Contents

List of Tables

[1]

[1] All tables were created autonomously

List of Figures

List of Abbreviations

AR	autoregressive model
ARCH	autoregressive conditional heteroskedasticity model
ARMA	autoregressive-moving-average model
BE/ME	price/book value
CAPM	capital asset pricing model
ETF	exchange-traded fund
GARCH	generalised autoregressive conditional heteroskedasticity model
HML	high minus low stocks based on financials; investment factor
IEA	International Energy Agency
MA	moving-average model
MGARCH	multivariate generalised autoregressive conditional heteroskedasticity model
P/E	$\frac{\text{price}}{\text{earnings per share}}$ Ratio
SMB	small minus big stocks based on market capitalisation; investment factor
SPGCE	S&P Global Clean Energy
SPGO	S&P Global Oil
OLS	ordinary least squares
VaR	Value-at-Risk
VAR	vector autoregression model

List of Symbols

The next list describes several symbols that will be later used within the body of the document.

α	GARCH parameter
$\bar{\gamma}$	Mean risk aversion
β	GARCH parameter
β	Level of correlation of an asset with the market according to CAPM
μ	Expected value of returns in the portfolio theory
ω	GARCH parameter, unconditional variance
σ	Volatility
σ^2	Variance
σ_{ij}	Correlation coefficient of two assets
θ	Unknown parameters of maximum likelihood estimation
$E(r_m)$	Expected return of the market
$E - V$	Return-risk maxim in the portfolio theory
E	Expected return of the portfolio in portfolio theory
e_t	Stochastic error term
$N^{(-1)}$	Inverse cumulative normal distribution function
p	Number of lags for the past squared residuals
q	Number of lags for the past variance
R^2	R-squared
r_f	Risk free rate
U	Utility function
V	Variance in the portfolio theory
X_i	Amount invested in the assets considering the portfolio theory

1 Introduction

At the beginning of the 21st century, the future of the energy industry is certain in the long-run. Considering the growing threats of global warming (IPCC, 2021), it is clear that there is an imminent physical need to reduce the usage of fossil fuels. Therefore, a market-based approach dealing with climate change has been adopted by several nations. In 2005, the EU launched the European Union Emissions Trading System to internalise the C02 emissions. This effort has been advanced to the Paris Agreement of 2015 with 196 parties of the United Nations, endorsing a carbon trading framework. The widened application of carbon-pricing has introduced financial incentives to reduce emissions by investing in carbon-neutral technology. BlackRock, currently the largest institutional manager of assets, urged for a more sustainable form of investing (BlackRock, 2020). It predicts that in the near future, both the physical risk of climate change and the transitional risk for several industries will affect assets and financial markets (BlackRock, 2020).

These proceedings show that there is a strong demand especially for the reduction of carbon emissions. A report predicts that the emissions stemming from energy production would need to fall by 70% until 2050 according to the International Energy Agency (IEA, 2017). It argues that investments worth $3.5 trillion are necessary in the energy sector each year between 2016-2050. However only $1.8 trillion have been invested in 2015 (IEA, 2017). Consequently, the report further predicts a decline of fossil investments in line with an 150% increase in green energy investment between 2015 and 2050 (IEA, 2017). Even though the green energy production needs to increase growth further than now in absolute terms, the current relative investment in 2019 already consisted of 78% renewables (UNEP, 2020). During the last decade, the global power generation by green sources rose from 5.9% in 2009 to 13.4% in 2019 (UNEP, 2020). The steady decline of renewable energy production cost has made it competitive during the last years and the decrease in cost is likely to continue (IEA, 2017). Therefore, it is feasible that the predicted green energy transition from the IEA is possible. Yet while the decline of coal would be one of the strongest compared to other fossil energy sources, the oil production would still play a role as it is not easily substituted (IEA, 2017). The IEA report is even arguing for future investments in new oil supply (IEA, 2017).

Contrary to this, a recent study by Welsby et al. (2021) urges that it is indispensable to refrain from using the majority of fossil fuels to mitigate climate change. About 60% of oil and methane gas and 90% of coal should not be extracted by

2050, to keep global temperatures below 1.5°C with a chance of 50% (Welsby et al., 2021). Consequently, the study predicts that oil and gas production must decline by 3% annually (Welsby et al., 2021), thereby opposing the predictions of the IEA for more oil supply to meet future energy demand. Out of physical necessity, the fossil industry will be compelled to mitigate emissions (Caldecott, 2017). Otherwise, the probable risk of stranded assets will expose carbon-intensive sectors toward financial risks (Caldecott, 2017) and thereby also threaten the investors like BlackRock.

In summary, the global energy production is shifting towards renewable .power generation and, therefore, it is supposed that the investments in green energy will increase even more (UNEP, 2020). Additionally, the fossil fuel industry is ecologically unsustainable and gradually more uncompetitive due to declining green energy prices (IEA, 2017). Nonetheless, the upcoming future of the fossil industry can still be a viable investment for the near future. Though new green investments might outweigh the fossil industry, the current energy production is still dominated by oil, gas and, coal when looking at the split of energy production (UNEP, 2020). Combined with a prospective rise in demand for energy, the fossil industry still can be a valuable investment. This makes any choice for investors quite difficult. Due to these differing predictions on the short to mid-term future of the fossil fuel industry, it is hard to evaluate the inherent risk of fossil or renewable assets. Generally, a higher risk perception for investments in fossil fuels and a lower one concerning renewable energy (Curtin et al., 2019; Welsby et al., 2021) is certain in the long run. But has there already been a difference in the comparative risk between the two industries? Additionally, concerning the future value of the investment in green and grey energy, which inherent economic risks drive the returns of those companies?

The focus of this thesis is on the returns and the risks of energy producers. The two main questions it will answer are the following. First, which type of investment has been more risky in the past? With regard to the risk of the energy type, a widely used proxy for the risk has been the Value-at-Risk (VaR) measure. This Value-at-Risk for fossil and green energy companies will be calculated using a generalised autoregressive conditional heteroskedasticity model (GARCH). It focuses on whether the VaR differs significantly between a wide array of renewable and fossil companies. Second, which type of underlying risks premiums affected the returns of the companies in general? This analysis will explore the effect of well researched investment factors representing the underlying economic risks and, therefore, demand profits. The factors are based on the portfolio theory and the capital assets pricing model (CAPM). These theories formulate a way to increase returns for a given amount of risk or alternatively, decrease the risk for a given amount of return. In addition, given the knowledge of the sector with the higher Value-at-Risk and the dynamic investment styles examined in the second question, the investor can act accordingly to maximise the returns while mitigating the risk. Particularly, this study examines data from the beginning of 2007 until the end of 2019 of 128 global stocks for the Value-at-Risk and from 2011 until 2019 for the investment factors. To answer the aforementioned questions, the thesis will proceed as follows.

In section 2, the literature on the financial behaviour concerning the returns and the risks of the energy industries will be summarised. Additionally, the fundamental literature on portfolio theory and factor investing will be illustrated. In section 3, the data used in the following analysis will be introduced and the methodology of this thesis will be explained with a focus on the quantification of risk. Specifically, the underlying theory of the GARCH process for the Value-at-Risk estimation will be illustrated. Consequently, the results of the regression analysis concerning the effects of the energy types on VaR and the influence of differing factors on the returns will be presented and discussed in section 4. The main findings are summarised in section 5 of this thesis.

2 Literature review

This thesis is based on research examining the returns of stocks from the fossil and renewable energy sector and the associated risks. In the following section 2.1, the main literature about the fossil and renewable industries will be summarised. Most notably, the variables affecting the returns and the risks, mostly represented as the volatility of the assets, σ, of said industries are going to be presented. This is done to contrast the subsequent results with the academic findings on the returns and risks of the energy producers. In subsection 2.2, the main theoretical literature on portfolios and factors is introduced. In detail, the modern portfolio theory and the capital asset pricing model are presented. These theories are useful, as they originated the trade-off between risk and return for investors and the merits of diversification. Therefore, they are the constitutive theoretical concepts behind the investment factors. The main of Fama and French (1993) and Carhart (1997) concerning the factors will be presented, as they explain excess returns through factors by using subjacent economic and behavioural reasons. Additionally, further research on the reasons and the effectiveness of the factors are summarised. Ultimately, the hypothesis of this thesis will be stated based on the previous literature on energy markets and financial theory in subsection 2.3.

2.1 Returns and risks of assets in energy markets

Firstly, the main findings on the effects and correlation between energy securities which most of the research agrees on are presented. Subsequently, the contradictory findings are discussed. Concerning the returns, the sparse literature on investment factors in energy sectors is introduced.

Research on the fossil and the renewable industries

Previous research has established that the effect of oil prices on other assets is prominent (Asl et al., 2021). The literature on the influence of oil prices on stock returns is quite established. Kaneko and Lee find that oil price changes are a significant factor in the changes of Japanese stocks returns [1995]. Further relations between oil futures (Huang et al., 1996) or oil price changes (Sadorsky, 1999) on U.S. stock returns are evident, as well. Furthermore, an asymmetric effect of oil price volatility is noted by Sadorsky (1999). For the Canadian market specifically Boyer and Filion (2007) find that there is a positive correlation between the Canadian stock market and rising oil and gas prices, whereas there is a negative connection to a rising level of production. While there has been a large amount of research on oil prices during the 2000s, the research on its volatility and stock market returns has been relatively sparse (Elyasiani et al., 2011). This changed in the recent decade as a number of interesting findings have filled this void. Generally, the oil price and its shocks do have a significant effects on the general market. This can similarly be applied to the market of green assets.

Due to the political and environmental pressure to act in response to climate change (Welsby et al., 2021), new policies evoking an influx of investments into renewable energies were present in recent years (Kyritsis and Serletis, 2019). The rise of the renewable energy sector has introduced a wide array of research focusing on the comparison of the the old fossil industry with new green producers. Whereas the green energy sector has been studied using its assets, the fossil industry has mostly been represented by the oil price as presented above. The main focus has been on the effects of oil on other assets, as well as correlations between two asset classes, e.g. energy and technology stocks. Moreover, the question whether hedging possibilities exist between grey and green energy has been studied. In contrast to that, only few studies examined the stock returns or comparative risks between the rivaling energy sectors (Saeed et al., 2021; Asl et al., 2021).

There is a bulk of evidence arguing for a relationship between oil prices and renewable energy stocks, both for the returns and the volatility. A reason is the strong link between the two asset classes. The renewable energy companies are dependent on the oil prices as they determine the usefulness of substituting oil for green energy production (Reboredo, 2015). Broadstock et al. (2012) use time-varying conditional correlation and asset pricing models to study the impact of oil shocks on energy stocks in China. They find an increased magnitude of the link after the financial crisis of 2008 and summarise that oil price changes are correlated with energy related stocks (Broadstock et al., 2012). Additionally, high oil prices and increased volatility raise the returns of energy stocks. Nevertheless, new energy stocks are less affected by oil shocks than other energy indices (Broadstock et al., 2012). Interestingly, the majority of research argues for similarities between technology stocks and clean energy stocks. Kumar et al. (2012) and Henriques and Sadorsky (2008) assert that they are perceived as equals. Bondia et al. (2016) find that green energy stocks are impacted by technology stocks, oil prices and, interest rates in the short run but there is no relationship in the long run. Kyritsis and Serletis (2019) examine the time period from 1983 to 2016 for the effect of oil prices and their uncertainty on stock returns of tech and green companies. Their finding is in contrast to the aforementioned, since the uncertainty of oil prices does not affect tech or green stocks significantly (Kyritsis and Serletis, 2019).

Concerning volatility, (Sadorsky, 2012) uses multivariate GARCH models to analyse volatility spillovers between oil and the stock prices of renewable energy and technology companies. A main finding is that the dynamic conditional correlation between green and technology stocks is higher than the correlation between green stocks and oil prices (Sadorsky, 2012). The effect of the risk of oil oil is still significant as Dutta (2017) points out that renewable energy returns are affected by an oil volatility index. Reboredo (2015) studied the systemic risk between oil and renewable energy stock prices. Generally, both oil and renewable energy markets co-move, meaning they *"booms and crashes together"* (Reboredo, 2015, p.35) due to their close relationship. For the period between 12/2005 and 12/2013, oil returns show significant average and tail dependence with all clean energy indices except solar (Reboredo, 2015). Additionally, the empirical findings show that about 30% of the risk of the renewable energy industry is driven by the oil price. Reboredo (2015) notes that this is specifically important for investors, as oil prices are a main contribution to the risk of renewables. This is in line with Bondia et al. (2016), finding that the effect of oil on green assets is unidirectional, however, only in the short run. Additionally, Maghyereh et al. (2019) argue that the volatile oil and technology markets reduce the resilience of the green market and thereby increase its risk.

The research on volatility is closely related to the study of hedging possibilities and generally its usefulness for portfolio diversification. Bondia et al. (2016) argue for tech stocks and oil as possibilities to diversify green investments but only in the short run. However, the cointegration of oil, green stock, and technological stock prices offer little possibilities for diversification in the long run as there is no reduction of unsystematic risk (Bondia et al., 2016). Reconfirming, Maghyereh et al. (2019) argue that a diversified portfolio should include oil and renewable energy but not for a long period of time. Furthermore, technology stocks are the cheapest hedge for oil (Maghyereh et al., 2019). This reassures the connection between green and technology assets as both are good hedges against oil. Additional research from Elie et al. (2019) specifies that oil is only a weak hedge for green assets. They study whether gold or crude oil can be used as a safe-haven for clean energy stock indices (Elie et al., 2019). They use a copula on daily data from 2003 to 2018 on the S&P Global Clean Energy (SPGCE) and the Wilder Hill Clean Energy index. While both are only weak hedges, they find that oil is superior compared to gold in case of *"infinitely extreme market movements"* (Elie et al., 2019, p.552). Asl et al. (2021) use a VAR-MGARCH(1,1) model to study return and volatility transmission using SPGCE and the S&P Global Oil (SPGO) indices. They find that both indices offer the highest hedging capabilities with each other (Asl et al., 2021). In particular, this means that a downturn in the oil market could be mitigated by holding green stocks. The authors argue that clean energy companies should diversify by investing in fossil companies instead of holding fossil commodities (Asl et al., 2021).

Ahmad (2017) present that green assets are very volatile, therefore, a hedge against this risk is necessary for investors. In the paper gold, crude oil, a general volatility index (VIX), a specific oil volatility index (OVX) and carbon prices are compared as possible safe investments for green energy stocks (Ahmad, 2017). Ahmad (2017) uses a MGARCH model for data from 2008-2017. The findings are that the VIX is the best hedge, while the crude oil and the OVX are the follow-ups (Ahmad, 2017). Contrasting that, Kocaarslan and Soytas (2019) find that there is a limited hedging possibility for oil and clean energy stocks. Their argument is that the appreciation of the US dollar due to decreased economic conditions reduced investments for oil, fossil, and tech stocks.

Opposing views on the linkage between green and fossil assets

There are no recent studies disagreeing with the fact that oil had an impact on renewable assets. An earlier paper from Henriques and Sadorsky (2008) argues that technology stock prices have a large effect on green energy stock prices, whereas the effect of oil price shocks is not significant (Henriques and Sadorsky, 2008). However, more recent research confirms the link between the returns of oil prices and renewable energy stocks (Saeed et al., 2021), as well as the close relationship with technology stocks (Sadorsky, 2012).
There are, however, two arguments (Asl et al., 2021) whether the correlation between green and fossil assets is still persistent. One side reasons that there was and is still a strong relation between fossil and green assets. Therefore, high oil prices lead to more demand for green energy, thereby, increasing green stocks (Xia et al., 2019). This argument is in opposition with the *"decoupling"* hypothesis (Asl et al., 2021, p.2). The decoupling hypothesis contends that green and fossil assets are no longer in the same market (Ahmad, 2017), as oil is primarily used for transport whereas the renewables produce electricity. This is in line with the argument made by Elie et al. (2019), stating that the disadvantages of oil, i.e. the advantages of renewables like reduced emissions, technological advancements, or a diversified national energy supply drive the green energy prices. Furthermore, as shown above there is ambiguity concerning portfolio diversification using green and grey energy stocks. While most papers agree that there is a possible diversification in using both fossil and green assets (Elie et al., 2019; Ahmad, 2017; Asl et al., 2021), Maghyereh et al. (2019) and Bondia et al. (2016) only find possible advantages in the short run. Kocaarslan and Soytas (2019) find only limited possibilities to hedge with oil and clean energy stocks.

To conclude, there is a vast amount of research examining the linkage between oil and renewable energy assets. Generally, there is a relationship between oil prices and green assets, especially considering the volatility/risk spillover from oil to green assets. However, the correlation between green and tech stocks is stronger and there are reasons to believe that this is because green and grey energy producers are in separate markets. However, the argument still continues as there is opposing evidence both for a strong correlation and a decoupling between fossil and green stocks. Generally, a drawback of the research so far is that only few papers investigate this relationship on equal terms, i.e. comparing fossil and renewable energy stocks to each other. However, as will be shown, the equal comparison will benefit the inquiry greatly. Consequently, the few papers comparing both industries equally based on their stocks will be summarised.

Saeed et al. (2021) investigated the connection between green and fossil energy assets using a quantile VAR model, criticising that most other studies solely study the relationship between oil markets and green energy stocks based on the mean. Consequently, the study researches the return spillover between green assets/bonds, and a fossil energy exchange-traded fund (ETF) (Saeed et al., 2021). There is evidence for a strong return connectedness in the tails which are time-varying and less volatile than in the mean (Saeed et al., 2021). In contrast to other findings, the main driver of the return spillover seems to be marcroeconomic, for example the US dollar index or the US term spread (Saeed et al., 2021). Asl et al. (2021) compare the assets of the green (SPGCE) and fossil (SPGO) indices as stated above to each other. They offer a more granular perspective on the discussion about the existence of decoupling and additionally, the significance of effects between fossil and green stocks. There is no significant spillover of returns from energy commodities, namely *"natural gas, heating oil, conventional gasoline, crude oil, and propane markets"* to green stocks (Asl et al., 2021, p.6) and vice versa. Additionally, there are positive return spillovers from the oil stocks to the cited commodities. The volatility shows no evidence of spillover between green stocks to energy commodities (Asl et al., 2021), whereas said volatility is linked from energy commodities to oil stocks. The oil, green stocks and the listed energy commodities are further linked by asymmetric shocks (Asl et al., 2021). Furthermore, the oil and green stocks offer high hedging capabilities (Asl et al., 2021). Surprisingly, by comparing green and grey assets to each other there is evidence that both industries are more *"interweaved"*(Asl et al., 2021, p.12) than energy companies are with fossil commodities. This profound analysis reinforces the usefulness of comparing stocks directly to each other, more specifically to use stocks from the fossil industry and not oil as a substitute.

Similar to the lack of research comparing the assets between the two energy industries, there is an absence of literature using multi-factor models to investigate the returns related to underlying economic risks which demand a premium on returns. Broadstock et al. (2012) apply the capital asset pricing model (CAPM) and the Fama French 3 factor model to assess if oil price changes are a reliable explanatory variable for energy stocks. They used weekly time series data of Chinese energy stocks and international oil prices from 2000 to 2011. The high stocks minus low stocks factor (HML) is based on book-to-market ratio. It invests in stocks with a 'high' key fianacials which denote value companies and shorts those companies without. The small minus big stock factor (SMB) is similarly based on market capitalisation, whereby it invests in small companies and divests big companies. The HML factor used by Broadstock et al. (2012) is insignificant for oil &gas and new energy companies whereas the SMB factor is significant. Nevertheless, the models have a relatively low R^2 around 0.15-0.29. Broadstock et al. (2012) summarise that oil prices only affected the period after the financial crisis and conclude that green energy stocks are more resilient to oil price shocks (Broadstock et al., 2012). Inchauspe et al. (2015) study the excess returns of renewable energy using a multi-factor asset pricing model with time-varying coefficients. They note that there is a strong influence of the MSCI World and tech stocks on excess returns of the WilderHill New Energy Global Innovation Index Inchauspe et al. (2015). Interestingly, the effect of oil on renewables is time-varying and increased from 2007 onwards (Inchauspe et al., 2015). A closely linked paper used the Carhart four-factor model to examine the returns of the renewable energy companies in Germany and confirms the results from Inchauspe Bohl et al. (2013). The findings note that there was a drastic overperformance until 2008 after which the financial crisis caused a strong underperformance. This difference can also be seen in the varying effect of the four factors, for example the momentum factor was positive for the time period between 01/2004-12/2007 and negative for the period between 01/2008-12/2011 (Bohl et al., 2013). The size factor SMB had a significant positive effect on the returns of renewable energies, whereas the value factor HML was negative and was insignificant. The market factor was also significant and the four-factor model exhibited a R^2 of around 0.34-0.53 (Bohl et al., 2013).

The research investigated leaves certain gaps. One of them is that most of the time, the fossil industry has been represented by the oil price. While this is a fair proxy, the renewable side has been represented by its stocks, thereby creating an unequal comparison. The few studies which do not use oil, instead look at energy ETFs or indices. Especially the study from Asl et al. (2021) present a more granular understanding by using the specific assets from fossil fuel companies.

Another critique is that the research has mainly been focused on the correlation and spillover of risk *between* green and grey energy. There has been evidence of volatility spillovers from the fossil to renewable sector (Reboredo, 2015). Additionally, it is supposed that the green stocks have been the riskier investment (Wen et al., 2014) due to higher volatility. However, there is no updated study if the green assets have still been comparatively riskier than fossil assets. Furthermore, the usage of multiple factor models like the one employed by Broadstock et al. (2012) is useful to investigate systematic risk which stems from underlying economic factors. However, there is scant research based on these methods. The gap of this research will be further explained in 2.3. Prior to this, the following subsection will present the theory on portfolios, the CAPM and the single and multi factor models. They are the constitutive framework for portfolio diversification based on risk, return, and the factors. Therefore, they are vital for the development of hypotheses and the following empirical review.

2.2 Portfolio theory and factors

The following subsection will explain the basis of the portfolio theory and consequently the investment factors which are grounded on this theory. More precisely, the theoretical ideas from the modern portfolio theory of Markowitz (1952) and the descending CAPM are summarised. This is done as they are the foundation to the factor theory, mainly the seminal models from Fama and French (1993) as well as Carhart (1997). Consequently, both models have inspired the following regression to explain the underlying risk factors influencing the returns of the energy stocks. Completing this introduction, the current empirical research based on the factors in the field of energy economics will be demonstrated.

Portfolio theory

Markowitz (1952) established the academic research into portfolio theory. The modern portfolio theory formulates a way for a risk-averse investor to maximise the expected return, given a concrete level of risk denoted by the variance of the portfolio and vice versa (Markowitz, 1952). The main idea is for a single investor to evaluate a portfolio of different securities based on their combined expected returns (denoted by E for expected return) and the underlying risks (denoted by V for variance). Thereby, the investor seeks to act according to the E-V maxim (Markowitz, 1952), based on fixed probability beliefs for the returns μ and the standard deviation as a proxy for the risk σ for a static model. The probability beliefs must be reasonable. In addition, Markowitz (1952) states the portfolio theory is more believable for investment and not for speculation. An example is given using three assets (Markowitz, 1952).

$$E = \sum_{i=1}^{3} X_i \mu_i \tag{1}$$

$$V = \sum_{i=1}^{3} \sum_{j=1}^{3} X_i X_j \sigma_{ij} \tag{2}$$

$$\sum_{i=1}^{3} X_i = 1 \tag{3}$$

$$X_i \geq 0 \text{ for } i = 1, 2, 3, \tag{4}$$

where E is the expected return of the whole portfolio, based on the fixed probability belief μ, and X_i, which is the amount invested under the condition (3) that all adds to 100% of the investment. The variance of the whole portfolio is denoted as V, based on the fixed σ_{ij}, i.e. the correlation coefficient of the assets. (3) is reduced to $X_3 = 1 - X_1 - X_2$ and substituted in (1) and (2) (Markowitz, 1952). This gives the following relations to construct a geometric representation.

$$E = E(X_1, X_2) \tag{5}$$

$$V = V(X_1, X_2) \tag{6}$$

$$X_1 \geq 0, X_2 \geq 0, 1 - X_1 - X_2 \geq 0 \tag{7}$$

The resulting optimisation can be seen in Figure 3 in the appendix. The triangle *abc* represents the attainable portfolios with all obtainable (E,V) combinations which satisfy the equation (7). The efficient portfolios are those with the maximum E for the given variance or the minimal V for the given expected return. The portfolio with the minimal variance is denoted by **X** in Figure 3, where it falls in the attainable set and is therefore efficient by offering the least amount of variance. Further efficient portfolios lie on the line **l** and the continuing bold $\overline{ab}$ line (Markowitz, 1952). Each tangent to the right of **X** between the isomean line (portfolios with the same return) and the isovariance curve (portfolios with same variance) is efficient until it reaches one boundary of the attainable set, the line $\overline{ab}$ (Markowitz, 1952). Continuing on said boundary, the efficient portfolios increase their expected returns while similarly increasing their variance. The portfolio with the greatest E lies on point **b** (Markowitz, 1952).

This optimisation holds for any number of different securities, i.e. between a bundle of different return-variance outcomes (Markowitz, 1952). According to Markowitz

(1952) E-V rule, the investor will always choose the most efficient combinations according to their preferences: Those minimise the variance for a given return or maximise the return for a given variance. In essence, the theory reasons to build efficient portfolios through a diversification of the assets in it. While some exceptions exist where diversification is not useful, for most securities the E-V rule implies the most efficient portfolio (Markowitz, 1952). Furthermore, the E-V rule shows that the strength of diversification stems from the minimisation of covariances, e.g. by not investing in a single industry (Markowitz, 1952). If the investor would diversify his investment between two industries, portfolios or assets with equal variance, typically the resulting variance would be less than before. The minimal covariance between two assets is therefore important, as it reduces the variance if the investor diversifies between securities (Markowitz, 1952). In summary, the modern portfolio theory from Markowitz established the value of diversification and mean-variance utility for the construction of portfolios (Ang, 2014).

The capital asset pricing model was created by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966), based on the mean-variance optimisation from Markowitz (Ang, 2014). This review will present the findings from Sharpe.
Sharpe criticised in 1964 that the capital market line (line of all efficient portfolios based on the E-V rule) only explains a linear relationship between the risk of an asset and its expected return (price of risk), though without any explanation which influences affect this price of risk (Sharpe, 1964). Therefore, a model to construct a market equilibrium theory of asset prices under conditions of risk (Sharpe, 1964) was developed. For this, the model assumes a single investor to maximise his mean-variance utility function based on the principles laid out by Markowitz portfolio theory. This means that the individual investment is viewed as decisions only based on expected value E_w and standard deviation, which can be modelled by the utility function:

$$U = f(E_w, \sigma_w),$$

where the utility is conditional on the expected value and its standard deviation, i.e. the risk. The investor is risk-averse like in Markowitz (1952) portfolio theory. To assess the market equilibrium, the model assumes a common rate of interest and homogeneous investor expectations, i.e. all investors assume the same values concerning the expected returns, standard deviations and correlations of assets and can borrow or lend money at an equal rate (Sharpe, 1964). While the assumptions are very restrictive, they are valuable as a test for the theory (Sharpe, 1964). Thereby, it assumes that every individual holds the market portfolio in differing amounts due to their risk preferences (Ang, 2014), because all means, correlations and volatilities of the assets are equal. Given these assumptions, the mean-variance efficient is the same for each investor, so that it is the market factor in equilibrium (Ang, 2014). Depending on his utility function, each investor can increase his portfolios exposure to the market portfolio or of risk free assets. The CAPM states that the main driver of the risk in equilibrium is the underlying factor risk coming from the market.

$$E(r_m) - r_f = \bar{\gamma}\sigma_m^2, \tag{8}$$

where $E(r_m) - r_f$ is the premium of the risk from the market, $\bar{\gamma}$ is the mean risk aversion and, σ_m^2 is the variance of the market (Ang, 2014). The risk premium is the difference between the expected return of the market $E(r_m)$ and the risk free rate r_f, for example a treasury bill (Ang, 2014). As the market variance increases, so must the expected return. Due to a higher variance, the average investors demand a higher expected return to equalise the higher variance according to their utility function. This is in line with the E-V rule from Markowitz (1952).
Each asset has a differing exposure to this market risk. The level of exposure is measured in an assets beta
β_i:

$$\begin{aligned} E(r_i) - r_f = \frac{cov(r_1, r_m)}{var(r_m)}(E(r_m) - r_f) \\ = \beta_1(E(r_m) - r_f), \end{aligned} \tag{9}$$

where r_i and β_i are the individual returns and correlation with the market of a single stock i. The model basically argues that assets which co-move with the market must earn additional returns, as their risk is dependent on the performance of the general market. The higher the β, the higher the correlation of asset i with the market, namely $\beta_1 = \frac{cov(r_1,r_m)}{var(r_m)}$. Therefore, assets with a low correlation to the market portfolio should garner a high return during a market crash, whereby they could act as a hedge against economic downturns. Exemplary assets with a low exposure are gold or treasury bills. In summary, the higher the exposure of an asset to the market, the higher its β and following the CAPM its expected return and the inherent risk of the investment.

Multiple-factor models

The CAPM explains the excess market returns of assets by one factor only: the exposure to the market portfolio through β_i. Based on the general idea that certain risks are rewarded by a premium, there have been additional models with multiple factors. In this subsection, the different factors used in this thesis will be illustrated. The factors at hand are the momentum, the size and the value factor. Whereas the first one is based on the Carhart four-factor model (Carhart, 1997), the latter two are grounded in the work from the Fama-French three-factor model (Fama and French, 1993). The factors will be summarised and additional empirical findings on each factor will present their impact on returns and the reasons for them.

Factors are the underlying risk which command the return of an asset (Ang, 2014). There are several different factors, all offering a several explanation on what drives the excess returns of an asset. These different factors add additional explanations offering particular reasons why and how certain assets outperform others. The theory behind the factors has two distinct ways on how to explain the risk premium the various factors offer. On the one side, the rational explanation argues with logic derived from economic theory. On the other side, the behavioural explanation assumes certain dynamics based on human behaviour, e.g. higher or lower stock prices due to overreactions to news (Ang, 2014).

In their seminal paper Fama and French (1993) examine the effects of common risk factors on bonds and stocks. The goal is to study whether the risk can capture the cross-section of average returns from bonds and stocks (Fama and French, 1993). This summary will concentrate on the stocks only, as bonds are not considered in this thesis. The main investigated factors are additions to the the market factor, namely the size and the book-to-market equity ratio. Furthermore, Fama and French (1993) study the portfolios with additional factors formed on the dividend/price (D/P) and earnings/price (E/P), respectively. The empirical findings suggest there is an economic story explaining why the size and the BE/ME factors affect the average stock returns of portfolios (Fama and French, 1993). For the size, the authors argue in favor of a link to profitability, as smaller firms tend to show less earnings on assets compared to larger ones. However, this only holds for the 1980s, as the firms at hand did not profit as much as big ones from the economic upturn (Fama and French, 1993). This lack of earnings might be a common risk for small companies, therefore explaining why there is a negative correlation between a companies size and the mean returns. For the BE/ME factor, the economic reasoning by the authors argues that a high BE/ME (low price/book value) tends to be a signal for distress (Fama and French, 1993). This translates to low earnings on assets and results in low stock prices. Contrasting, a low BE/ME (high price/-book value) is connected to growth stocks, thus high earnings relative to book equity, which is followed by relatively high stock prices (Fama and French, 1993). In that sense, the BE/ME factor is the Value-Growth factor, rewarding investors for financing companies with relatively low earnings. The following paragraph will explain the creation of the multiple factor model in detail to illustrate the methodology and to take recourse to in the following subsection 3.3.

Fama and French (1993) calculate the market capitalisation ($shares_t \times price_t$) for each stock for a period of time as a proxy for the size. They rank the companies according to their size and take the median size of the New York Stock Exchange as a threshold (Fama and French, 1993). Companies with a larger size are denoted as big, smaller companies are therefore denoted as small. Then they subtract the big companies from the small ones for every month as a way to emulate the returns related to the size of a company (Fama and French, 1993). The book-to-market equity groups are divided into three groups, the bottom 30%, middle 40% and top 30% bracket based on their rank (Fama and French, 1993). The exact calculation of the BE/ME is the *"book common equity for the fiscal year ending in calendar year t-1, divided by market equity at the end of December of t-1."* (Fama and French, 1993, p.8). No negative BE/ME ratios are used. Based on the two size groups and three BE/ME groups, six portfolios are formed for each variation possible. Following, the monthly returns are calculated for the upcoming 12 months (Fama and French, 1993). The size factor is build by a SMB (small minus big) portfolio. It calculates the average of all three small sized portfolios with their respective BE/ME groups minus the same average of the big sized companies (Fama and French, 1993). This is done to control for the influence of the book-to-market equity. The difference of returns describes the risk premium, so the additional expected returns by investing in small firms. The BE/ME portfolios are defined as HML (high minus low) and are calculated likewise as the SMB. The average of the two high BE/ME minus the average two low BE/ME portfolios are calculated each month (Fama and French, 1993), whereby the HML represents the risk premium of the higher book-to-market equity over the lower one due to lower expected earnings. In their study, Fama and French (1993) find that the SML and HMB affect the monthly returns significantly. The high Earnings/Price portfolios increase the mean returns. Similarly, the lower D/P affects the returns only marginally, akin to growth stocks whereas the high D/P have higher average returns, indicating riskier investments (Fama and French, 1993). Therefore, they find that the D/P and the BE/ME are positively related (Fama and French, 1993).

The following section will present the additional momentum factor introduced by (Carhart, 1997). In the context of the four-factor model, Carhart (1997) proposed the addition of the momentum factor to the three factor model of Fama and French (1993). The idea of the momentum factor is to invest in stocks which have been rising in the past and short those which performed poorly (Jansen, 2018). There are several possible reasons why this factor has been observed in the past. Among them are the behaviour of investors, feedback loops, and the structure of the market. The behavioural reasoning argues for an under-reaction to news, followed by an over-reaction, which infers strongly from recent news (Jansen, 2018). A positive feedback loop between certain assets and the general market might be a driver for a trend, as economic growth increases the price of assets. As a consequence, the price increase leads to higher wealth and higher spending, whereby it drives economic growth (Jansen, 2018). The momentum factor of this analysis is computed as the price momentum. The rolling returns of every stock from the past twelve months are calculated, omitting the most recent month to prevent short-term reversal effect (Jansen, 2018). With regard to the three factors mentioned above and their theoretical construction, their historical performance, and the economic or behavioral reasons for their risk premium will be summarised.

Hawawini, G., and D.B. Keim (1998) conclude that the size factor has been apparent in many studies for most of the developed economies, stating that the negative relationship between the size and the returns was consistent except for Canada and France. However, Zhang (2004) presents that the factor has disappeared in the last 20 years. Ang (2014) reiterates the finding. Consequently, he explains the disappearance of the size factor is either due to data mining or because the formerly existing size factor has disappeared due to increased investments using the size strategy. Fama and French (1993) explain this factor with the inherent risk of a smaller company. Following studies argued that the reasons among others are information uncertainty (Zhang, 2004) or default risk (Vassalou and Xing, 2004). While the former argues from a behavioural perspective, the latter is in line with theoretical economic reasoning. Zhang (2004) proposes that the size of a company is likely a proxy of information uncertainty, whereby smaller firms exhibit greater uncertainty. The greater the information uncertainty, the stronger the underreaction of investors. This can result in unequal reactions, depending on the news. Accordingly, the returns of small firms are comparatively less (more) affected by bad (good) news than big companies. Vassalou and Xing (2004) argues that the size effect only appears in the quintile with the highest default risk. The risk of a default is evidently higher in smaller firms and is the true reason behind the size factor (Vassalou and Xing, 2004).

Fama and French (2012) investigate the value, size and momentum factors from 1989 to 2011 for 23 countries using the CAPM, the three- and the four-factor model. They found that both the value and the momentum factor offer significant premiums. Furthermore, for both factors the excess return decreases with the firm size, i.e. for bigger companies both strategies result in lower returns compared to the same strategy used on smaller companies (Fama and French, 2012). The momentum strategy is mainly explained through the behaviour of investors. For example, (Daniel et al., 1998, p.1841) attribute the momentum effect to *"biased self-attribution"*, an effect in which investors overstate information which approves of their action and suppresses new information which does not. Due to this, new public information which confirms the view of the investor will lead to an overreaction to good news (Daniel et al., 1998). In doing so, the momentum of stocks gradually rises for a short amount of time, usually 3-12 months (Daniel et al., 1998). After that amount of time, the overstated price tends to equate due to additional information from the fundamentals which curbs the momentum factor (Daniel et al., 1998).
There are several explanations for the reasoning behind the value factor. Zhang (2005) proposes that due to two reasons value stocks are riskier than growth stocks. Firstly, it is harder for value companies to cut cost than to acquire new capital. Secondly, a *"countercyclical price of risk"*(Zhang, 2005, p.68) results in increased risk for value firms. Chen and Zhang (1998) find that the higher risk of value companies is due to stronger distress and financial leverages. Consequently, the higher risk results in a greater return compared to growth stocks. Likewise, the dividend yield is also a factor describing the value of a company, with value companies offering higher payout. Dimson et al. (2011) investigate financial data for the time period from 1900-2011 of 19 countries. They find that historically, the dividend yield has been the dominant factor. One explanation for the additional return of high yield companies is due to the higher expected earnings in the future (Arnott and ASNESS, 2003).
In conclusion, the four factors summarised are the momentum, size and two value factors ased on the P/E ratio and the dividend yield. Following the hypotheses for the returns will be based on these conclusions.

2.3 Hypotheses

This thesis will complement the aforementioned research in two ways. Firstly, it asks which energy type is riskier. To do this, the GARCH model will be used to construct a time-varying Value-at-Risk estimator for the fossil and renewable energy sector, respectively. The hypothesis which will be investigated are:

- H1: The energy type of the producer affects the VaR statistically different.
- H2a: The renewable energy is more hazardous than the fossil portfolio, therefore the VaR is higher.
- H2b: The fossil energy portfolio is more hazardous than the green portfolio, therefore the VaR is higher.

The reason for these hypotheses is the following. In the research, the renewable energy companies have often been classified as more risky due to higher volatility, e.g. Wen et al. (2014). In contrast, the business model of the fossil industry will most certainly decline heavily during the following years (Welsby et al., 2021; Caldecott, 2017). This gives reason to assume that the future risk of the grey industry should already be considered by markets and investors. In summary, the first part of the empirical examination will identify which industry has been the riskier investment during the last 13 years. Based on the research shown in factor investing and the risk and returns of assets, specifically in the energy market, this thesis will postulate four hypothesis for the factors.

- H3: The factors can be investigated using an OLS model.
- H4: The momentum and quality factors will affect the returns significantly.
- H5: The size factor will not affect the returns significantly.
- H6: The alternative energy companies will have a risk premium on returns compared to fossil companies.

The first hypothesis will be considered using a panel OLS and test for poolability. Besides, there are economic reasons from the literature to assume that all factors do affect the individual returns exept for the size factor (Zhang, 2004). For one, the fast growth in the green energy market during the last decade (IEA, 2017) could have driven the momentum of investments heavily. In particular, the behaviour of investors could have been shifted toward green assets, especially due to increased attention to climate change, thereby, confirming their behaviour through positive news on the necessity of green investments (Kyritsis and Serletis, 2019; Daniel et al., 1998). The quality factors are assumed to be equally significant. One reason is that the fossil companies have been well established with a historically safe demand. Therefore, it is possible that they are considered value stocks. Equally, the fast growth of the green energy market (IEA, 2017) could potentially mark the renewable stocks as growth stocks. The last hypothesis will be tested with a dummy variable to verify if green companies gain higher returns on average due to their supposed higher risk (Wen et al., 2014). To summarise, this thesis will examine the effect of the energy type of the VaR through time and the influence of factors on the returns on the companies. This is done to verify that the green companies are riskier. If so, the factor models explain in more detail where this risk might stem from. Additionally, it will check if the supposed higher return of green assets result in higher average returns.

3 Methodology and data

First of all, the following subsection 3.1 will present the data used to answer the question concerning the risk of the renewable and fossil market. Subsequently in subsection 3.2, the theoretical background of VaR and GARCH is explained as it is the methodological basis so the investigation. Concluding in subsection 3.3, the specific calculation of the VaR and the factors are presented.

3.1 Data

The data used in this model stems from *Yahoo! Finance* and *Morningstar*. *Yahoo! Finance* has been used to download the daily adjusted closing prices of every stock. The 128 daily returns are stationary according to the Dickey-Fuller test. Additionally, they cover at least one quarter of the considered time period and have GARCH estimates according to the limitations mentioned in 3.2. *Morningstar* provided a source for fundamental data. The annual dividend yield, the outstanding shares and the $\frac{\text{price}}{\text{earnings per share}}$ (P/E ratio) of the examined 128 companies were downloaded. *Yahoo! Finance* is a provider of financial news and data. It was used due to the easy accessibility through the Python API *yfinance*, as the necessary models and subsequent calculations were written in Python. *Morningstar* is a widely used source for financial data.

The used stocks have been inspired by the current MSCI Global Alternative Energy Index and the MSCI World Energy Index. The latter consists of companies denoted as part of the energy sector based on the Global Industry Classification

Standard (GICS). Specifically, this includes *"exploration & production, refining & marketing, and storage & transportation of oil & gas and coal & consumable fuels. It also includes companies that offer oil & gas equipment and services."* (MSCI, 2021a, p.1). The alternative companies are included because they *"derive 50% or more of their revenues from products and services in alternative energy"* (MSCI, 2021b, p.1). Generally, the companies should be involved in the supply of either green or fossil energy, to the very least in an intermediate way.

3.2 Methods to quantify risk

The upcoming section is a review of the Value-at-Risk measure and the foundational GARCH which is used to estimate the VaR. Following, the usefulness of the GARCH model is explained theoretically (3.2.2) and then mathematically (3.2.3).

Volatility and Value-at-Risk

The Value-at-Risk is an instrument to summarise the possible risk of a portfolio. The theory was constructed in 1990 by adapting the portfolio theory from Markowitz (Hull, 2015). The goal was to offer executives at J.P. Morgan a summarised metric of the risk their bank is facing during the next 24 hours (Hull, 2015). Furthermore, the VaR is being used by the Basel Committee as a measure of the required capital of loans for banks in the 1996 Amendment (Hull, 2015).
The main variables are time, value and the certainty of (not) losing said value in percentage points. To give an example, consider a portfolio with a value of \$1.000.000, a necessary confidence interval of 99% and a proposed time horizon of 6 months. With the assumption that the future returns will be normally distributed, the VaR is either equal to the percentile of the distribution of losses or the percentile the gains of the distribution, with inverse percentiles respectively. This means that the exemplary VaR is either \$2.13 (loss) or \$-2.13 million (gains), depending on which way the distribution of returns is rotated. In this thesis, the distribution of gains will be used, therefore the VaR will be represented by a negative number. To calculate the VaR, the time, the confidence level and the volatility is needed:

$$VaR = \sigma N^{(-1)}(X), \tag{10}$$

where $N^{(-1)}$ is the inverse cumulative normal distribution function, σ is the standard deviation of the portfolio and X is the confidence level (Hull, 2015). The assumption of normality is quite common though it is often not a good estimate (Hull, 2015). As the equation shows, the value at hand is irrelevant, so the VaR is always the same regardless of how big the portfolio is.

For the usage of VaR, the volatility σ_t needs to be known. This volatility is a proxy for the risk of the asset. The VaR is based on historical information and can be calculated using either the historical simulation, Monte Carlo simulation or the variance-covariance approach (Cabedo and Moya, 2003). In this thesis, the variance-covariance model is used based on the Autoregressive Conditional Heteroskedasticity Models, specifically the generalised model GARCH. The GARCH model estimates the time-varying volatility of each stock.

The usefulness of GARCH models

The foundational ARCH model was created by Engle (1982). His reasoning was that the conditional variance in conventional econometric models did not depend on prior information. Typically, time-series models assume homoscedastic disturbances, i.e. errors with a constant variance σ^2 (Bollerslev, 1986). In doing so, the prior models assumed *"constant one-period forecast variance"* which Engle considered inconceivable (Engle, 1982, p.987). The new ARCH model incorporated a variance dependent on the past (Engle, 1982). Subsequently, the ARCH model was succesfully applied to a wide variety of economic problems, namely inflation uncertainty (Engle, 1982) or foreign exchange markets (Bollerslev, 1986). Following Engle's contribution, (Bollerslev, 1986, p.308) generalised the model to enable a *"more flexible lag structure"*. Bollerslev (1986) expanded the ARCH model akin to the extended autoregressive model (AR), the auto-regressive-moving-average model (ARMA), by adding the lagged volatility σ_{t-1}, to explain present volatility. A more thorough review of the mathematical background will be explained in the following subsection 3.2.
In summary, the GARCH model was created to include the heteroscedastic nature of certain financial data. Examples are the volatility of inflation or of stock market returns, which show several examples of volatility clustering (Greene, 2012). Confirming this, the GARCH model has been used extensively in the research mentioned in section 2. Some examples include the multivariate GARCH model (Asl et al., 2021; Ahmad, 2017; Sadorsky, 2012). For the task at hand, the stock prices of the energy producers are analysed. This is a problem which can be solved applying the GARCH model, because common speculative prices are typically non-stationary, similar to a random walk and financial data typically displays time-varying volatility. Therefore, stationary data is used by using the log first difference returns of each stock price and the GARCH model incorporates heterogenous levels of volatility. There are several reasons for time-varying volatility:

- News: Any new information can result in high rates of changes for financial markets (Lütkepohl and Krätzig, 2004). Common examples are new decisions of the US Federal Reserve (FED) or news on legislation or the quarterly reports of certain companies or whole industries.

- Leverage effect: This effect refers to the assumed negative correlation between the rising (falling) asset returns and its declining (rising) volatility (Sheppard, 2021).
- State uncertainty: The price of assets are expressions of certain beliefs about the economy, held by investors. Due to uncertainty about the future, small changes can result in a feedback loop which may lead to a strong volatility in the market (Sheppard, 2021).
- Volatility feedback: This happens if the volatility of an asset is priced by a model. By a feedback loop a declining price might increase the volatility of that asset. This in turn further decreases the price and the volatility increases again (Sheppard, 2021).
- Trading: A reason for volatility is from the movements of the trading itself (Hull, 2015).

Following this introduction, the formulas of a simple ARCH (1) and GARCH (1,1) model will be explained and their estimation will be explained briefly.

Mathematical exposition of GARCH

The GARCH model consists of several equations. A foundational time-series (like Y_t below) can take any form.

$$
\begin{aligned}
Y_t &= \beta_0 + \beta_1 Y_{t-1} + \gamma_1 X_{t-1} + u_t \\
Y_t^* &= \beta_0 + u_t \\
u_t &\sim N(0, \sigma_t^2),
\end{aligned}
\tag{11}
$$

where Y_t and $Y_t{}^*$ are an ARMA and a mean time-series, respectively, with X_t being an exemplary dependent variable and u_t are the respective errors with normal distribution and a variance conditional on time. The foundation of the GARCH model can be a model of the returns with only the intercept like the second Y_t^*. This is a usual occurrence when applying GARCH to the returns of financial assets (Lütkepohl and Krätzig, 2004). The returns are assumed to be unpredictable, so the model consists of the systematic mean and the errors. The GARCH model can be represented by only the foundation and the time-varying model errors, or it can be shown explicitly with three equation, that the errors consist of iid normal errors times the variable volatility σ_t.

$$\begin{aligned}
Y_t^* &= \beta_0 + u_t \text{ with } u_t \sim N(0, \sigma_t^2) \\
Y_t^* &= \beta_0 + \epsilon_t \\
\epsilon_t &= \sigma_t e_t \\
e_t &\sim \text{ iid } N(0,1),
\end{aligned} \tag{12}$$

where the errors u_t of the foundational time-series can either directly assumed to be normally distributed with a time-varying variance σ_t^2 (Stock and Watson, 2007). Alternatively, they can be modelled as ϵ_t, consisting of one normally distributed error with constant variance times a time-varying variance σ_t (Sheppard, 2021; Lütkepohl and Krätzig, 2004). This time-varying variance is the dependent variable of the GARCH(q,p) model, as it is modelled on its past squared errors, representing the volatility and its past variance.

$$\begin{aligned}
\sigma_t^2 &= \omega + \sum_{j=1}^{J} \alpha_p \epsilon_{t-j}^2 \\
\sigma_t^2 &= \omega + \sum_{j=1}^{J} \alpha_p \epsilon_{t-j}^2 + \sum_{k=1}^{K} \beta_q \sigma_{t-k}^2,
\end{aligned} \tag{13}$$

where σ_t^2 is the variance conditional on time t, ω is the unconditional variance, ϵ_{t-j}^2 are the past squared residuals (or returns) at lag p and σ_{t-k}^2 are the past variances at lag q. Shown above are the ARCH and GARCH models in (13) respectively. The ARCH model is similar to an moving-average model (MA), as it models σ_t^2 based on the distributed lag of past squared errors. The GARCH model is similar to the ARMA model, as σ_t^2 depends on past squared errors and past σ_t^2 (i.e. variances). The following sufficient conditions for a positive conditional variance must be held by the parameters (Lütkepohl and Krätzig, 2004).

$$\omega > 0, \quad \alpha_i, \beta_j \geq 0, \quad i = 1, ..., q, \quad j = 1, ..., p.$$

The additional requirement of $1 - \alpha - \beta > 0$ is necessary to ensure stationarity in a GARCH (1,1) model (Sheppard, 2021).

The GARCH models are estimated using the maximum (log) likelihood estimation. This ML function finds the unknown parameters θ (here: ω, α, β) of a random sample using the datas distribution, which maximise the likelihood of randomly sampling the observed data (Sheppard, 2021). To do this, we take a random sample of data and calculate the joint probability density function. This joint probability function will be a function of the unknown parameters θ. The maximum likelihood function is a function of θ given the observed data u_T (Sheppard, 2021). Optimising this equation to the highest value will give the parameters, which maximise the function i.e. maximises the probability of finding the data using the optimal parameters.

$$\begin{aligned} l(\theta|u_1, ..., u_T) &= \sum_{t=1}^{T} l_t \\ &= \sum_{t=1}^{T} -\frac{1}{2}\left(log(2\pi) - \frac{1}{2}log\sigma_t^2 - \frac{1}{2}\frac{u_t^2}{\sigma_t^2}\right). \end{aligned} \tag{14}$$

Here the ML estimator $\hat{\theta}$ is estimated with iterative optimisation routines to find the maximal value of the likelihood function. Shown above is the log-likelihood representation of *"normally distributed disturbances"* for T observations (Greene, 2012, p.375). The log-likelihood estimation is used, as it simplifies the function and the maxima stay the same after the transformation using a logarithm. The maximal likelihood will give the optimal parameters for α, β and ω. These estimated parameters will be used to model the volatility of the given residuals and can furthermore be used to forecast volatility given past squared residuals and past variances.

3.3 Methodology of the thesis

Using the abovementioned GARCH (1,1) model, the conditional volatility of the 128 stocks will be estimated. The resulting volatility is used to calculate the respective Value-at-Risk for each companies stock. The following section will give an overview over the methodology to estimate the VaR in 3.3 and to calculate the used factors in 3.3.

Calculation of Value-at-Risk

Using the log first difference, the daily returns are used to create 128 time series of each stocks performance. Then each stock not in US-Dollar is converted by the respective exchange rate of said day to avoid currency risk. Using the stocks adjusted closing prices, the Friday from each company is taken due to several zero values in between the days. This implies days without trading but it has been consistent throughout, so to avoid a frequency sampling problem the frequency was changed to a weekly one. Those weekly returns are then used to estimate the variance trough the GARCH model using the maximum likelihood estimation for the parameters. Given these parameters, the conditional variance σ_t^2 is calculated for each stock. This variance is transformed into the standard deviation σ_t and then build into the Value-at-Risk model for each stock. The used confidence level is at 97,5%. Each time series is at least longer than 25% of the 13 years. The VaR is used as the dependent variable in a regression with a dummy encoded variable based on the type of energy production.

Calculation of the factors

The quarterly return of every stock is used as the dependent variable in a regression. The independent variables try to explain which multi factors influence the risks. The momentum, size and the value factors based on dividend yields and P/E are used with the annual data from *Morningstar*. Furthermore, the effect of the type of energy produced on the returns is investigated with a dummy variable. The objective will be to see if the returns of those companies will be affected by intrinsic risk premiums and if the green and grey energy producers have a return premium through higher VaR. Following is a closer explanation on how the factors have been calculated.

The size factor will be calculated in a similar way as Fama and French (1993). Looking at the present market capitalisation, the factor will invest in small companies and short large companies for every current quarter. In contrast to Fama and French (1993), the size factor of this thesis will not use the median of the NYSE. Instead it will take $10 billion as a threshold to divide between large capitalisation stocks and mid to small capitalisation stocks. This is done due to its simplicity as $10 billion are a common threshold to distinguish between the size of global companies. Due to the relatively short time period of 13 years, this nominal threshold will stay relatively consistent, therefore it is seen as appropriate.
The momentum factor of this analysis is computed as the price momentum. The rolling returns from the past 12 months is calculated for every stock, omitting the most recent month to prevent short-term reversal effect (Jansen, 2018). Furthermore, the momentum is build by calculating the highest 30% stocks minus the lowest 30% stocks for every quarter. Generally, the momentum factor will therefore take the shape as in Carhart (1997).
The P/E factor is calculated using the annual P/E ratio from four quarters ago.

The lower the P/E ratio, the higher the value of the company. Consequently, the bottom 30 percent minus the top 30 percent of stocks form the factor for every quarter, omitting the middle 40 percent. The dividend factor is constructed similarly, the only difference is that a higher dividend yield constitutes a better value. The calculation is therefore inversed, taking the top 30 percent minus the bottom 30% of the stocks in regard to their prior dividend yield. The splits for the top and bottom stocks based on the ME/BE ratio from Fama and French (1993).
To summarise the methodology used for the following results, the regression equations are described below. The data for the factor model is from 2011 - 2019. The data for the VaR t-test of the dummy variable ranges from 2007-2019.

$$Returns_{it} = \beta_1 MOM + \beta_2 SIZE + \beta_3 P/E + \beta_4 DIV + \beta_5 ET + \epsilon_t, \tag{15}$$

where MOM is the momentum factor, the MC is the market capitalisation, denoting the size factor. P/E and DIV are quality factors. ET are the respective energy types the company mainly supplies.

$$\begin{aligned} VaR &= \beta_0 + \beta_1 ET_i + \epsilon, \\ VaR_{adjusted} &= \beta_0 + \beta_1 ET_i + \epsilon, \end{aligned} \tag{16}$$

where ET_i denotes the energy type as a dummy variable. The VaR adjusted is adjusted to the market capitalisation, which will be explained shortly. Additionally, the VaR regression will be considered for the whole time period and for each third of said time period. This is done to get a clearer understanding of the changing VaR and the effect of the energy dummy similar to the time segmentation used by Bohl et al. (2013). The dummy's encoding is $ET_1 = 1$ for alternative energy stocks and $ET_0 = 0$ for fossil stocks. Furthermore, graphical representations of the combined VaR respective of their energy type are produced. The graphic representations depict the weekly VaR estimate for both portfolios. The portfolios are based on the mean VaR for every week for the 70 fossil companies and the 58 renewable energy companies, respectively. The first graph present the undadjusted VaR, whereas the second one presents the VaR adjusted for market capitalisation. This adjustment is done using the mean of the combined VaR, once unadjusted and once adjusted for the market capitalisation. The adjustment is calculated like this: $VaR * \frac{\text{Market Cap}_i * 100}{\sum \text{Market Cap}_i}$. As mentioned in the **??**, the ADX data is missing from *Morningstar* and the calculated market capitalisation TLW.L was implausible with a share of 20% of the whole portfolio. As a substitute, the current market capitalisation of \$2.267B for ADX and \$642.48M for TLW.L was taken from *Yahoo! Finance*. This is an overstatement for ADX and an understatement for TLW.L.

The stock price of ADX currently peaks, whereas TLW.L is at its lowest since 2012. However, it is decided that the data for the market capitalisation should rather include small errors than to omit a company completely. In comparison, the supposed overvalued (undervalued) market capitalisation should only lead to a marginally bigger (smaller) VaR for the whole portfolio of the fossil industry.

4 Results

The following results will go through each hypothesis from subsection 2.3. Each finding will be discussed in light of the literature presented in section 2. First of all, the Value-at-Risk of the respective green and fossil energy portfolios will be examined to see whether there is a difference between the energy producers (H1) and if either the fossil (H2b) or the green (H2a) portfolio is riskier. Consequently, the factors are investigated. The feasibility of the OLS estimate for the factors is tested (H3). Secondly, it is supposed that the momentum and quality factors affect the returns significantly (H4), whereas the size factor will not (H5). Concluding is the final assessment if alternative energy producers facilitate higher returns (H6).

The following paragraphs present the finding from the regression in Table 1. In addition, the two graphs for both the undjusted and the adjusted portfolio of the mean VaR for the green and the fossil portfolio will be discussed.
A significant difference is shown in the t-test of the unadjusted Energy Type as seen in Table 1. The weekly VaR for all 70 fossil companies and for all renewables 58 respectively exhibit a p-value of 0.00 based on the t-test. Therefore, the significant difference between the VaR of the fossil and renewable portfolio is confirmed. The coefficient is at -0.5593 for the whole unadjusted period. As the alternative energy has been encoded as 1, this result means that the weekly mean VaR during 01/2007-12/2019 has been consistently higher by -0.5593 points. This significant difference holds for the following time periods and is illustrated by the graph below. Through most of the time for the unadjusted VaR, the alternative VaR stays consistently higher than the fossil time-series. Interestingly, the local levels of volatility are quite different. For example, the alternative VaR from 2012-2015 has been volatile which is represented by the larger coefficient of -0.9992 for the alternative energy for the second period. Though the VaR of the alternatives are generally higher, it is on a more consistent level than the fossil VaR. Furthermore, whereas the gap between fossil and alternative risk widened from 2010-2014, this gap was consistently smaller after this period, which is depicted in the declined coefficient of 0.3481 for the third period. The main finding for the unadjusted

representation is, that the VaR of the alternative energy sector is significantly different and for most of the time exceedingly higher can be confirmed.
In contrast to that, the market capitalisation adjusted VaR is similarly significant but the coefficient of the dummy is positive. The β_1 coefficient of the energy dummy is at 2.6207, whereas the constant for the mean fossil VaR is consistently negative at -3.6055 for the whole period. In addition, this holds for each subperiod. This is again reinforced by the apparent difference shown in the second graph, in which the gap between fossil and green energy is wide. The interpretation is that the alternative energy has a lower VaR compared to the fossil portfolio after adjusting it to the market capitalisation and is therefore less risky.

Table 1: OLS Regression: VaR - Energy Type; for different periods

	(1) 2007 - 2019[1]	(2) 2007 - 2011[1]	(3) 2011 - 2015[2]	(4) 2015 - 2019[2]
VaR unadjusted				
β_1 ET	-0.5593	-0.3517	-0.9992	-0.3481
	(0.00)	(0.00)	(0.00)	(0.00)
β_0	-3.7680	-4.2759	-3.3163	-3.7882
	(0.00)	(0.00)	(0.00)	(0.00)
VaR MC Adj.[3]				
β_1 ET	2.6207	3.1031	2.2325	2.5676
	(0.00)	(0.00)	(0.00)	(0.00)
β_0	-3.6055	-4.2949	-3.1935	-3.4334
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	76642	21903	26066	28673

[1] Periods from: (1) 05.01.2007 - 27.12.2019, (2) 05.01.2007 - 02.05.2011
[2] Periods from: (3) 02.05.2011 - 02.09.2015, (4) 02.09.2015 - 27.12.2019
[3] VaR is adjusted to market capitalisation. $VaR * \frac{marketcapitalisation_i * 100}{\sum marketcapitalisation_i}$
Coefficient of regression on the top
p-value based on t-statistic in parentheses below
Note: Standard Errors are HAC using 1 lags and without small sample correction
HAC: Heteroscedasticity and autocorrelation robust

In summary, the results from the unadjusted VaR confirm both H1 and H2a while they reject H2b. The type of energy has a statistically different effect on the VaR and the alternative energy is the more risky investment over all time periods if

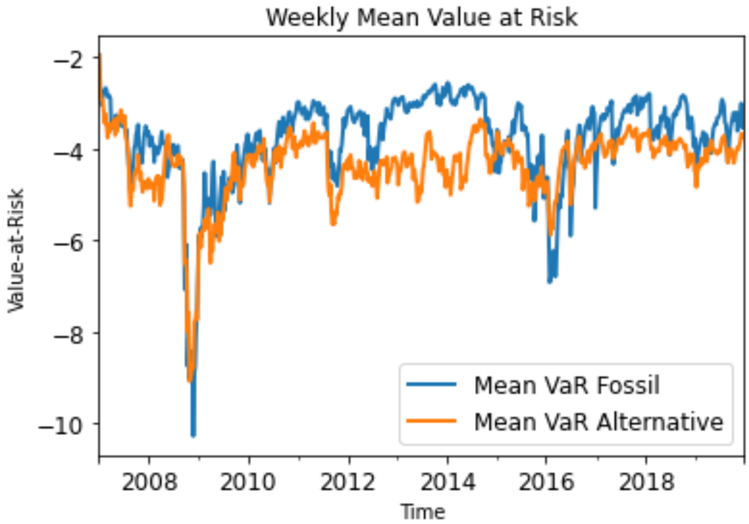

Figure 1: Unadjusted Weekly Mean Value-at-Risk

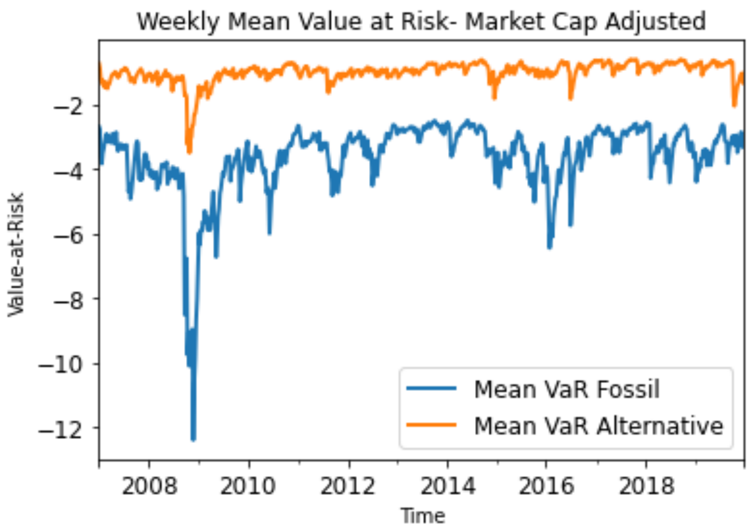

Figure 2: Weekly Mean Value-at-Risk adjusted to market capitalisation

the VaR is not adjusted to the market capitalisation. However, in the case of the market adjusted VaR, the fossil energy has been the riskier investment. Due to the positive coefficient of the energy dummy, it increased the negative VaR significantly. In comparison, the mean of the fossil industry as denoted by β_0 suggests a higher risk. Considering the size of the respective industry, the fossil industry has a higher risk based on the calculated VaR. This leads to an opposing result. On the one hand, the alternative energy has been the more risky investment considering the unadjusted VaR. On the other, this circumstance alternates after adjusting to the market capitalisation.

The main question is which VaR represents the risk more accurately. Affirming the adjustment, many portfolios have some kind of bias toward market capitalisation, e.g. the MSCI Indices are adjusted to market capitalisation (MSCI, 2021b,c). Additionally, the risk of stranded assets (Caldecott, 2017) need to be regarded. Due to the size of BP or Exxon, it is very hard to dispose of the capital already invested especially as there is probably little demand for their assets like oil rigs (IEA, 2017; Welsby et al., 2021), even if they can reutilise some for assets for green energy production, e.g. transport hydrogen in gas pipelines (UNEP, 2020). Additionally, the rising disadvantages of oil (Elie et al., 2019) will effect the whole industry and in regard of a global fossil energy supply of 86,6% in 2019 (UNEP, 2020), the industry's size should be represented fairly by the market capitalisation of its companies.
Contrary to that, the argument for the size factor is appropriate. Most renewable energy firms are much smaller, therefore they are more susceptible to default risk (Vassalou and Xing, 2004) or are inherently riskier simply due to their size (Fama and French, 1993). Those arguments would speak in favor of an inversed adjustment to market capitalisation. However, in regard of the global economic dependency on the fossil industry, the current adjustment seems reasonable. Therefore it is decided that H2a is rejected and concluded that the fossil industry has been the riskier investment for the period from 2007 to 2019. This is in opposition to Wen et al. (2014) who assumed that the green industry is the riskier investment. Nonetheless, the hedging opportunities between green assets and fossil assets (Asl et al., 2021), commodities like oil (Elie et al., 2019) or oil's volatility (Ahmad, 2017) are certainly still valid as green investments reduce the risk of fossil investments. Still, comparing both graphs it is apparent that both VaR co-move through time. As Reboredo (2015) found, the risk of the renewable energy industry is heavily influenced by the oil price which might be one possible explanation for the comovement of the VaR portfolios. To conclude, the alternative industry is a less

risky investment compared to the fossil industry, when the investments are based on market capitalisation. A risk-averse investor should therefore invest more in stocks from renewable energy companies compared to fossil companies but still use the latter industry to diversify the portfolio. It is assumed that the possible diversification suggested by research still holds.

As of now, the riskier assets are the fossil stocks, if they are bought according to their market capitalisation. Nevertheless, it is still unclear according to which strategy the investor could use in particular. The following section will present the results of the regression models based on the returns. Firstly, the effect of the factors and the energy type on the individual returns will be presented. The OLS regression is feasible due to a panel OLS. A balanced panel of 105 companies ranging from 01.04.2011 to 10.07.2019 is created. The model is estimated using the quarterly factors as the independent and the returns as the dependent variable. Using the F-test on the panel OLS tests whether there are no individuals effects present (H_0: all individuals effects = 0) or if some individual effects are apparent. If H_0 was rejected, the fixed effects model would be considered. The F-test for poolability has a p-value of 0.8629, therefore the OLS model is appropriate as the presence of individual effects is rejected.

As can be seen in Table 2, the investment factors remain inconclusive due to the small explanatory value of the models. Generally, the dividends are the most important factors. The major role of the dividend factor is clarified by the model (2), which drop the dividend yield. The R^2 is reduced from 0.065 to only 0.020, alluding to the explanatory strength of the dividend factor. In all models the coefficient of the dividends is negative. To reiterate, the factor is constructed by going long on the top 30% companies with the highest dividend yield for every past years and shorting the bottom 30%. This indicates, that firms with a better dividend yield exhibit worse returns. This could be explained by the difference in dividend yield between the fossil and the green energy industries. The Table 3 in the appendix shows the mean of the dividend yield for the fossil and alternative companies. The mean dividend yield over the whole time period of the fossil companies lies at 1.105, while the mean of the renewables is at only 0.684. The same trend is visible for every year. Established value companies in the fossil sector like Exxon or BP have, therefore, offered significantly higher dividends, especially compared to young companies from the green energy sector. In contrast, the young renewable energy sector was characterised by a strong growth, leaving little possibility for dividends, in particular the very high ones. In consequence, the dividend yield factor mainly incorporates fossil companies. When comparing it to the dummy

Table 2: OLS Regression: Returns - Factors and Energy Dummy

	(1) Model All Variables	(2) No Dividends	(3) No Energy Type	(4) No Momentum
Momentum	0.0393 (0.061)	0.0349 (0.108)	0.0412 (0.054)	
Energy Type	0.7355 (0.000)	0.8104 (0.000)		0.7393 (0.000)
Dividends	-0.4155 (0.000)		-0.4184 (0.000)	-0.4068 (0.000)
Size	0.0984 (0.087)	0.0744 (0.197)	0.1016 (0.078)	0.0957 (0.097)
P / E Ratio	0.1364 (0.027)	0.1817 (0.006)	0.1377 (0.028)	0.1376 (0.025)
Observations	4225	4331	4225	4226
R^2	0.065	0.020	0.059	0.061

Coefficient of regression on the top
p-value based on t-statistic in parentheses below
Note: Standard Errors are HAC using 1 lags and without small sample correction
HAC: Heteroscedasticity and autocorrelation robust

variable, it is clear that the alternative stocks have a significant higher return on average. Therefore, it is consistent that dividend factor is negative, as it mainly consists of investments in fossil sompanies. The P/E factor is similar, yet it rewards a low P/E ratio. In regard to the summary table (3) from the fundamental data, the mean P/E ratios vary widely over the years for both sectors, especially for the alternative one. The green companies offered a lower P/E ratio during the first years though it increased heavily since 2018. Therefore, an investor using the P/E factor would have mainly invested in green assets during the first 3 years and slowly shifted the portfolio toward the cheaper stocks since 2018 toward fossil investments. Compared to the dividend factor, this approach allowed for a wider diversification and gained more returns.

The size factor affects the returns positively, meaning that the smaller, mostly alternative energy companies do exhibit a certain amount of risk premium. Yet, this effect is not significant, confirming the hypothesis H5. This is at odds with the significant size effect sound by Bohl et al. (2013) and Broadstock et al. (2012). While a non-significant size factor has been established by the literature, the momentum factor is surprising. The general effect is insignificant and the coefficients are the lowest of any variable in the model. As such, there is no apparent effect of the momentum factor in the portfolio. As follows, it can be seen in model (4) 'No Momentum' in Table 2 that omitting the momentum barely changes the R^2, suggesting a difference to the literature (Fama and French, 2012). A single similar finding is from Bohl et al. (2013), who found that for the whole analysed period between 2004-2011 and the sub period from 2008-2011 the momentum factor was not significant for renewable stocks in Germany. However, the explanation is based on the economic downturn and a shift in the view of renewable energy stocks. This is contrary to the findings of the strong surge in renewable investments mentioned in the introduction.

In conjunction with the findings of the dividend factor, there is a risk premium for investments in alternative energy while fossil companies offer a higher dividend yield with worse returns on their stocks. This finding confirms the hypothesis H6 which argued for higher returns from alternative energy companies. A possible reason is the riskier business as presented by a higher beta (Henriques and Sadorsky, 2008) which is partly confirmed by the unadjusted VaR regression shown earlier. Additional reasons for a higher risk could have been the risk premium of smaller companies. But the supposed riskier companies are evidently not rewarded with excess returns as seen by the non-significant size factor. Incidentally, this return premium from the alternative energy sector could be caused by a higher risk perception as the unadjusted Value-at-Risk demonstrates. However, the growing disadvantages and worsening outlook of the oil industry and the high growth rate of the green energy market are good reasons to believe that the fossil market should be seen as the riskier investment.

5 Summary and Conclusion

The rapid advancement of the renewable energy sector has led to a lot of investment in this field. Due to the necessity to mitigate emissions, it is expected to grow even stronger (IEA, 2017). Yet, at this moment, the choice between the new and volatile energy sector and the established fossil fuel sector is still unclear. There is certain evidence of volatility spillover between renewable and fossil energy assets (Reboredo, 2015). The renewable energy stocks have mostly been considered the more risky investment (Wen et al., 2014). Furthermore, research suggests that investors and companies should diversify using both fossil and green assets, possibly extending their portfolio to technology stocks which are closely related to renewable energy stocks. The question remains which investment is less risky and which drivers affect the returns. This thesis was set out to assess the comparative risk between fossil and alternative energy portfolios. Additionally, the economic reasons for the individual returns were examined using different dynamic factors.

By comparing 128 companies based on two MSCI indices, these results add to the research presented earlier. The Value-at-Risk of 70 fossil companies and 58 renewable global energy companies over the time-span of 13 years was compared. This VaR is based on a GARCH model. Using a dummy variable, the different VaR from the two portfolios were contrasted. Additionally, each return for each company was assessed for the affect of investment factors, namely the momentum, the size and two factors related to the value, the P/E ratio and dividend yield.

Main findings are a significant difference in the VaR between green and fossil stocks. In particular, the renewable energy portfolio exhibits an increased VaR by 0.05593 without market adjustment and a decreased VaR by 2.6207 for the whole period. The unadjusted VaR is rewarded with a higher return as the energy type dummy on the returns confirms. However, both the declining coefficient of the VaR and the positive coefficient of the adjusted VaR are a possible indication for a decrease in the risk perception of the green energy sector. Given the strong growth and future business opportunities regarding climate change (UNEP, 2020), this is a possible assumption. Additionally, the rising risk of the fossil industry can be seen in the high volatility in both VaR graphs. Given the criticism from institutional holders (BlackRock, 2020) and the risks stemming from stranded assets (Caldecott, 2017), these proceedings likely increase the risk perception of fossil assets.

The explanatory power of the investment factor is surprisingly small for the individual asset returns. By and large, all factors offer positive risk premiums save for the dividend yield. However, the size and momentum factor did not offer a significant risk premium, though the momentum factor is in proximity of the 0.05 p-value. Both quality factors, the P/E ratio and the dividend yield were significant. Surprisingly, the former affected the returns positively whereas the latter affected them negatively. In other words, the higher the dividends and P/E ratio, the lower the according return. A possible explanation could be that most fossil industries pay dividends while many newly established renewable firms did not or to the very least not in that amount as the summary table 3 in the appendix confirms. On the other hand, the P/E ratio of the fossil companies compared to the green industry is changing strongly, as the renewable companies turned from value into growth companies relative to the fossil P/E.

In conclusion, the fossil energy sector has been the riskier investment during the time period of 2007-2019 when adjusted to its market capitalisation whereas the green industry has been riskier for the unadjusted period. Nonetheless, the return on the green stocks has been higher. This is in accordance with the CAPM theory, which advocates for higher returns from higher risks. Assuming the past 13 years are a valid basis of investment choice, a risk-averse investor should decrease the investments in green energy and possibly hedge against it with fossil stocks as has been suggested (Asl et al., 2021). However, it is likely that the portfolio is adjusted to the market capitalisation. In this case, the investor should decrease the investments of the riskier fossil stocks. Given the inconclusive factor analysis, it is uncertain if it is feasible to draw any conclusions from it. However, assuming they can work, it is promising to invest in the P/E factor and to divest companies with a high dividend yield. Given the literature on the diversification, the portfolio should possibly include a wide range of renewable and fossil stocks as both are a promising hedge to each other (Asl et al., 2021). Additional assets for a wider diversification are volatility indices and crude oil (Ahmad, 2017), technology stocks (Maghyereh et al., 2019) as an extension to green stocks. However, the portfolio should not be held for a long duration (Bondia et al., 2016). Conclusively, for the upcoming short time period an investment in fossil energy is still feasible as a hedge for the green investments. However, the green energy stocks offer comparatively higher returns while also lowering the comparative risks. Accordingly, green investments are the best choice for future investments.

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A Appendix

A.1 Figures

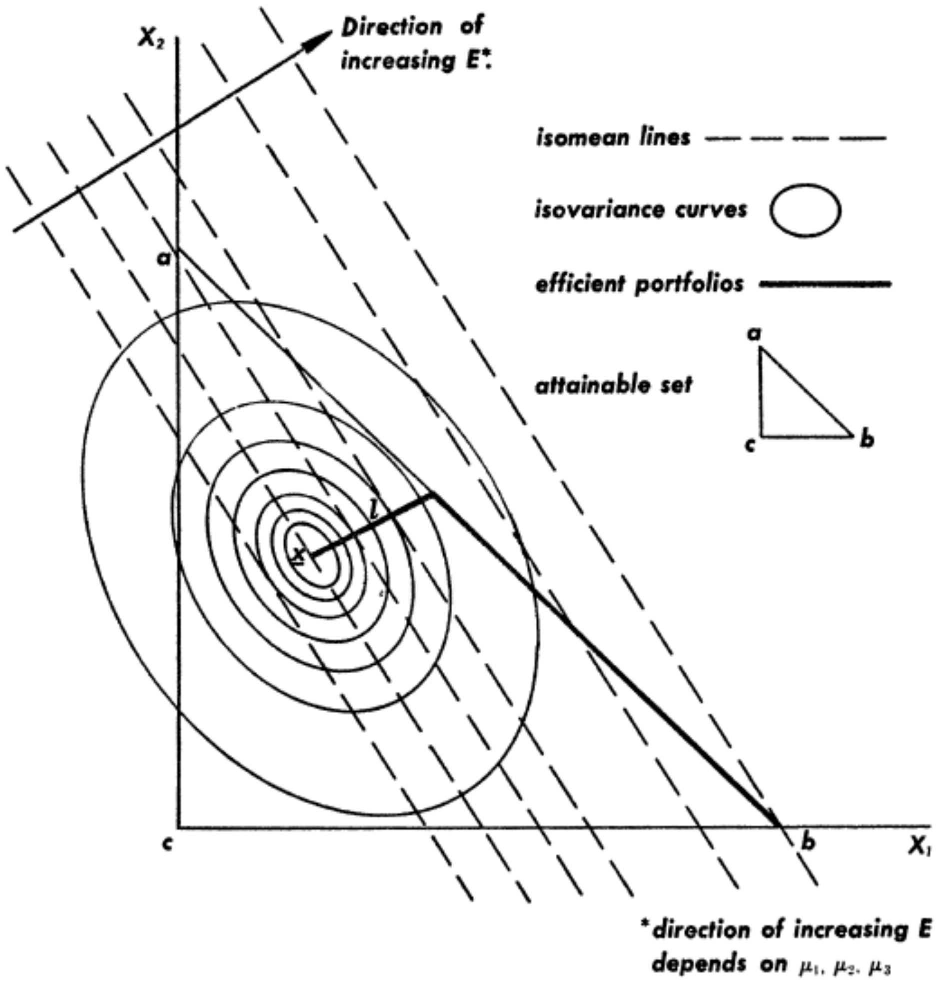

Figure 3: Portfolio optimization for three assets (Markowitz, 1952)

A.2 Tables

Table 3: Summary statistic: mean of financial data per year / whole period

Year	DIV Fossil	DIV Alternative	P/E Fossil	P/E Alternative
2011	1.022	0.656	24.774	23.173
2012	1.097	0.627	27.387	21.347
2013	1.190	0.560	45.492	23.081
2014	1.300	0.704	22.151	30.756
2015	1.319	0.683	52.393	36.108
2016	1.128	0.562	39.994	31.277
2017	1.206	0.600	39.385	43.192
2018	1.290	0.708	20.600	35.310
2019	1.418	0.685	17.742	85.025
2020	1.184	0.742	43.252	82.994
Whole Period	1.105	0.684	30.288	37.569

Table 4: Origin of data used in this thesis
Note: The access to the yfinance is https://github.com/ranaroussi/yfinance. The Morningstar Key Ratios can be accessed by searching for the company ticker, e.g. XOM for Exxon. Gieven the site of the company, a click on Key Ratio and then on Full Key Ratios Data will lead to an spreadsheet of the Financials and Key Ratios. This is the source of the data represented in this thesis.

Data	**Source**	**Day Retrieved**	**Exceptions**
Daily Adjusted Stock Prices 144 companies	yfinance package	24.08.2021	None.
Daily Exchange rates (Foreign Currency/USD) 15 exchange rates	yfinance package	24.08.2021	TWD / USD was manually replaced for 2011-10-25 and 2014-12-31 due to incorrect data from the data source.
Annual P/E Ratio 127 companies	*Morningstar* Full Key Ratios Data: Valuation History	04.08.2021	None.
Annual Dividends in specific currency; 127 companies	*Morningstar* Full Key Ratios Data: Key Ratio	04.08.2021	No data available for ADX.
Annual Shares Outstanding in Million; 127 companies	*Morningstar* Full Key Ratios Data: Key Ratio	04.08.2021	No data available for ADX.
ADX Market Capitalisation 14.09.2021	*Yahoo! Finance* ADX Quote 14.09.2021	14.09.2021	None.
TLW.L Market Capitalisation 17.09.2021	*Yahoo! Finance* ADX Quote 17.09.2021	17.09.2021	None.

B Statement of Authorship

"I hereby declare that I wrote this thesis paper independently, without assistance from external parties, and without use of other resources than those indicated. All information taken from other publications or sources in text or in meaning are duly acknowledged in the text. The written and electronic forms of the thesis paper are the same. I give my consent to have this thesis checked by plagiarism software."

Kiel, 26.09.2021

Location, Date

Signature