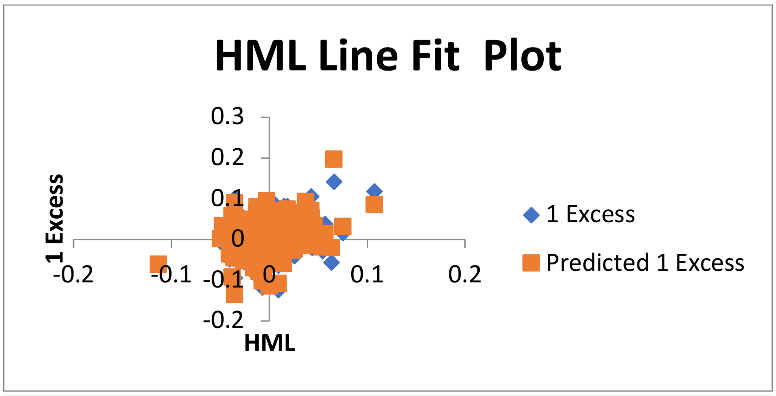
Variable	VIF	1/VIF
hml	7.35	0.135963
cma	4.37	0.228752
rmw	3.49	0.286861
mktrf	2.49	0.401864
smb	1.79	0.557531
gmb	1.11	0.904551
Mean VIF	3.43	

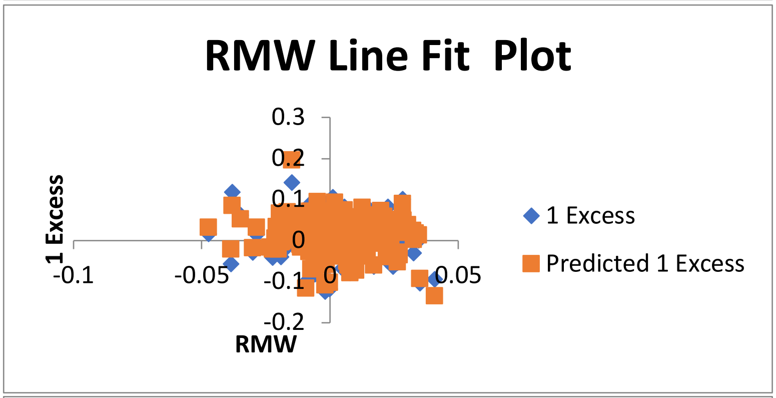
HIGH S

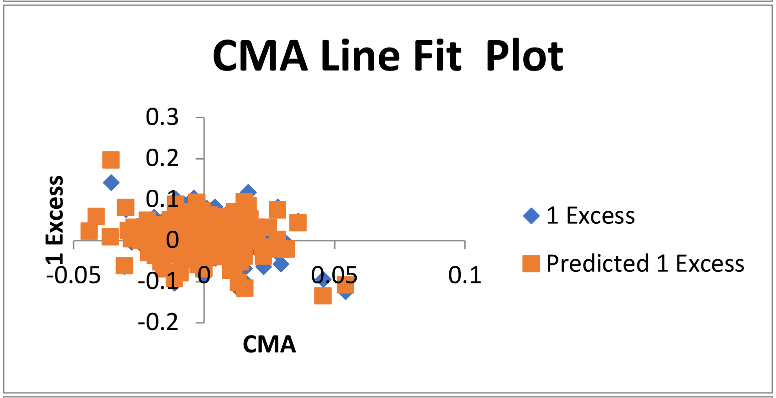
Assumption 1

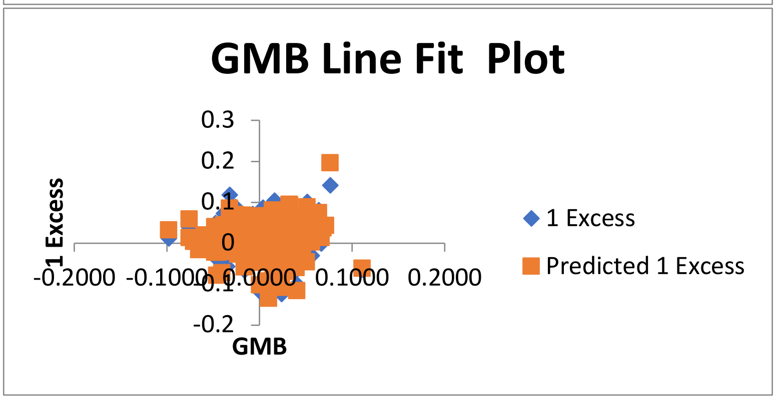




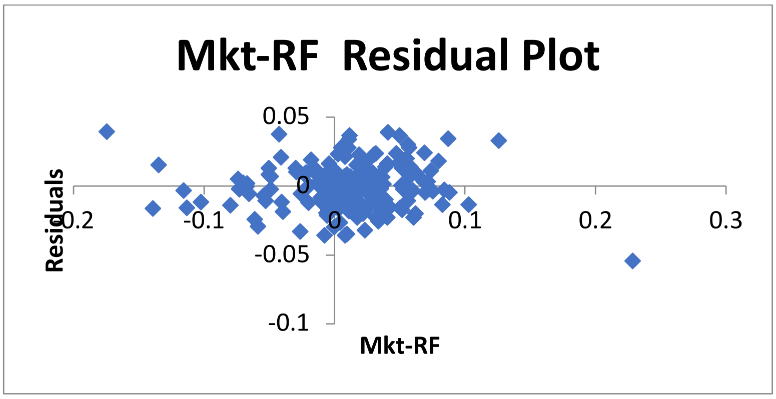


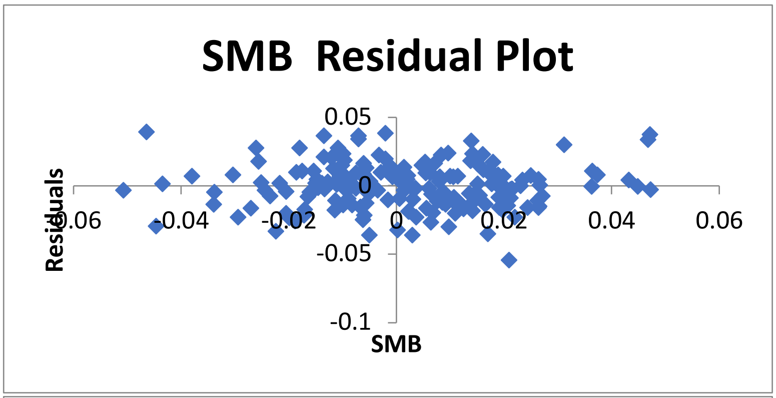


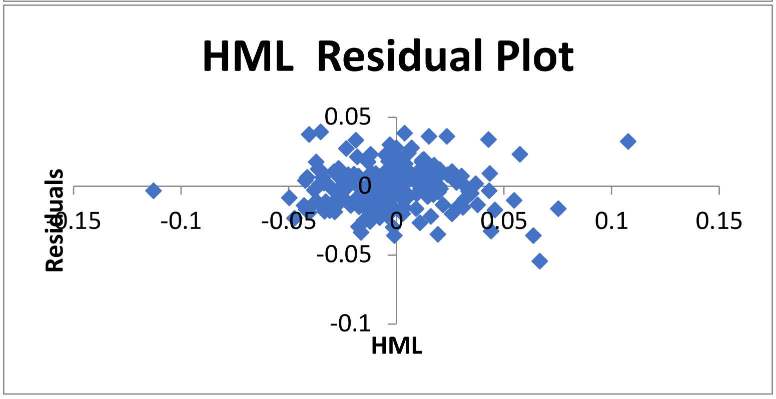


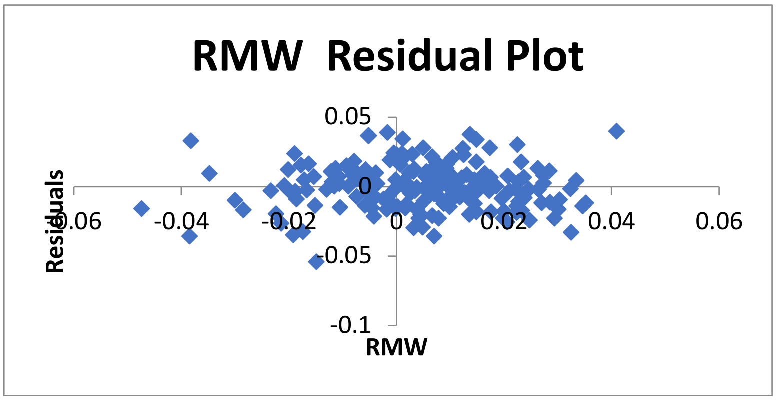


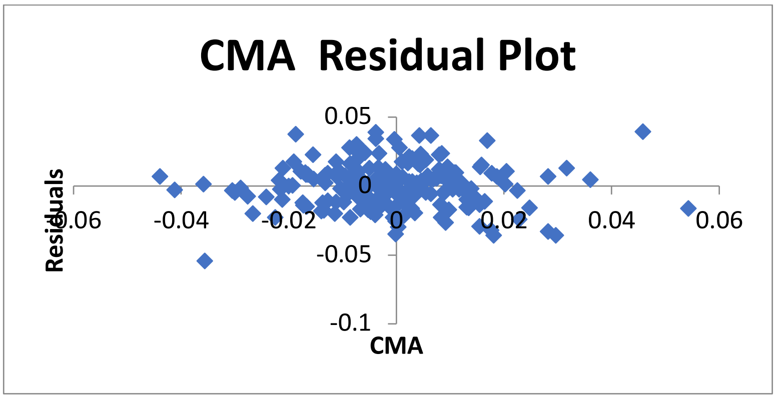
Assumption 2

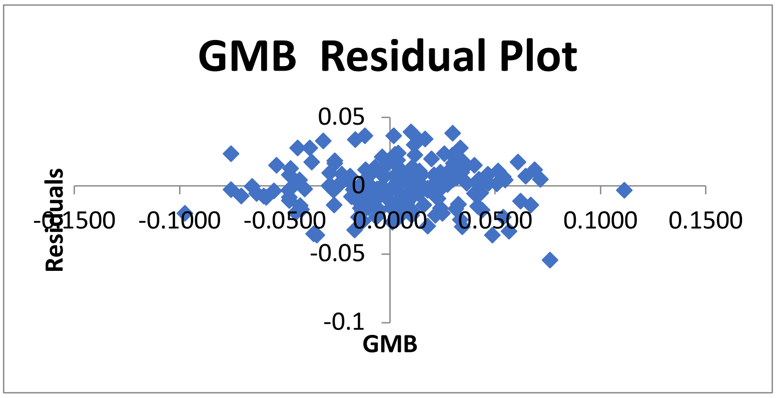

Mkt-RF Residual Plot
0.05
0
-0.05
-0.1
-0.2
-0.1
0
0.1
0.2
0.3
Residuals
Mkt-RF


SMB Residual Plot
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Residuals
SMB


HML Residual Plot
0.05
0
-0.05
-0.1
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
Residuals
HML

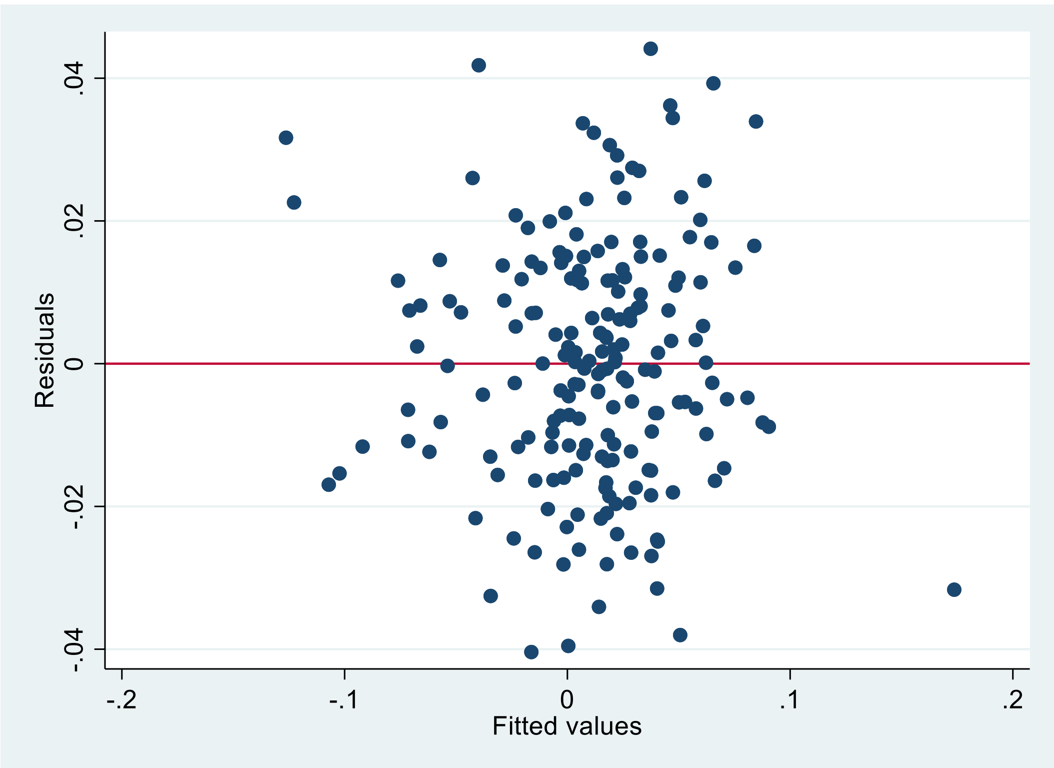

RMW Residual Plot
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Residuals
RMW





	Mean residuals
High S	-3,61979E-16

Assumption 3

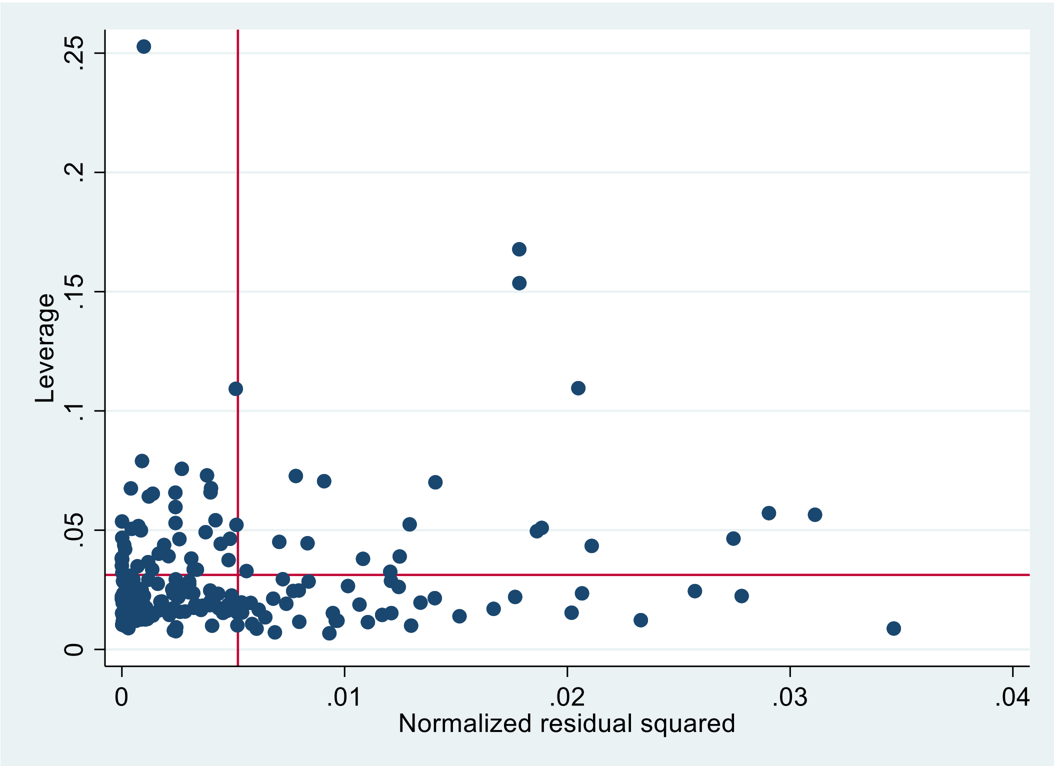


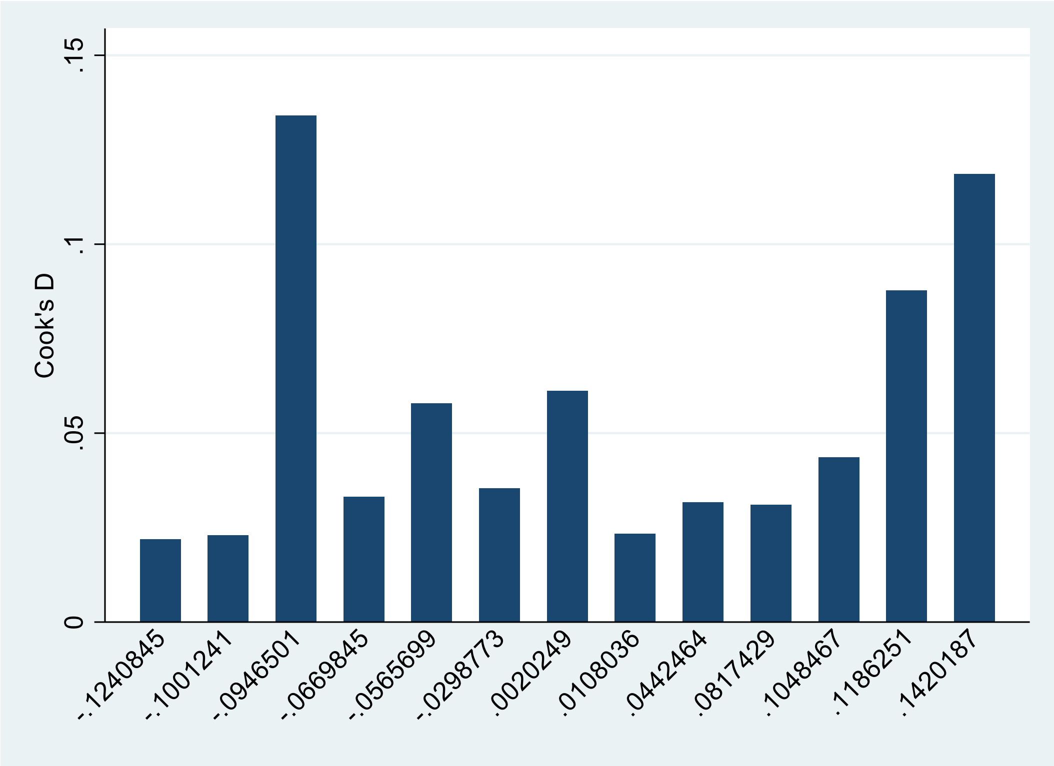
```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =     0.67
         Prob > chi2  =   0.4135
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =     188.06
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8482
                                                Root MSE          =     .01738
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.9801209	.032683	29.99	0.000	.9156439	1.044598
smb	-.1437087	.0745987	-1.93	0.056	-.2908769	.0034596
hml	-.4585765	.0948733	-4.83	0.000	-.6457427	-.2714104
rmw	-.0770471	.1308107	-0.59	0.557	-.3351104	.1810161
cma	.5310249	.1142644	4.65	0.000	.3056041	.7564457
_cons	.0008749	.0013615	0.64	0.521	-.0018111	.0035609

Assumption 4





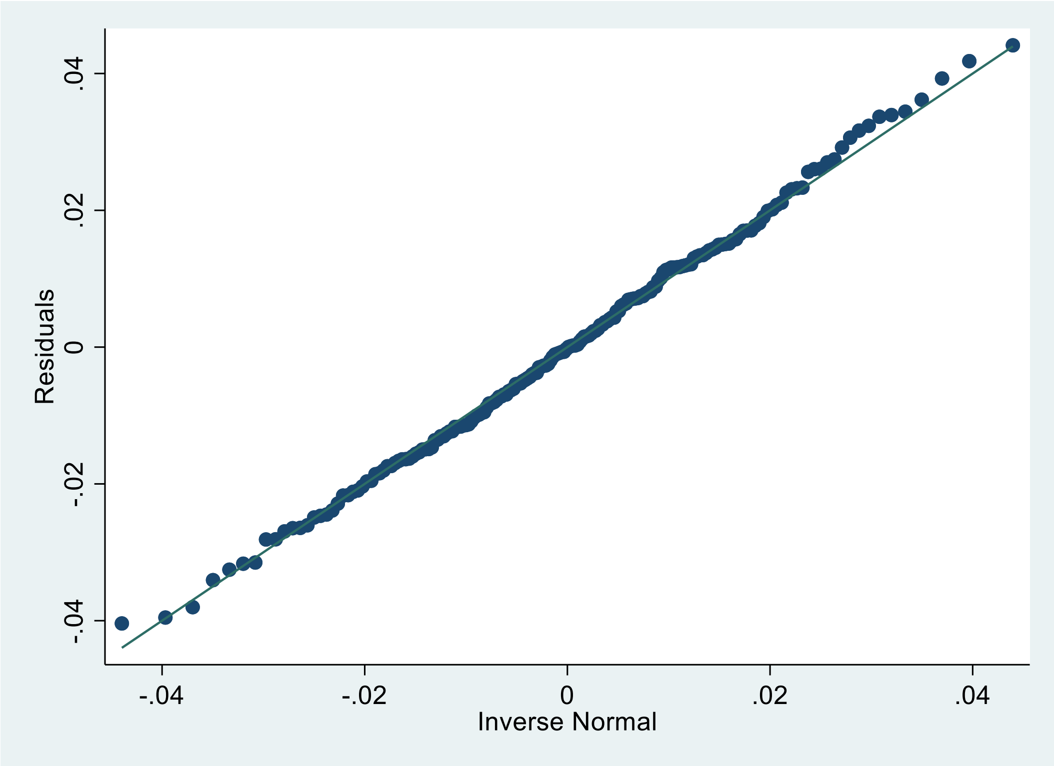
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**0.226**	**1**	**0.6343**

H0: no serial correlation

Assumption 7

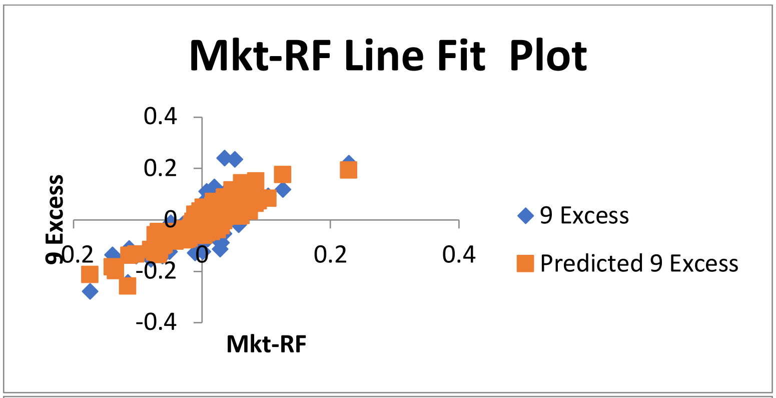


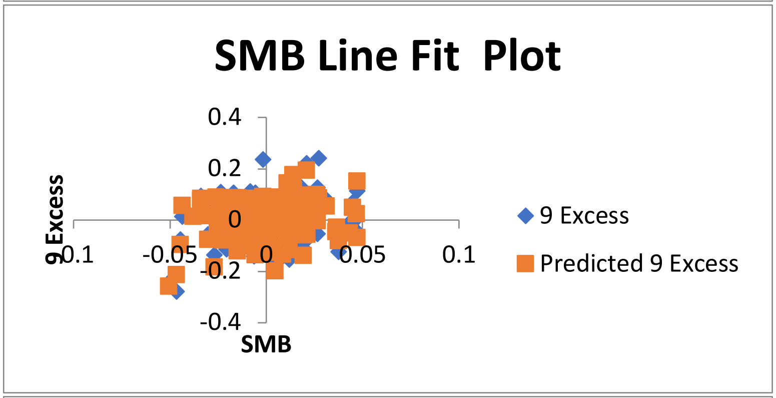
Shapiro-Wilk W test for normal data

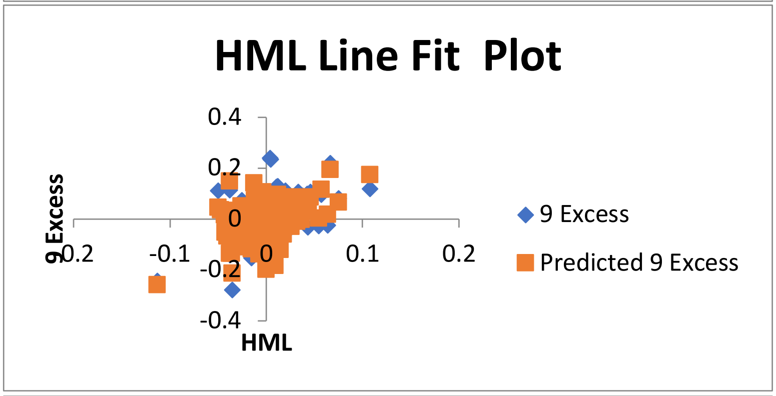
Variable	Obs	W	V	z	Prob>z
resid1	192	0.99540	0.663	-0.944	0.82739

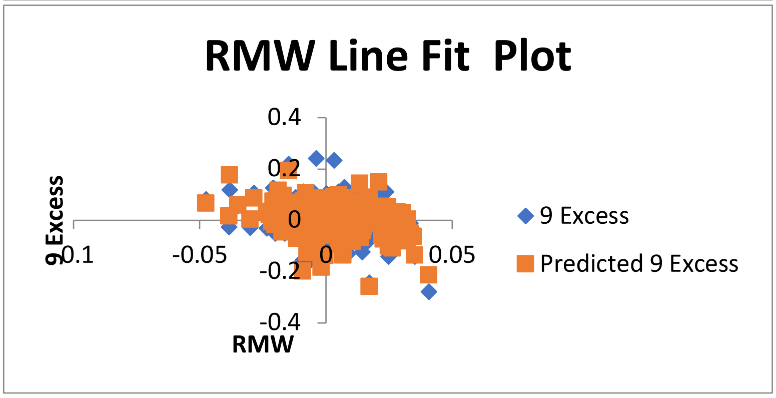
LOW S

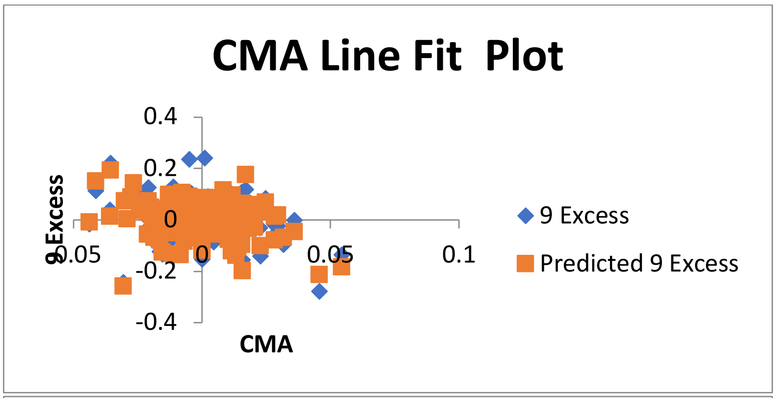
Assumption 1

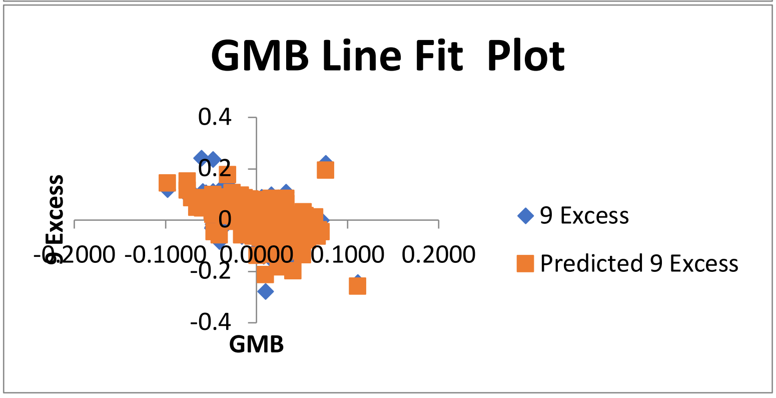

Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess


SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

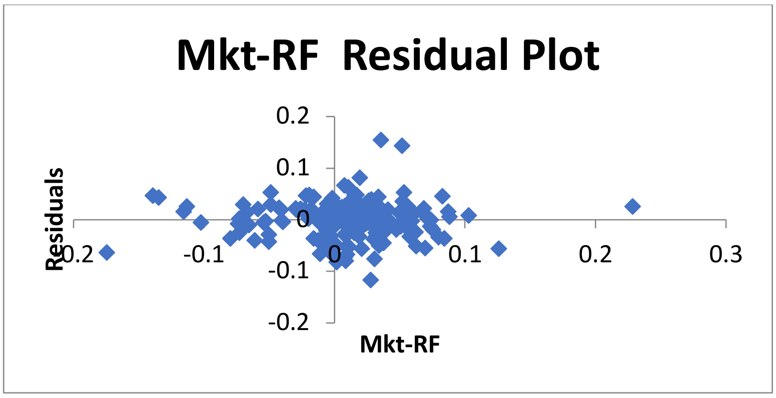

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

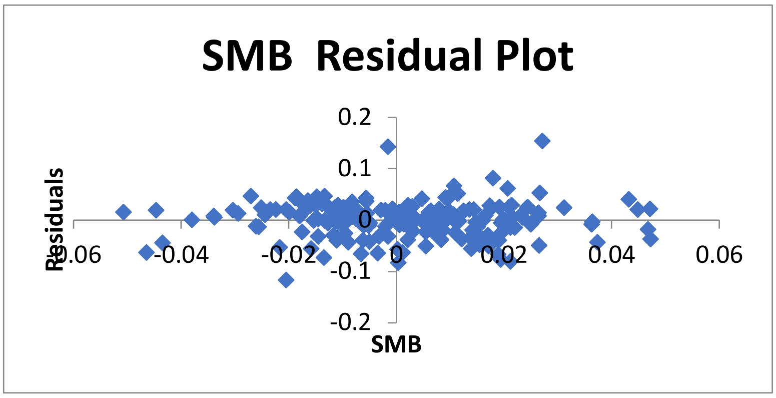

RMW Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
9 Excess
RMW
9 Excess
Predicted 9 Excess

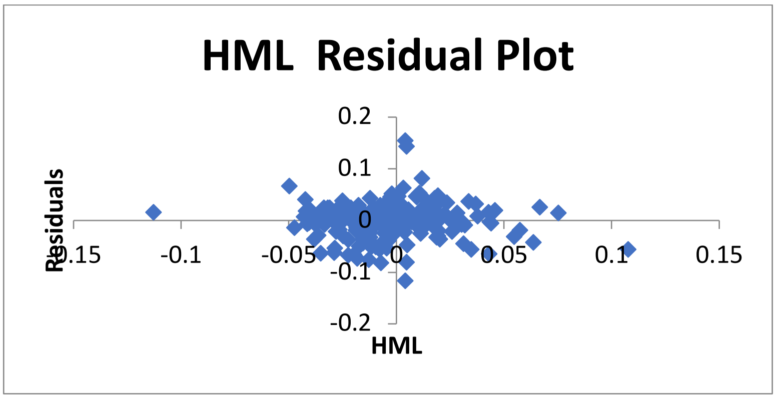


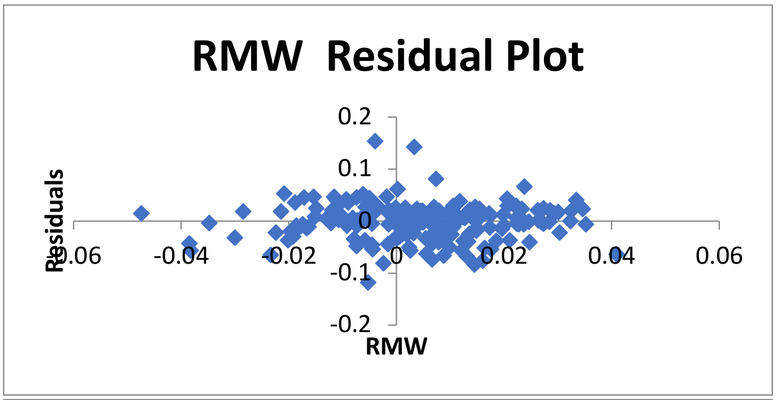


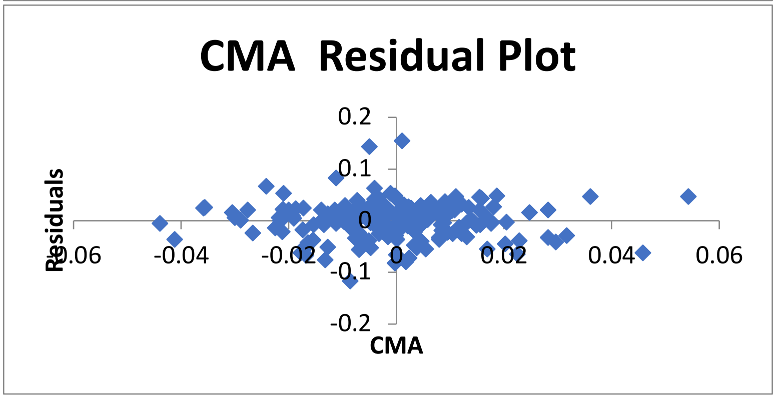
Assumption 2

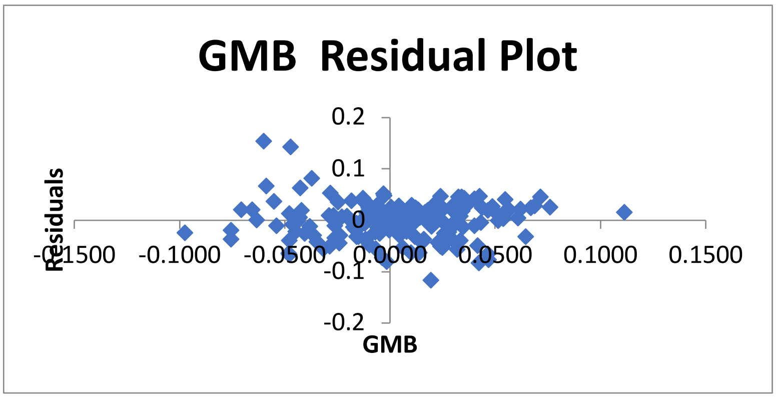






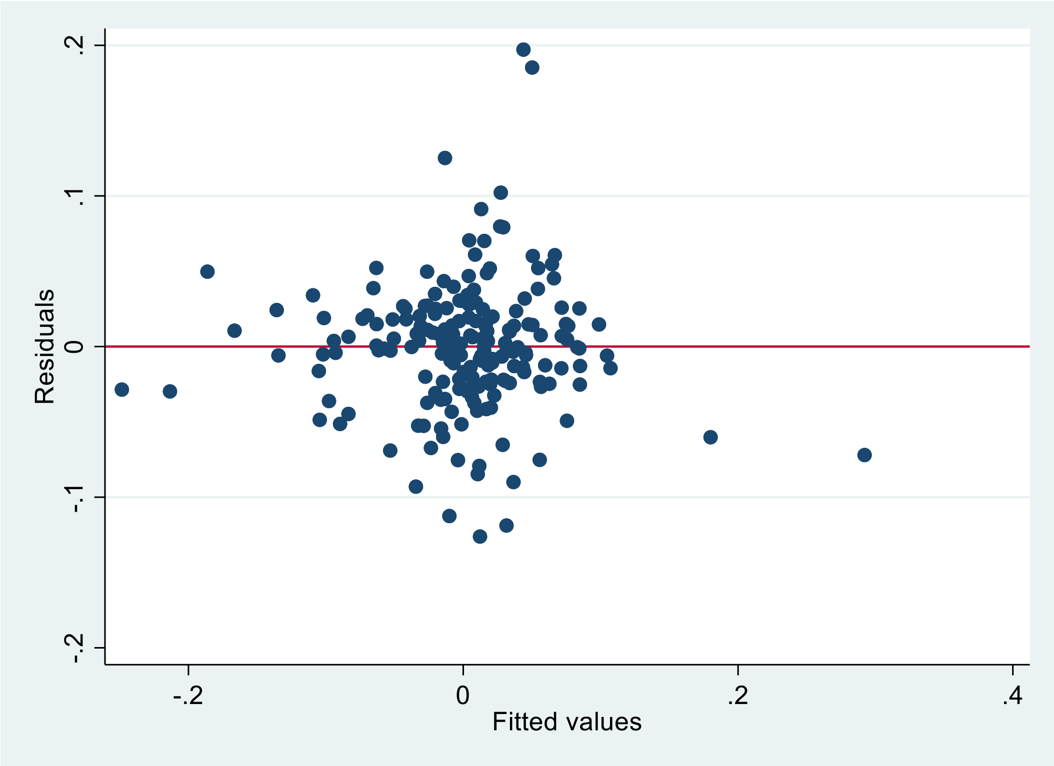






	Mean residuals
Low S	1,26057E-16

Assumption 3

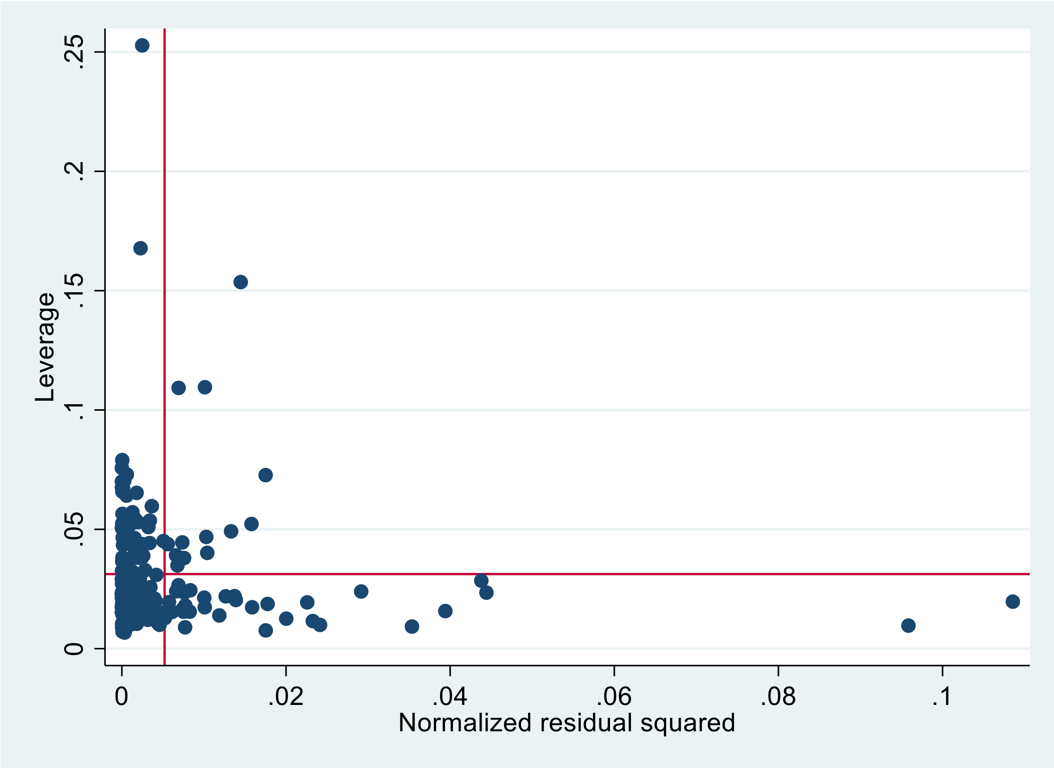


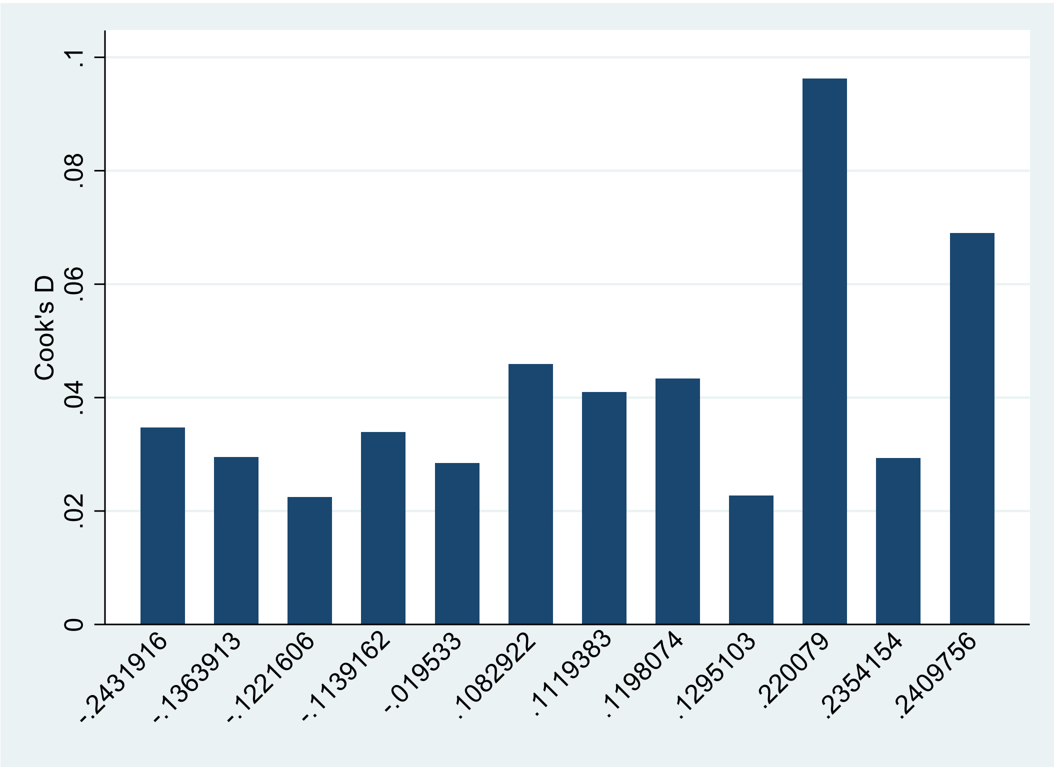

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     6.16
         Prob > chi2  =   0.0130
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      80.33
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6609
                                                Root MSE          =     .04387
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.145815	.0702279	16.32	0.000	1.00727	1.284361
smb	.4936132	.1797443	2.75	0.007	.1390136	.8482129
hml	.4461018	.2053475	2.17	0.031	.0409922	.8512115
rmw	.1557943	.2623563	0.59	0.553	-.3617822	.6733709
cma	-.1022592	.2760529	-0.37	0.711	-.6468564	.442338
_cons	-.0112517	.0032383	-3.47	0.001	-.0176403	-.0048631

Assumption 4





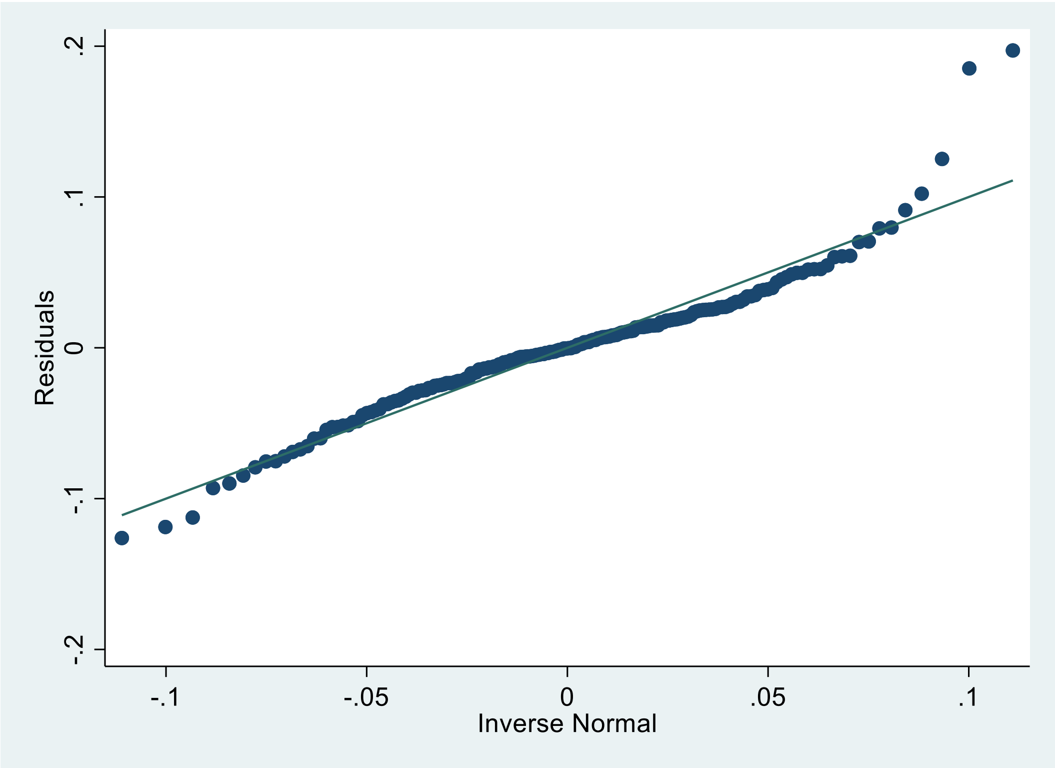
Assumption 6

```
Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
1	**3.268**	**1**	**0.0706**

H0: no serial correlation

Assumption 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.94235**	**8.301**	**4.859**	**0.00000**

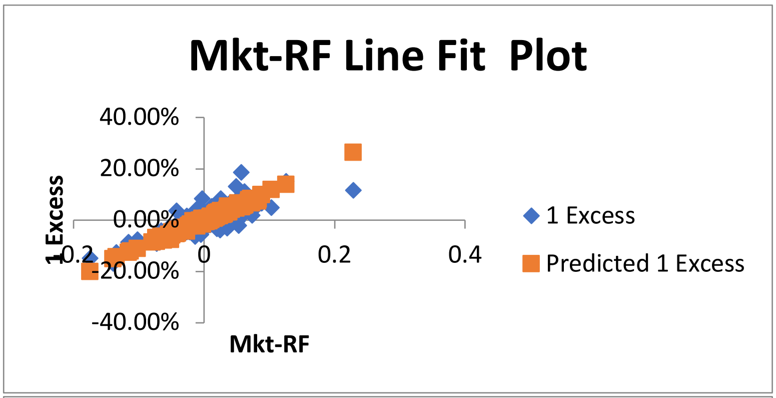
G – Assumption 5

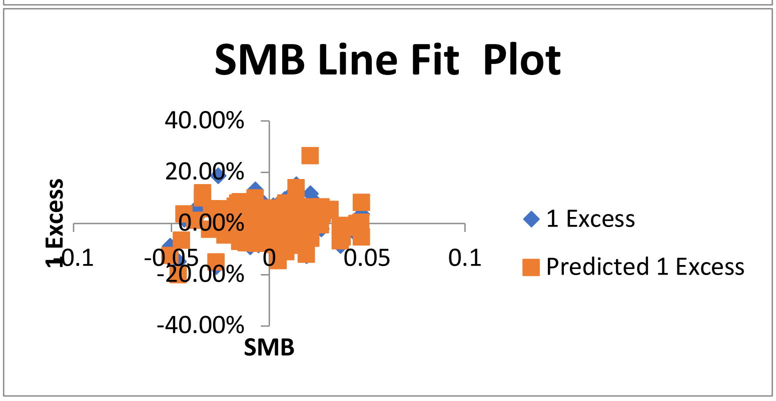
	mktrf	smb	hml	rmw	cma	gmb
mktrf	1.0000					
smb	0.3600	1.0000				
hml	0.5681	0.1099	1.0000			
rmw	-0.1344	-0.0626	-0.7449	1.0000		
cma	0.2565	-0.2889	0.7769	-0.6818	1.0000	
gmb	0.1241	-0.0113	0.1192	-0.2485	0.1784	1.0000

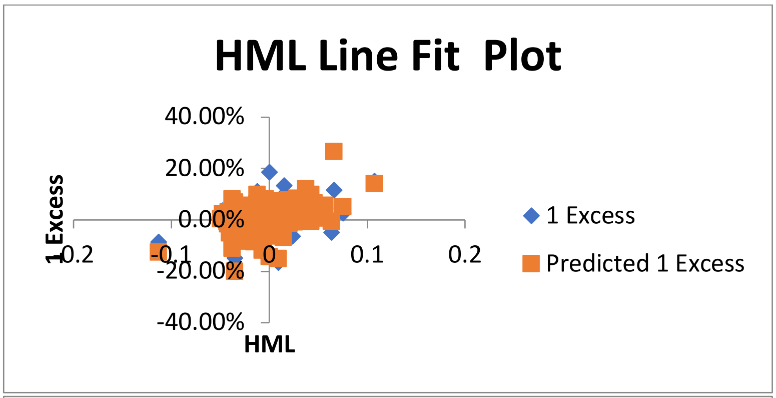
Variable	VIF	1/VIF
hml	7.34	0.136191
cma	4.33	0.231079
rmw	3.80	0.263257
mktrf	2.65	0.376766
smb	1.80	0.556194
gmb	1.17	0.852012
Mean VIF	3.52	

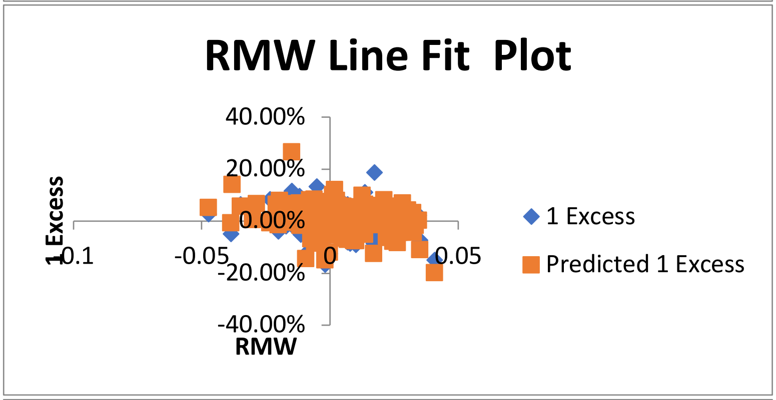
HIGH G

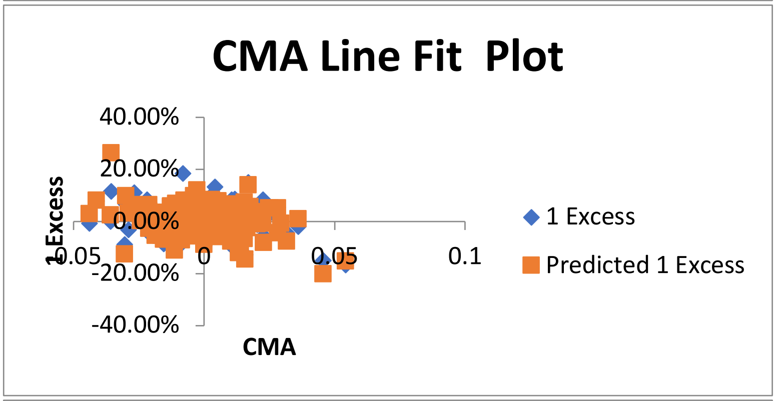
Assumption 1

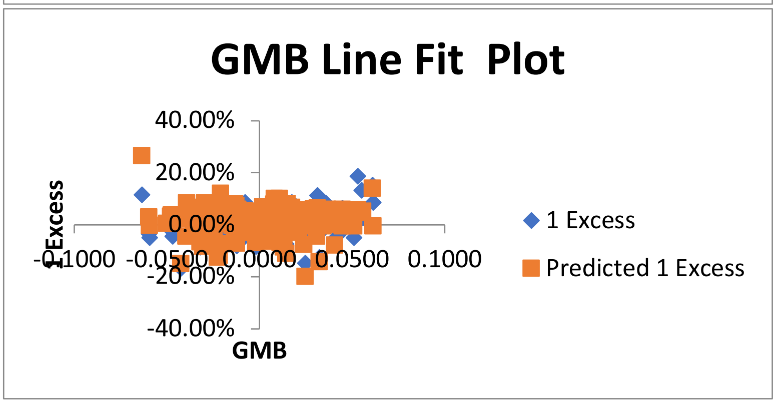




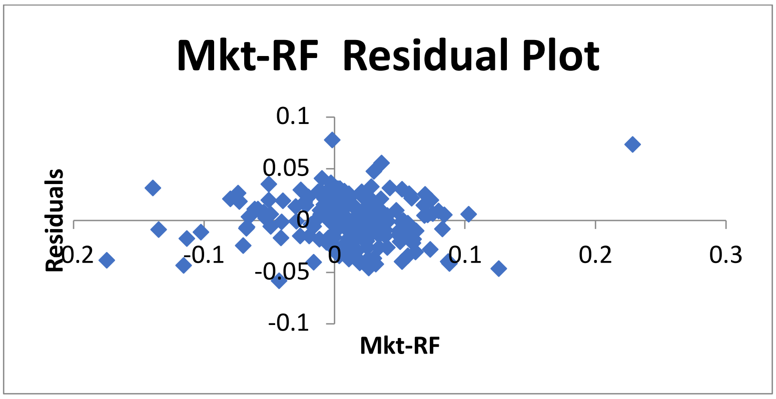


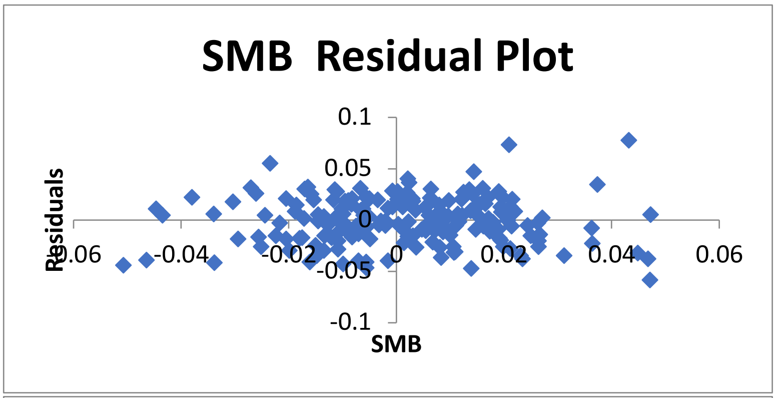


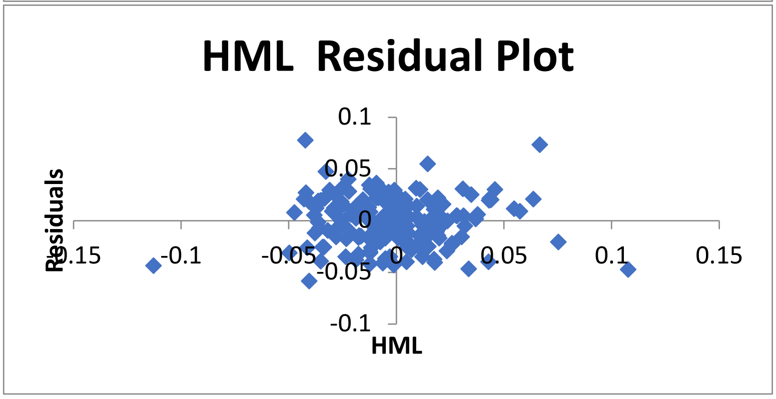


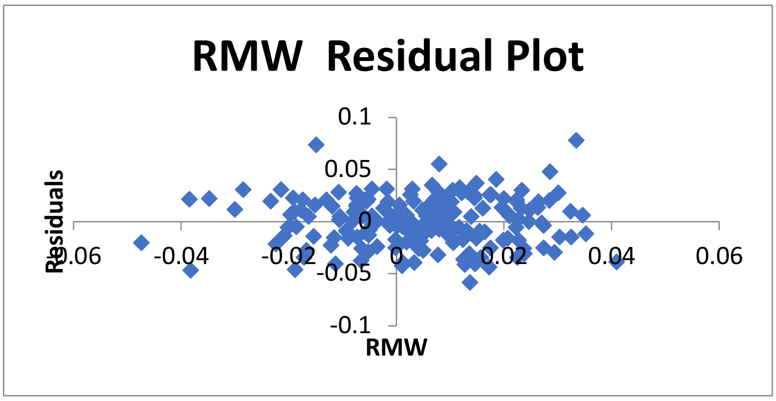


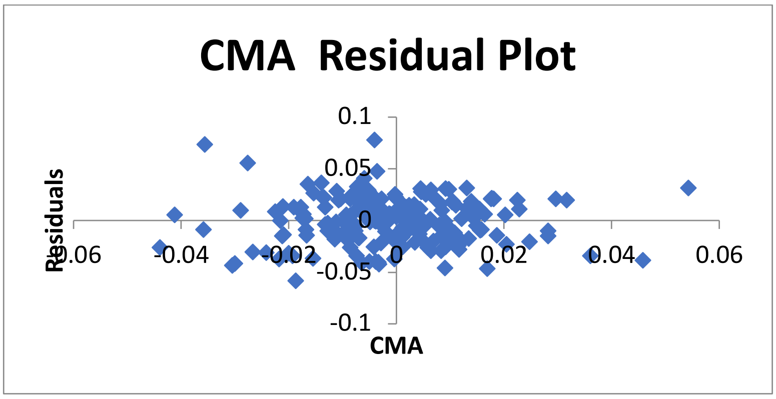
Assumption 2

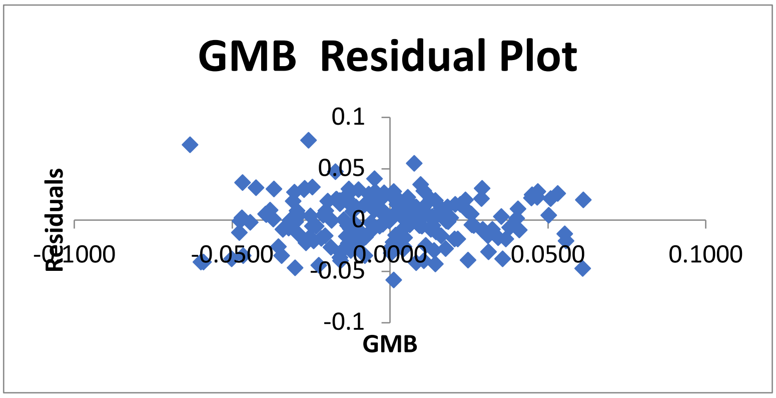

Mkt-RF Residual Plot
Residuals
Mkt-RF
0.1
0.05
0
-0.05
-0.1
-0.2
-0.1
0
0.1
0.2
0.3


SMB Residual Plot
Residuals
SMB
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06


HML Residual Plot
Residuals
HML
0.1
0.05
0
-0.05
-0.1
-0.15
-0.1
-0.05
0
0.05
0.1
0.15

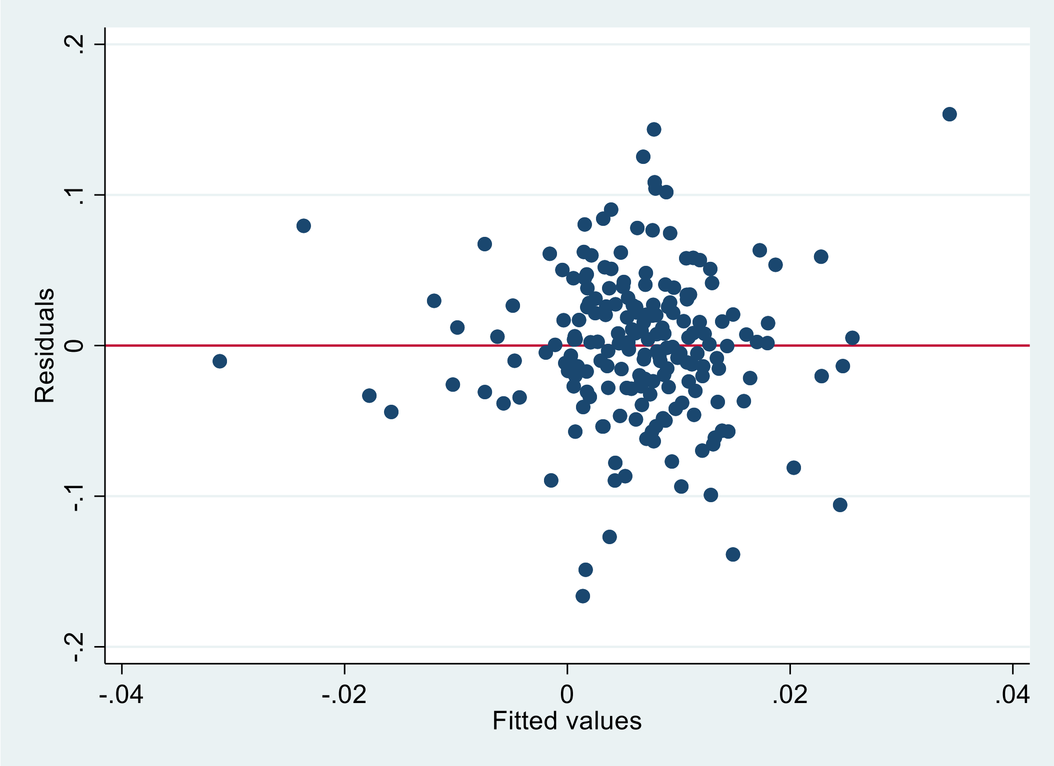

RMW Residual Plot
Residuals
RMW
0.1
0.05
0
-0.05
-0.1
-0.06
-0.04
-0.02
0
0.02
0.04
0.06





	Mean residuals
High G	2,90566E-16

Assumption 3

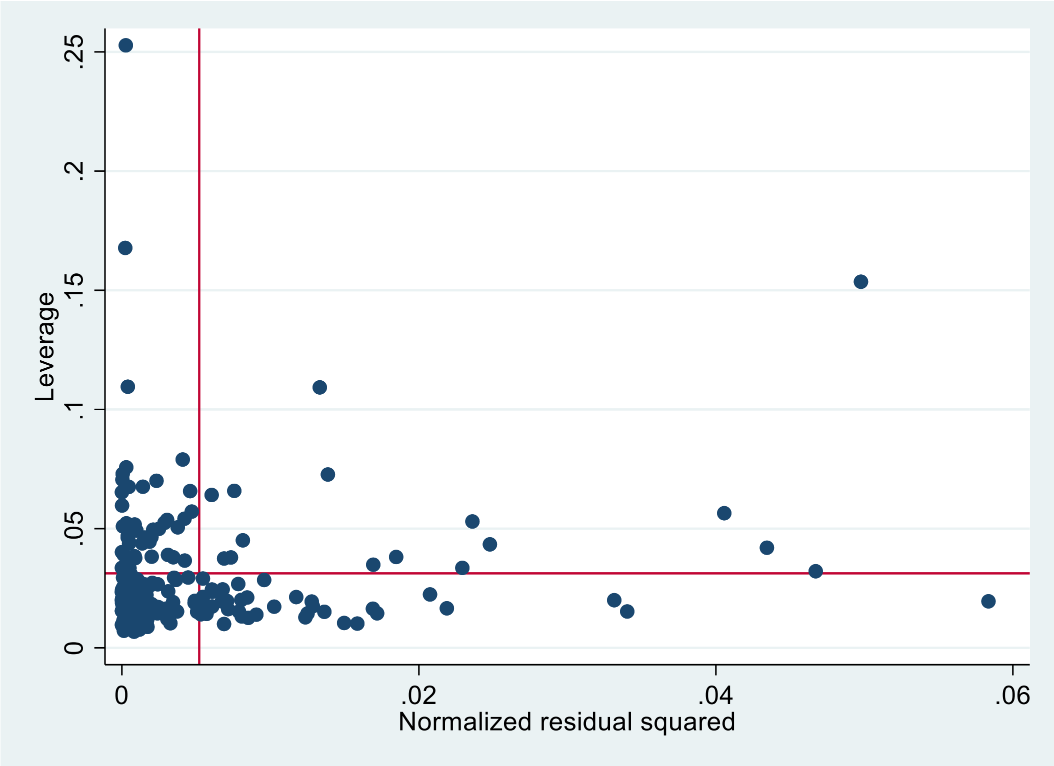


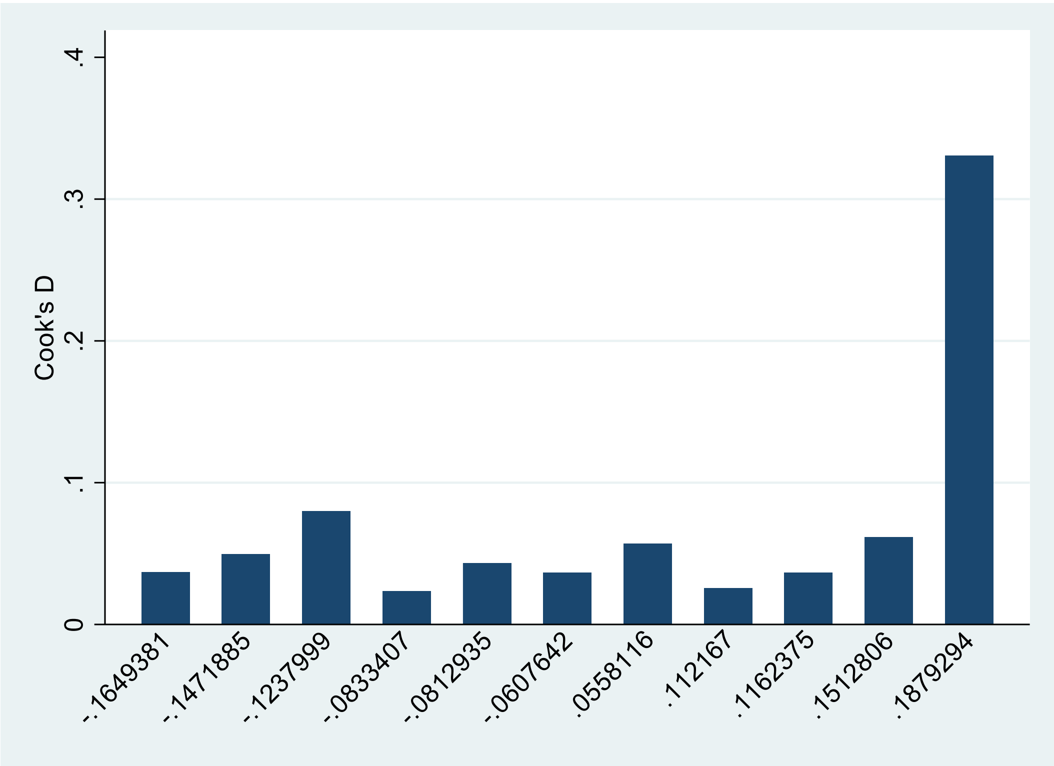

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf1

         chi2(1)      =    12.80
         Prob > chi2  =   0.0003
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      58.20
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6582
                                                Root MSE          =     .02961
```

pf1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	.8564277	.0540323	15.85	0.000	.7498329	.9630226
smb	.0026248	.1305765	0.02	0.984	-.2549766	.2602262
hml	.0990709	.1556141	0.64	0.525	-.2079248	.4060665
rmw	.1085276	.220488	0.49	0.623	-.3264512	.5435064
cma	.1306327	.1996678	0.65	0.514	-.263272	.5245374
_cons	-.0032927	.0022502	-1.46	0.145	-.0077319	.0011465

Assumption 4





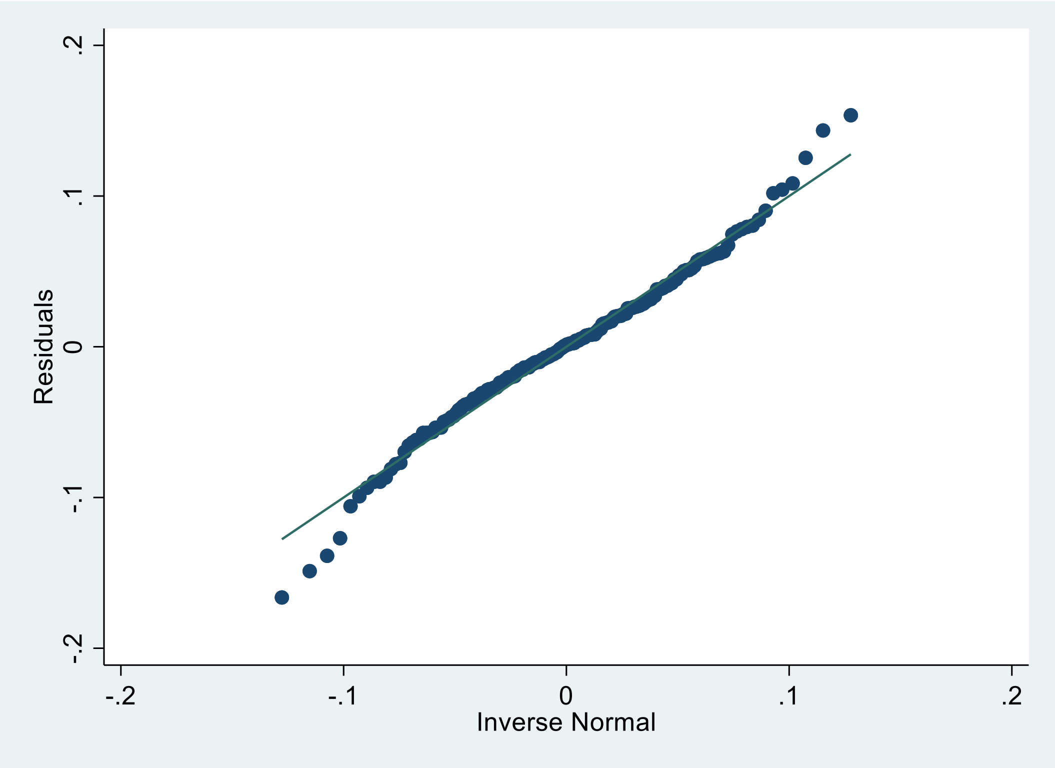
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	**7.310**	**1**	**0.0069**

H0: no serial correlation

Assumption 7

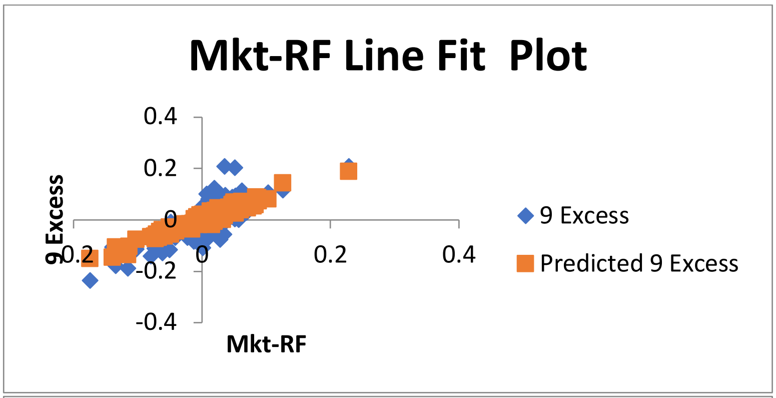


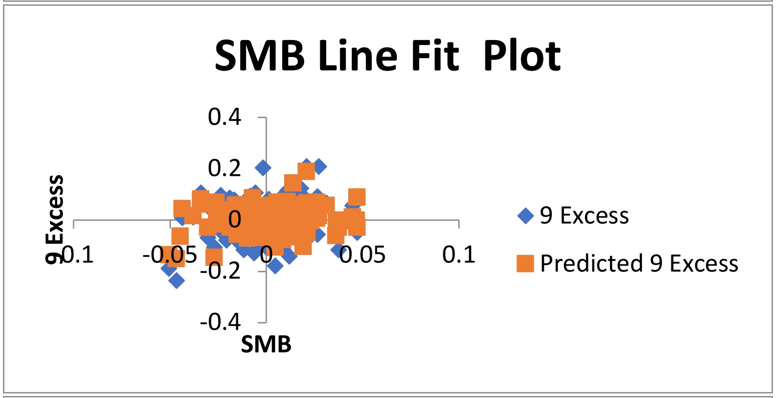
Shapiro-Wilk W test for normal data

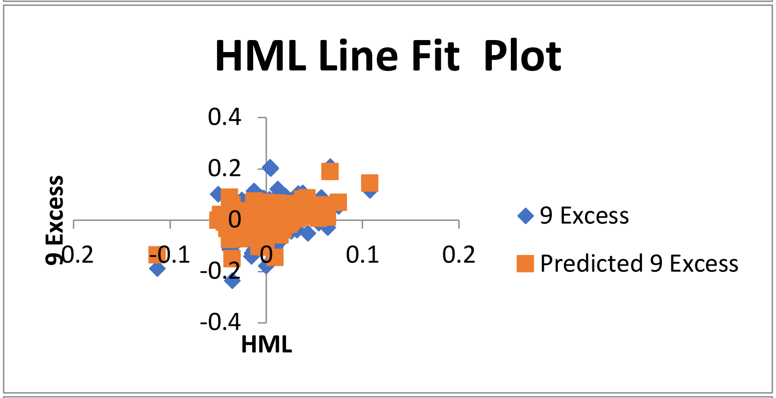
Variable	Obs	W	V	z	Prob>z
resid1	**192**	**0.96210**	**5.458**	**3.897**	**0.00005**

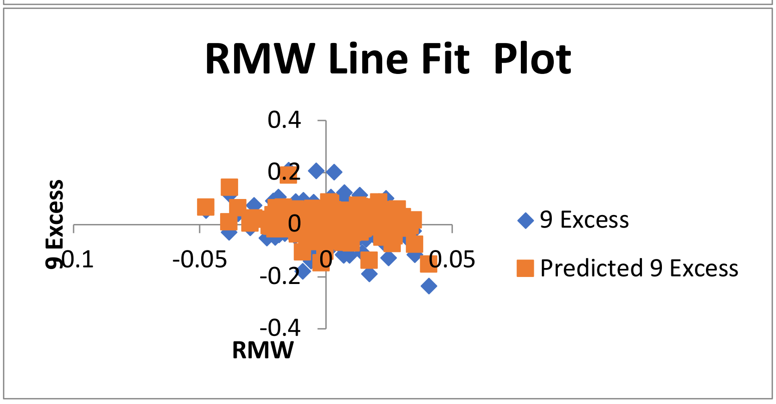
LOW G

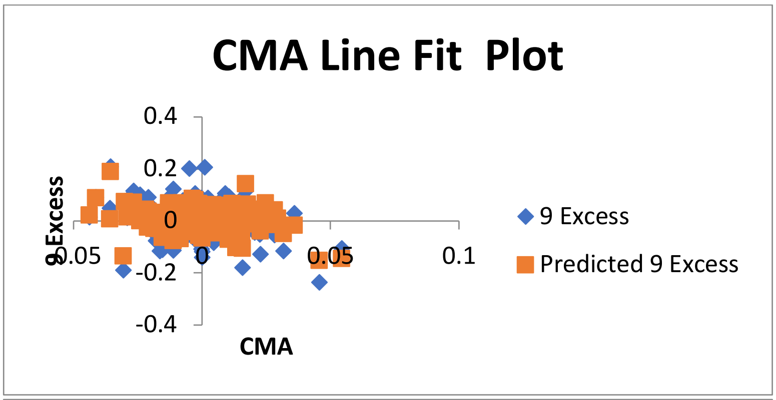
Assumption 1

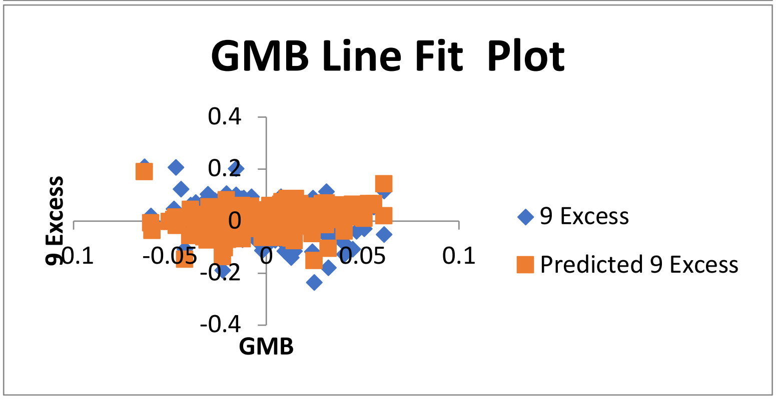

Mkt-RF Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
0
0.2
0.4
9 Excess
Mkt-RF
9 Excess
Predicted 9 Excess


SMB Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
0.1
9 Excess
SMB
9 Excess
Predicted 9 Excess

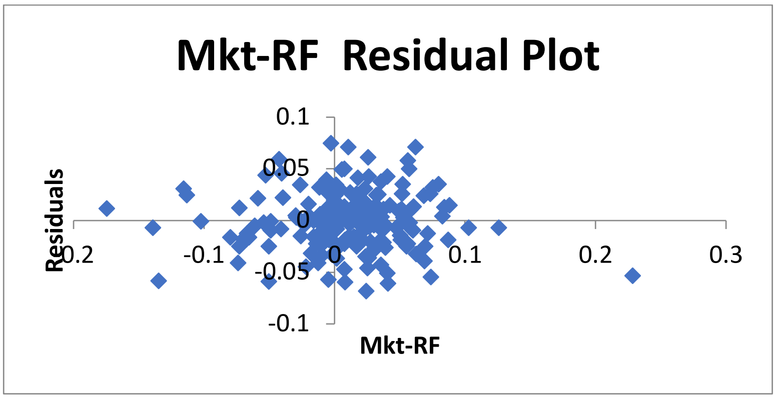

HML Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.2
-0.1
0
0.1
0.2
9 Excess
HML
9 Excess
Predicted 9 Excess

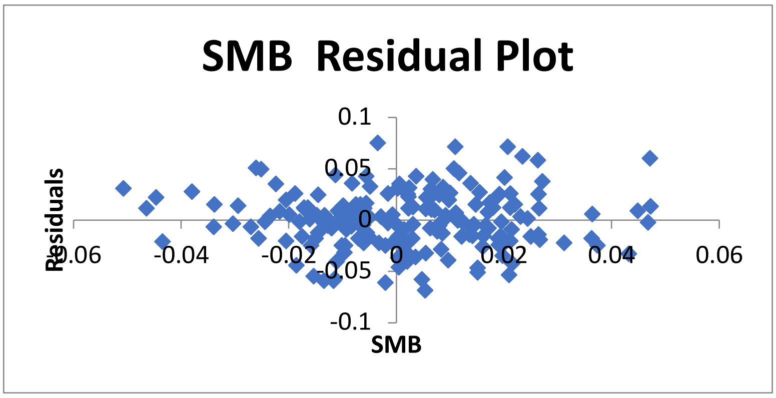

RMW Line Fit Plot
0.4
0.2
0
-0.2
-0.4
-0.1
-0.05
0
0.05
9 Excess
RMW
9 Excess
Predicted 9 Excess

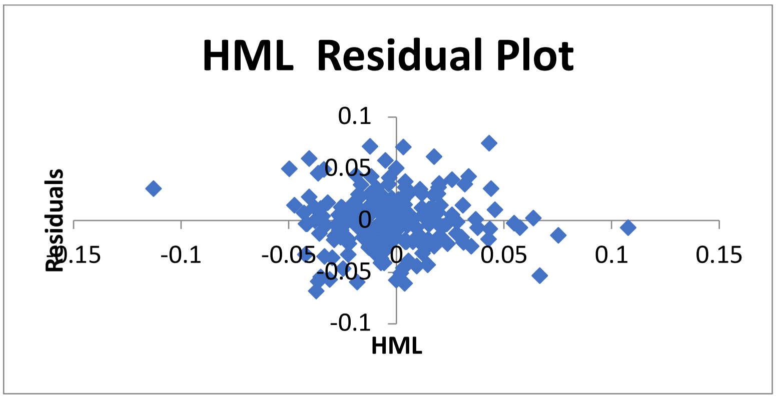


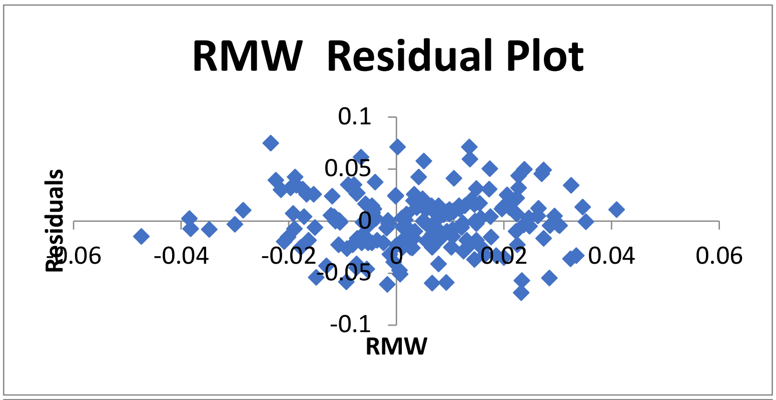


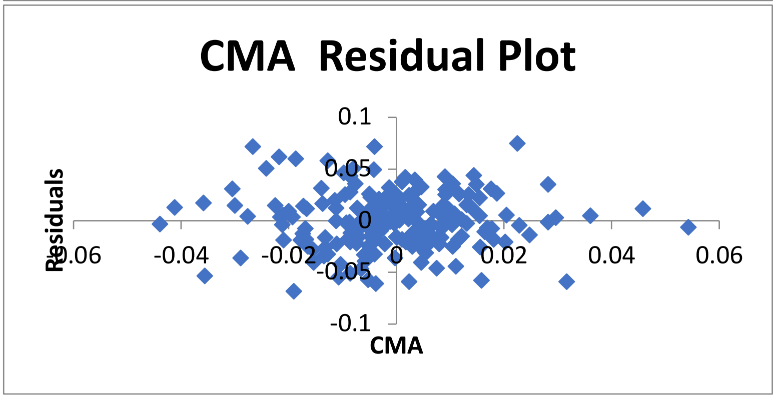
Assumption 2

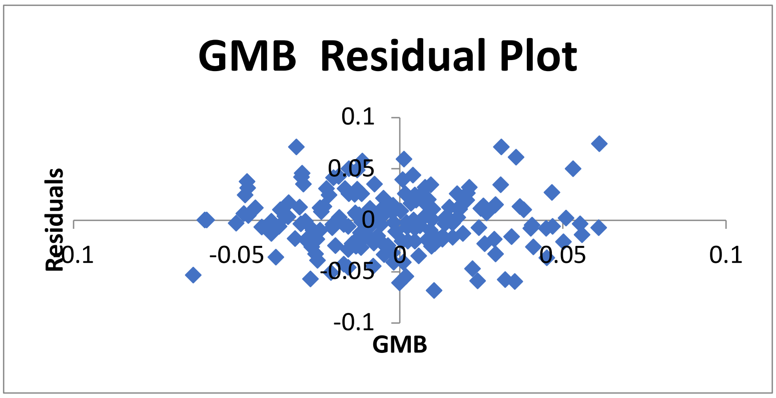






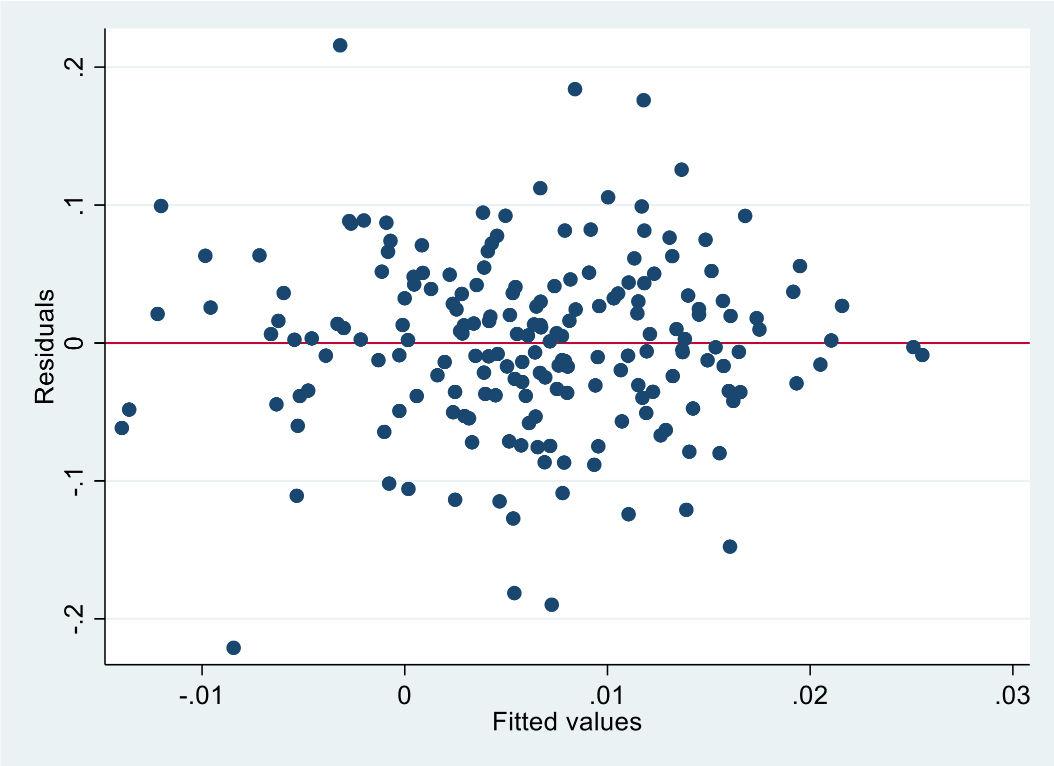






	Mean residuals
Low G	3,81278E-18

Assumption 3

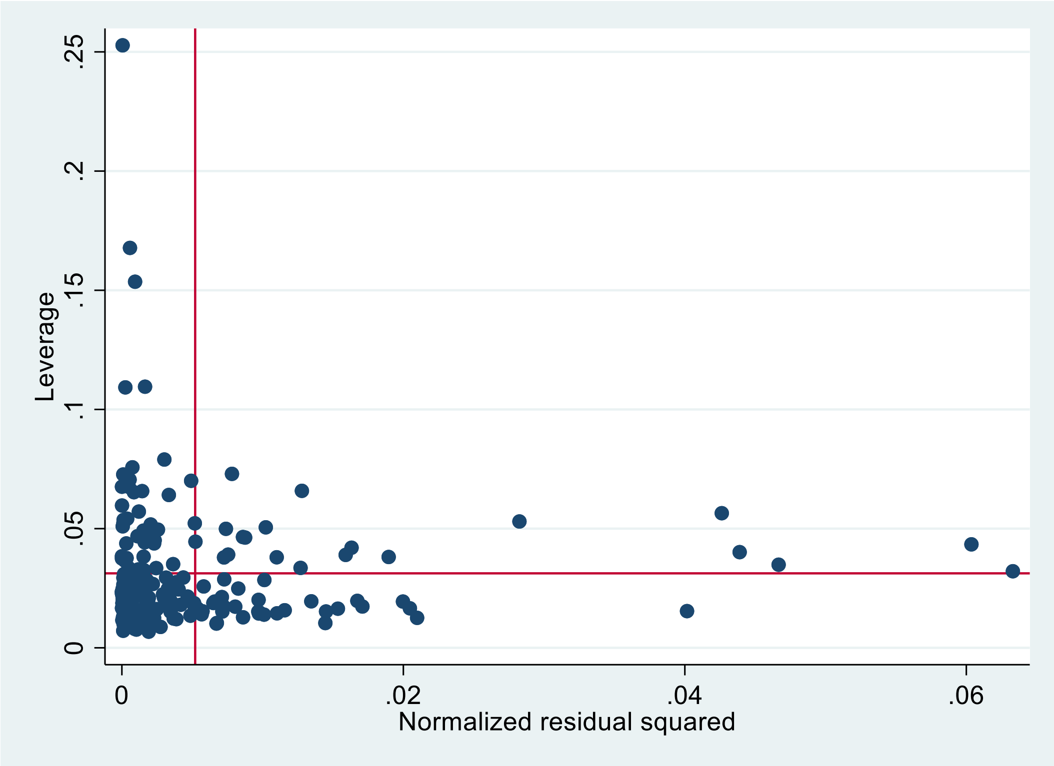


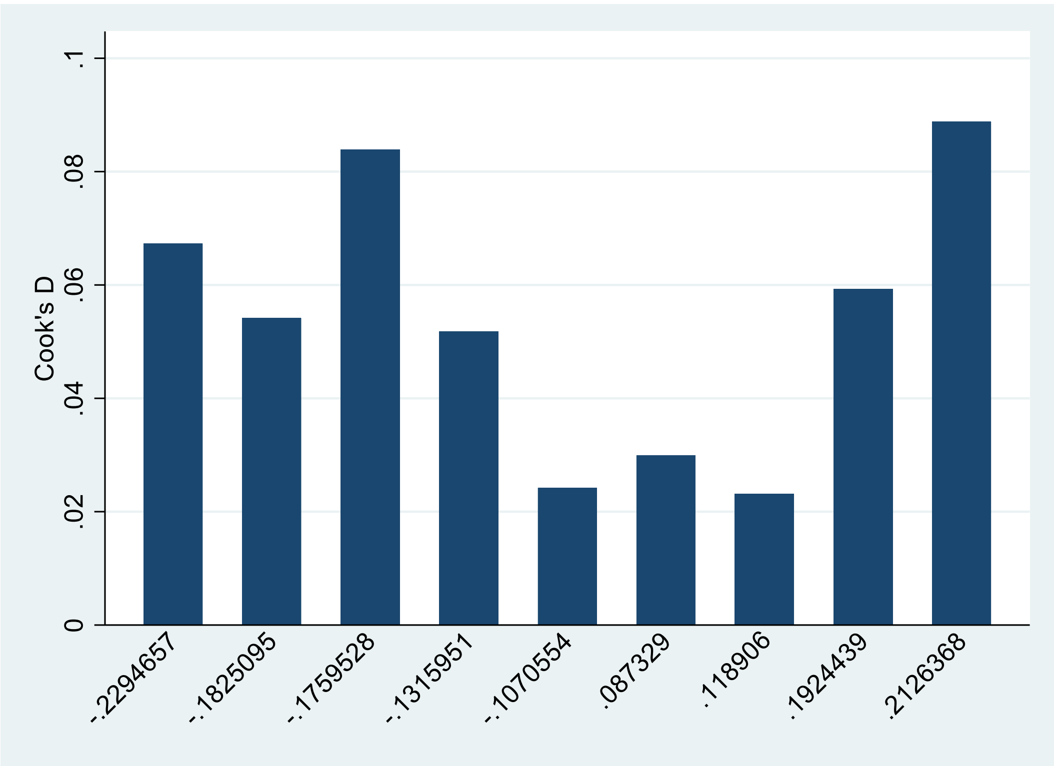

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of pf9

         chi2(1)      =     1.80
         Prob > chi2  =   0.1791
```

```
Linear regression                               Number of obs     =        192
                                                F(5, 186)         =      87.01
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6705
                                                Root MSE          =     .03784
```

pf9	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
mktrf	1.032841	.0641383	16.10	0.000	.9063089	1.159373
smb	.3282308	.1527891	2.15	0.033	.0268083	.6296532
hml	.3338751	.1724772	1.94	0.054	-.0063879	.6741382
rmw	.246136	.2139336	1.15	0.251	-.1759122	.6681842
cma	-.2350603	.2432045	-0.97	0.335	-.7148541	.2447336
_cons	-.008565	.0028335	-3.02	0.003	-.0141549	-.0029751

Assumption 4





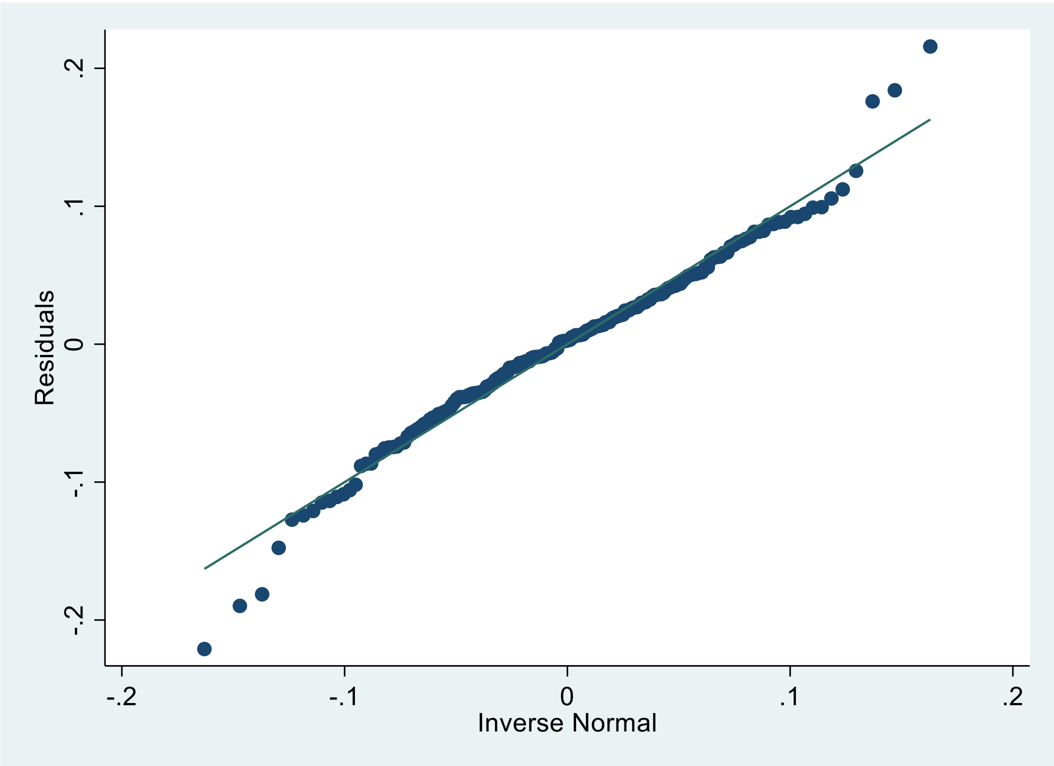
Assumption 6

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	**3.642**	**1**	**0.0563**

H0: no serial correlation

Assumption 7



Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
resid9	**192**	**0.94798**	**7.490**	**4.623**	**0.00000**

Annex 7

Regression output including P-values for Average Allocated portfolios

P-values from Regression Outputs for Average Allocated high ESG Portfolios

ESG portfolio	High	Low	E	High	Low
Alpha	-0,0019	-0,0093***	Alpha	0,0009	-0,0113
Beta	1,0186***	1,0558***	Beta	0,9801***	1,1458

SMB	-0,0641	0,438**	SMB	-0,1437**	0,4936
HML	-0,1788	0,4373*	HML	-0,4586***	0,4461
RMW	0,0264	0,2126**	RMW	-0,0770	0,1558
CMA	0,3185**	-0,1851	CMA	0,531***	-0,1023
Adj. R^2	0,8348	0,644	Adj. R^2	0,8441	0,6518
p-values	High	Low	p-values	High	Low
Alpha	0,2438	0,0049	Alpha	0,5252	0,0014
Beta	0,0000	0,0000	Beta	0,0000	0,0000
SMB	0,4482	0,0116	SMB	0,0483	0,0075
HML	0,1028	0,0505	HML	0,0000	0,0602
RMW	0,8632	0,4961	RMW	0,5577	0,6386
CMA	0,0215	0,509	CMA	0	0,7311
S	High	Low	G	High	Low
Alpha	-0,0019	-0,0037	Alpha	-0,0033	-0,0086***
Beta	1,1246	1,0710	Beta	0,8564***	1,0328***
SMB	-0,0063	-0,0291	SMB	0,0026	0,3282**
HML	0,1650	0,0048	HML	0,0991	0,3339
RMW	-0,0394	0,1418	RMW	0,1085	0,2461
CMA	0,2368	0,0751	CMA	0,1306	-0,2351
Adj. R^2	0,8383	0,8131	Adj. R^2	0,649	0,6616
p-values	High	Low	p-values	High	Low
Alpha	0,3091	0,0520	Alpha	0,1614	0,0047
Beta	0,0000	0,0000	Beta	0	0
SMB	0,9490	0,7687	SMB	0,983	0,0384
HML	0,1983	0,9701	HML	0,5347	0,1026
RMW	0,8263	0,4303	RMW	0,6279	0,39
CMA	0,1429	0,6415	CMA	0,5157	0,3603

Regression output including P-values for Yearly Allocated portfolios

Regression output with p-values: high and low portfolio, yearly allocated

ESG	High	Low	E	High	Low
Alpha	0,0020	0,0048	Alpha	0,0023	0,005
Beta	1,0179***	0,9697***	Beta	0,9776***	1,0714***
SMB	-0,0976	0,1981	SMB	0,068	-0,1183
HML	0,1869	0,4601***	HML	0,377***	0,1495
RMW	0,3325**	0,2189	RMW	0,3391**	0,1268
CMA	0,1828	-0,5048**	CMA	0,1064	-0,4856***
Adj. R^2	0,7882	0,7491	Adj. R^2	0,7896	0,8044
p-value ESG	High	Low	ESG E	High	Low
Alpha	0,2864	0,0408	Alpha	0,2323	0,0138
Beta	0,0000	0,0000	Mktrf	0,0000	0,0000
SMB	0,3310	0,1079	SMB	0,5021	0,2697
HML	0,1388	0,0032	HML	0,0034	0,2665
RMW	0,0681	0,3249	RMW	0,0654	0,5127

CMA	0,2632	0,0122	CMA	0,5184	0,0058
S	High	Low	G	High	Low
Alpha	0,0041**	0,0012	Alpha	0,0016	0,0022
Beta	1,0486***	0,9349***	Beta	0,8957***	1,0516***
SMB	-0,2204**	0,3242**	SMB	-0,0493	0,0926
HML	-0,4098***	0,8591***	HML	0,8516***	0,0888
RMW	-0,1302	0,3186	RMW	0,3862**	0,1399
CMA	0,4766***	-0,6298***	CMA	-0,2487	-0,4452**
Adj. R^2	0,7222	0,7082	Adj. R^2	0,7697	0,7757
p-value S	High	Low	p-value G	High	Low
Alpha	0,0542	0,6584	Alpha	0,4468	0,3066
Beta	0,0000	0,0000	Beta	0,0000	0,0000
SMB	0,0490	0,0276	SMB	0,6661	0,4181
HML	0,0037	0,0000	HML	0,0000	0,5360
RMW	0,5182	0,2292	RMW	0,0631	0,4988
CMA	0,0091	0,0087	CMA	0,1821	0,0175

Regression output including P-values for Average Allocated Portfolios with GMB factor

Regression output with p-values: high and low portfolio, with GMB factor

ESG	High	Low	E	High	Low
Alpha	-0,0020	-0,0070	Alpha	0,0002	-0,0084
Beta	1,0239***	0,9837***	Beta	0,9732***	1,1758
SMB	-0,0442	0,1691	SMB	-0,0559	0,1146
HML	-0,1748	0,3839*	HML	-0,3778***	0,0975
RMW	0,0300	0,1642	RMW	-0,0806	0,1712
CMA	0,3062	-0,0192	CMA	0,4561***	0,2210
GMB	0,0598**	-0,8082***	GMB	0,1951	-0,8423
Adj. R^2	0,8304	0,7250	Adj. R^2	0,8616	0,7697
p-value ESG	High	Low	p-value E	High	Low
Alpha	0,2071	0,0156	Alpha	0,8750	0,0036
Beta	0,0000	0,0000	Beta	0,0000	0,0000
SMB	0,6107	0,2774	SMB	0,4281	0,4558
HML	0,1108	0,0509	HML	0,0000	0,6180
RMW	0,8449	0,5499	RMW	0,5151	0,5258
CMA	0,0276	0,9382	CMA	0,0001	0,3661
GMB	0,3239	0,0000	GMB	0,0000	0,0000
S	High	Low	G	High	Low
Alpha	-0,0019	-0,0026	Alpha	-0,0032	-0,0086***
Beta	1,1253***	1,0361***	Beta	0,8847***	1,0058***
SMB	-0,0035	-0,1594*	SMB	0,0972	0,2377
HML	0,1655	-0,0211	HML	-0,032	0,4594**
RMW	-0,0389	0,1183	RMW	0,117	0,238
CMA	0,2350	0,1555	CMA	0,0952	-0,2011

GMB	0,0085	-0,3916***	GMB	0,632***	-0,6053***
Adj. R^2	0,8374	0,8430	Adj. R^2	-0,0032	-0,0086***
p-value S	High	Low	p-value G	High	Low
Alpha	0,3071	0,1374	Alpha	0,1046	0,0020
Beta	0,0000	0,0000	Beta	0,0000	0,0000
SMB	0,9726	0,0887	SMB	0,3569	0,1043
HML	0,1983	0,8574	HML	0,8147	0,0157
RMW	0,8290	0,4728	RMW	0,5385	0,3663
CMA	0,1485	0,2954	CMA	0,5772	0,3949
GMB	0,9049	0,0000	GMB	0,0000	0,0000