MASTER THESIS

The influence of interest rates, oil and carbon prices on stock returns of clean technology companies – the European case

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Abstract

The influence of macroeconomic factors on clean technology stock returns has been studied before. Previous research primarily focused on the clean technology sector in the United States, implementing macroeconomic variables applicable to companies situated in the United States. Limited research has been conducted on the European situation. This thesis partially fills this research gap, by focusing on the European case.

It provides insight and understanding on the relation between the three European macroeconomic variables (returns of carbon prices, interest rates and returns of crude oil prices) and European clean technology stock returns. This thesis focused on the period 2008 – 2018.

It finds evidence for positive relations between lagged and non-lagged European interest rates, twelve month lagged return of European crude oil prices and the return of European clean technology stock prices in the full period 2008 – 2018 and in sub period 1 2008 – 2012. The return of European carbon emission prices are empirically not significantly related to the return of European clean technology stock prices.

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1 Introduction

Over the past decades the clean technology sector has grown substantially. Environmental awareness together with rising traditional energy prices is seen as major drivers behind this development. According to the United States Energy Information Administration (EIA) (2018a), sources of clean technology and renewable energy will be the fastest growing source of electricity for years to come. The International Renewable Energy Agency (IRENA) estimates that the total share of renewable energy will rise from 18% of total consumption in 2015 to approximately 60% by 2050. Simultaneously, in order to flourish, substantial investments are needed in the sector (IRENA, 2018). Increasing (financial) investments in the clean technology sector requires insights in, and possible identification of, potential factors that fundamentally influence the risk-return trade-off of investments in the sector. In this thesis it is attempted to back this demand of additional research by examining the relation between macroeconomic variables and clean technology stock returns.

1.1 Clean technology and renewable energy

By definition of the United States Energy Information Administration (EIA) (2018e), renewable energy is energy from sources that are naturally replenishing but flow-limited; renewable energy sources are virtually inexhaustible in duration but limited in the amount of energy that is available per unit of time. EIA distinguishes five types of renewable energy:

1. Biomass: As organic material produced by photosynthesis, biomass contains stored energy from the sun. Biomass includes vegetation, organic waste and animal wastes. Biomass is argued to be the only form of renewable energy large enough in quantity to substitute fossil fuels (Klass, 2004);
2. Geothermal energy: As thermal energy generated by and stored in the earth, geothermal energy is a source of renewable energy as it is continuously replenished. It emerges as water or steam, being a source of heat that can be used to generate electricity (Jacobsen, 2008);
3. Hydropower: Generated through the use of gravitational force of water driving a turbine or generator, hydropower comes in different forms. Tidal power derives from oscillating currents in the ocean, whereas the majority of hydroelectricity is generated by falling water from dams (Jacobsen, 2008);
4. Solar energy: As the conversion of sunlight into electricity, solar power comes in different forms. Solar photovoltaics are arrays of cells that contain certain materials that convert solar radiation into electricity and are increasingly common (Jacobsen, 2008); and,
5. Wind energy: As energy from moving air, wind energy is generated by wind turbines that convert the kinetic energy of the wind into electricity (Jacobsen, 2008).

Renewable energy is not a new occurrence as people used renewable sources to generate energy for centuries. Examples include the use of wind energy to drive ships and mills, and hydropower to drive watermills. Together with increased awareness of fossil fuel depletion, renewable energy obtained substantial interest in the 20th century. Over the past years the renewable energy sector has grown rapidly and the International Energy Agency (IEA), an independent research organisation that examines the full spectrum of energy issues, estimates that renewable energy will continue to be the fastest growing component of global energy demand within the next decades (IEA, 2017).

Pernick and Wilder (2007) identify six drivers that boost the so-called 'cleantech revolution'. These drivers are costs, capital, competition, China, consumers and climate. (1) Decreasing costs of the production of renewable energy as a result of technological progress, together with potentially rising costs of fossil fuels (Hotelling's rule), will stimulate a substitution effect and concurrent renewable energy adoption. With increasing interest in renewable energy, the supply of (2) financial capital available to invest in the sector increases. This will stimulate the adoption of renewable energy. (3) Competition among governments and other organisations stimulate them to build greener societies, in which (4) China is a vital player. The largest nation on earth by population and, as a consequence, its extensive demand for energy, plays a decisive role in the future adoption of renewable energy. (5) Consumers, globally, become increasingly environmentally conscious and shift to the consumption of greener alternatives. Lastly, Pernick and Wilder identified (6) climate change, and awareness of the matter, as a driver of the adoption of renewable energy. Other researchers classify labour (Zhao & Luo, 2017), economic growth (Apergis & Payne, 2010) and government policies (Omri & Nguyen, 2014) as additional determinants of increased implementation of renewable energy, while rising oil prices are researched to be of negative impact on renewable energy adoption (Sadorsky, 2009).

Over the last two decades several renewable and/or clean energy stock indices have been created to facilitate investments in the sector. Subject in this thesis, and one of the most influential indices in terms of liquidity (ETFdb.com, 2018) and research (Kumar et al., 2012, Inchauspe et al., 2015, Bondia et al., 2016, Bohl et al., 2015) is the WilderHill New Energy Global Innovation Index (Ticker: NEX). Launched in 2006, the WilderHill New Energy Global Innovation Index can be considered as the first global stock market index for renewable, clean and alternative energy stocks. Included in the WilderHill New Energy Global Innovation Index are companies whose innovative technologies and services focus on generation and use of cleaner energy, conservation, efficiency and advancing renewable energy generally. The companies are relevant in the matter of climate change, as they research, develop and implement new technologies to avoid or reduce carbon emissions relative to the use of fossil fuel (WilderHill, 2018). As per the start of the third quarter in 2018, the index is composed of 114 companies globally of which 36 are situated in Europe. The NEX is assumed to provide suitable characteristics for the study of renewable energy stocks, at both a global and a European scale (Inchauspe et al., 2015).

Figure 1 illustrates the historical development of the PowerShares Global Clean Energy Portfolio ETF (PBD), an exchange traded fund that commenced tracking the NEX in June 2007. The fund generally invests at least 90% of its total assets in securities that comprise the WilderHill New Energy Global Innovation Index.

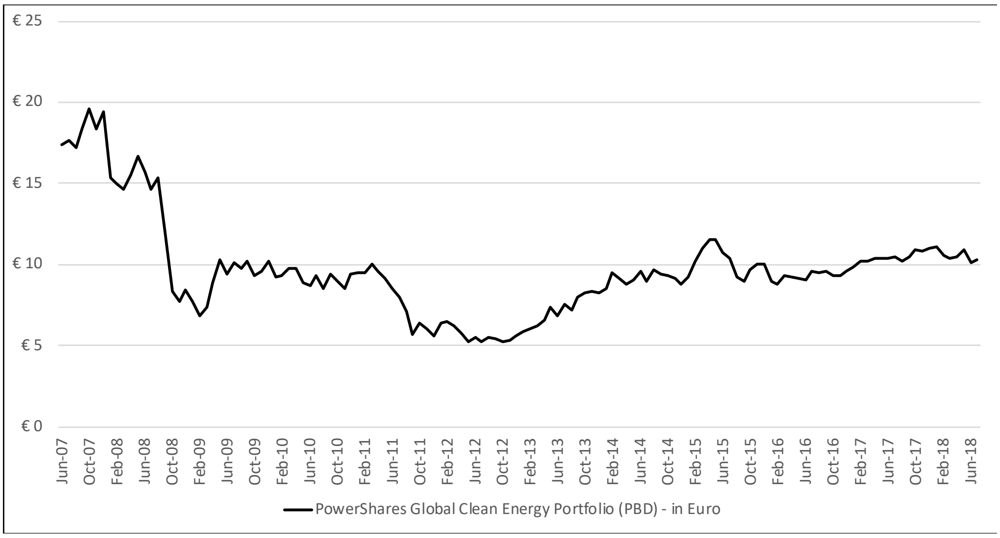

Figure 1 - Historical prices PowerShares Global Clean Energy Portfolio ETF (Yahoo! Finance)

The influence of macroeconomic factors on clean technology stock prices has been studied before. Primarily these researchers focused on the clean technology sector in the United States, studying macroeconomic variables applicable to companies situated in the United States. For example, Henriques & Sadorsky (2008) and Managi & Okimoto (2013) examined the relation between West Texas Intermediate crude oil prices and United States Treasury Bill interest rates with the United States' renewable energy sector. Limited research has been conducted on the European case, implementing macroeconomic variables that are applicable to European companies. This thesis intents to partially fill this research gap, by focusing on the European case.

Macroeconomic variables that are subject in this thesis are returns of carbon prices, interest rates and returns of crude oil prices. It is for a variety of reasons insightful to assess the matter of these macroeconomic variables in relation to clean technology stock returns in a European case, and reasonable to suspect possible deviations from prior research that focused on the United States. One of those reasons is the difference between applicable interest rates for both geological locations, as research that subjected interest rates on stock performance in the United States, implemented United States' Treasury Bill rates. Contrary, European companies deal with the Euro Interbank Offered Rate, or Euribor. In terms of returns of crude oil pricing, for European companies the most widely used benchmark is Brent Blend, whereas for United States' companies this is West Texas Intermediate (WTI). Lastly, research on the relation between returns of European carbon prices and European clean technology stock returns is currently very limited. As stated by Kumar, Managi and Matsuda (2012), who anticipate a growth in alternative energy sources because of concerns of global climate change, it is interesting to study the impact of policy makers in this field which is in Europe mainly formed by the European Union Emission Trading System. It will further clarify and add to the debate whether the current political idea of stimulation investments in clean sources by levying carbon taxes is of significant matter.

1.2 Research goal and question

The main research goal of this thesis is to provide insight and understanding on the relation between three European macroeconomic variables (returns of carbon prices, interest rates and returns of crude oil prices) and European clean technology stock returns. Hence, the research question in this thesis is formulated as follows:

What is the influence of European interest rates, returns of European crude oil prices and returns of European carbon prices on index returns of European clean technology companies in the period 2008 – 2018?

Theoretically, the association of macroeconomic indicators and stock performance is explained by a variety of theories and pricing models. The majority of these theories and models find their background in Fama's (1965) efficient market hypothesis, from where these theories and models pursue to explain how stock prices change. Most influential asset-pricing theories are Sharpe's (1964) and Lintner's (1965) capital asset pricing model (CAPM) and, later, Ross's arbitrage pricing theory (APT), of which the latter is of particular importance in this thesis as it acts as the foundation of the implemented multiple regression model. All theories will be extensively discussed in later stages of this thesis.

This thesis will contribute to academic literature by examining the relation between macroeconomic variables and the return of clean technology stock prices, in which it focuses specifically on the European case. The examination of this relation, in that it implements variables particularly applicable to European companies, has rarely been conducted. In addition, the timeframe of this research, April 2008 until June 2018, is of particular interest, since it covers both a period of financial crises and economic recovery. In a practical sense, the arbitrage pricing theory included in this thesis supports policy makers and investors in their understanding of the relation between implemented variables and stock performance. This helps these practitioners in their risk-return trade-off, investment decisions and monetary policy.

The rest of this thesis is organised as follows. Chapter 2 provides a literature review on the relation between macroeconomic indicators and stock returns, including the efficient market hypothesis, the concept of the risk-return trade-off, the capital asset pricing model and the arbitrage pricing theory. It further elaborates on the various variables implemented in this thesis, as it provides a literature review on the concept of (return of) carbon prices, interest rates and (return of) crude oil prices, and their relation with clean technology stock returns. Chapter 3 elaborates on the implemented methodology and describes the data used in this thesis. Chapter 4 will outline and discuss the results of the conducted multiple regression. At last, Chapter 5 will conclude with both limitations of this thesis together with propositions for future research.

2 Literature review

This chapter discusses the underlying theoretical framework of the relation between macroeconomic indicators and stock returns. It includes Fama's efficient market hypothesis (1970), the risk-return trade-off of an investment, the capital asset pricing model of Sharpe (1964) and Lintner (1965) and finally Ross's arbitrage pricing theory (1976). These theories are explained in this chapter as they provide background information that supports the understanding of the relation between (macroeconomic) factors and stock returns. Hereafter, the macroeconomic variables included in this thesis are discussed in detail by means of a literature review.

2.1 Efficient market hypothesis

An important background behind asset pricing models is the Efficient Market Hypothesis. The efficient market hypothesis (EMH) implies that asset prices fully reflect all available information at all times (Fama, 1970). Or, as Oppenheimer & Schlarbaum (1981) explain, in an efficient capital market, security prices fully reflect available information in a rapid and unbiased fashion and thus provide unbiased estimates of the underlying values. The hypothesis suggests that security prices adapt to new information by supply and demand among investors and are, consequently, accordingly priced. The pillar of EMH is the concept of random walk. In the concept of random walk, price changes are independent of each other because in price series, subsequent price changes represent random departures from previous prices since historic information is yet reflected in past price adjustments (Malkiel, 1973).

In his work on the efficient market hypothesis, Fama (1970) classified the market in three forms of efficiency:

1. Weak form: Security prices reflect historical information, adhering to random walk theory;
2. Semi-strong form: Security prices reflect all publicly available information and adjust instantly to reflect new publicly available information; and,
3. Strong form: Security prices reflect all publicly available and privately held information.

As security prices are, under the hypothesis, close to their intrinsic values, in turn, EMH implies that it is impossible for investors to 'beat the market' without being exposed to above average risk. Although the efficient market hypothesis is extensively studied among academics of the social sciences, there is no consensus as to whether the hypothesis holds. The fact that some investors consistently seem to be able to 'beat the market' and, in addition, the occurrence of stock market crashes such as Black Monday in 1987 or the Dot-com collapse in 2000, oppose the assumption that security prices reflect fair value. In conflict with his prior theory, Fama (1990) later found that a substantial amount of securities did not follow a random walk. These ‘value stocks’, securities that are priced lower than their intrinsic value based on their (financial) fundamentals such as dividends, earnings and sales, outperformed the market.

The acceptance of the efficient market hypothesis, and to what extend the hypothesis holds, is essential in the understanding of movements of security prices. The hypothesis enables an explanation as to what variables force security prices to change and, consequently, as changes in prices trigger returns, an explanation as to what variables force stock returns. For this reason, it is an important aspect of this thesis as it aims to research the relation between several macroeconomic variables and stock returns of clean technology companies.

2.2 Risk and return

The risk–return trade-off explains the relationship between an investment’s inherent risk and the expected return accompanied by that investment (Ross, Westerfield & Jordan, 2008). The expected return on an asset is positively linked to its risk; in general, to be compensated, the investor’s expected return of an investment grows with an increase in its risk since investors tend to be risk averse (Eun & Resnick, 2014). To study why and in what level investment returns vary it is helpful to research the determinants of associated risk. Deeper understanding of these determinants provide insight in various asset pricing models that relate risk with return.

As developed by Markowitz (1952), in modern portfolio theory, the variance of an investment return is its appropriate measure of risk. The variance of an investment return illustrates the historic dispersion of returns around their mean (or expected) return, in which return equals profit divided by amount invested (Ross et al., 2008). In modern portfolio theory, risk is divided in systematic and unsystematic risk. Systematic risk of an investment is the portion of the investment’s return variance that is explained by market movements, whereas unsystematic risk is the portion of return variance that cannot be explained by market movements (Hillier, Grinblatt & Titman, 2012). Systematic risk arises from dynamics in a market that affect all stakeholders in that market, whereas unsystematic risk arises from dynamics that solely affect specific stakeholders in that market. Examples of systemic risk are (but not limited to) macroeconomic factors resulting from fiscal, monetary or regulatory policy, or natural phenomena such as earthquakes or storms that affect all stakeholders in a market. In turn, examples of unsystematic risk are (but not limited to) microeconomic factors resulting from fiscal, monetary or regulatory policy, labour strikes or natural phenomena such as drought that affect single stakeholders in a market.

As investors are by assumption risk averse they tend to balance their investments among multiple securities in order to lessen risk; the investor ‘does not put all his eggs in one basket’. This is called diversification (Hillier et al., 2012). As an investor adds investments to his portfolio, the additional investments diversify the portfolio of investments if the added investment does not covary with prior investments executed by the investor. In theory, under the risk-return trade-off of modern portfolio theory, systematic risk, risk factors that affect all stakeholders in a market, is non-diversifiable risk. Contrary, unsystematic risk is diversifiable in a portfolio of investments, as this category of risk is firm specific and can be reduced, but not eliminated, by a multiple of investments across non-covariant investments. Figure 2 illustrates the concept of diversification.

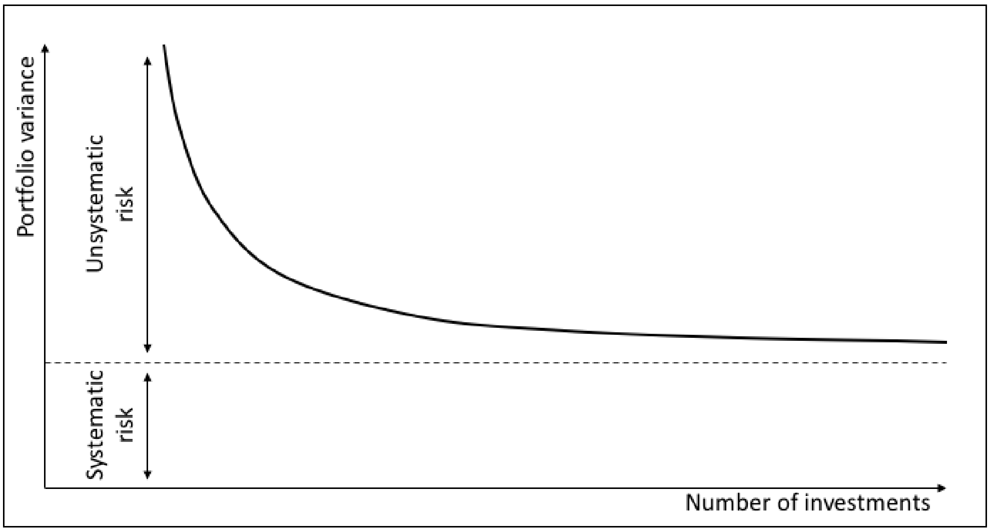

Figure 2 - The concept of diversification (Hillier et al., 2012)

From the concept of diversification summarised in Figure 2, it can be concluded that investors expect to receive a return by bearing systematic risk. For this reason, under the risk-return trade-off in modern portfolio theory an investor's expected return is positively related to the systematic risk this investor encounters. This is illustrated in Figure 3.

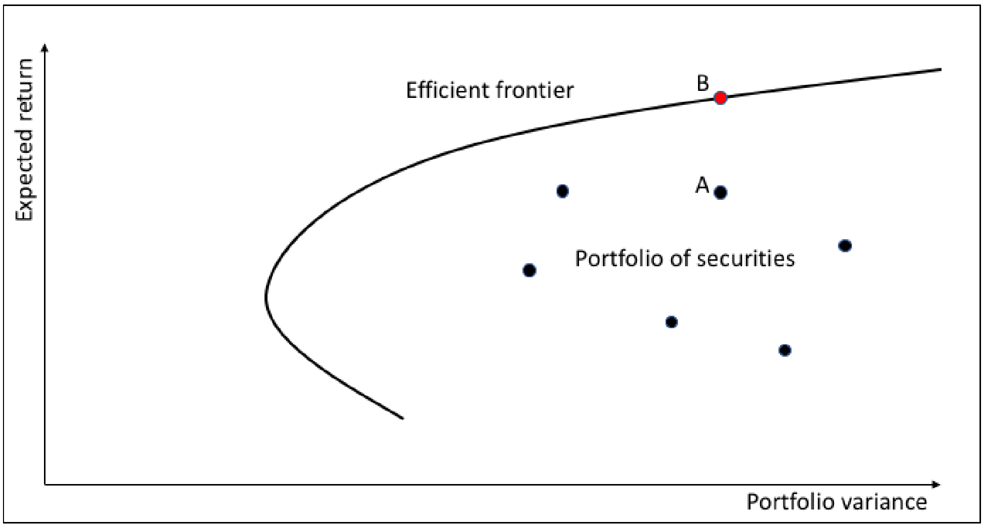

Figure 3 - Modern portfolio theory (Hillier et al., 2012)

The top, positive half of the boundary in Figure 3 is the efficient frontier of risky portfolios of securities. The efficient frontier represents the expected returns and variances of the efficient portfolios. Since portfolio B yields a higher expected return but an equal amount of variance compared to portfolio A it is considered to be more efficient; the efficient frontier is the most efficient trade-off between risk and return (Hillier et al., 2012).

From the understanding of the risk-return trade-off in the modern portfolio theory, various asset pricing models have been developed. The Capital Asset Pricing Model, which is the most notable and basic asset pricing model, and an extension of this model, the Arbitrage Pricing Theory, will be discussed in the following sections. The latter is subject in this thesis.

2.3 Capital asset pricing model

The previously discussed risk-return trade-off acts as the foundation of the most commonly used asset pricing model for securities valuation, the Capital Asset Pricing Model (Hillier et al., 2012). The capital asset pricing model (CAPM) is a model to estimate the expected rate of return from an investment. The CAPM was extensively studied by William F. Sharpe. His paper on the framework titled "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk", published in 1964, was awarded the Nobel prize for Economics. Hereafter, John Lintner (1965) contributed with his work on the subject of valuation of risky investments from the perspective of the issuing corporation instead of the investor.

In essence, the capital asset pricing model (CAPM) dictates to what extent investors must be compensated for the time value of money and its coherent risk. The CAPM claims that investors must be compensated for their investments' systematic risk, since, in contrary to unsystematic risk, this type of risk cannot be eliminated by portfolio diversification (Ross et al., 2008). The methodology constructs the appropriate expected rate of return by summation of multiple (security-related) risk components in order to derive a yield at which an investor is willing to invest in the particular security. In theory, CAPM states that the required rate of return of an investor equals the sum off the risk-free rate and the valued security's systematic risk, computed as beta multiplied by the security's appropriate market risk premium. This translates in the Sharpe-Lintner Capital Asset Pricing Model equation as follows (Fama & French, 2004):

$$E(R_i) = R_f + \beta_{iM} [E(R_M) - R_f]$$

where,
$E(R_i)$ = expected rate of return of security i;
R_f = rate of return of risk-free security;
β_{iM} = security i's market beta; and,
$E(R_M)$ = expected rate of return of market portfolio.

The Sharpe-Lintner equation clearly summarises the three fundamentals of the capital asset pricing model (Ross et al., 2008):

1. Time value of money as measured by the rate of return of a risk-free security, R_f;

2. Systematic risk as measured by the security's market beta, β_{iM}. The systematic risk of the security illustrates the contribution of the security to the total risk of a portfolio (Kadan, Liu & Liu, 2013). Beta shows a security's variance in return compared to its market portfolio. In equation, this translates as follows:

$$\beta_{iM} = \frac{Covariance\ (R_i, R_M)}{Variance\ (R_M)}$$

   The above equation illustrates that a security's beta is calculated by (1) the covariance between that security's return and the market portfolio return divided by (2) the variance of the market portfolio return e.g. (1) the security's return relative to that of the market portfolio divided by (2) the market portfolio return relative to its expected return; and,

3. The reward for bearing systematic risk as measured by the market risk premium, $E(R_M) - R_f$. The market risk premium is the average expected return that investors require in surplus of the expected return of a risk-free security for bearing higher risk due to higher variance in returns of its investments (Dimson, Marsh & Staunton, 2003).

Security Market Line is referred to as the visual illustration of the capital asset pricing model. As illustrated in Figure 4, the security market line (SML) is the graphical representation of a security's expected rate of return versus systematic risk, noted by beta.

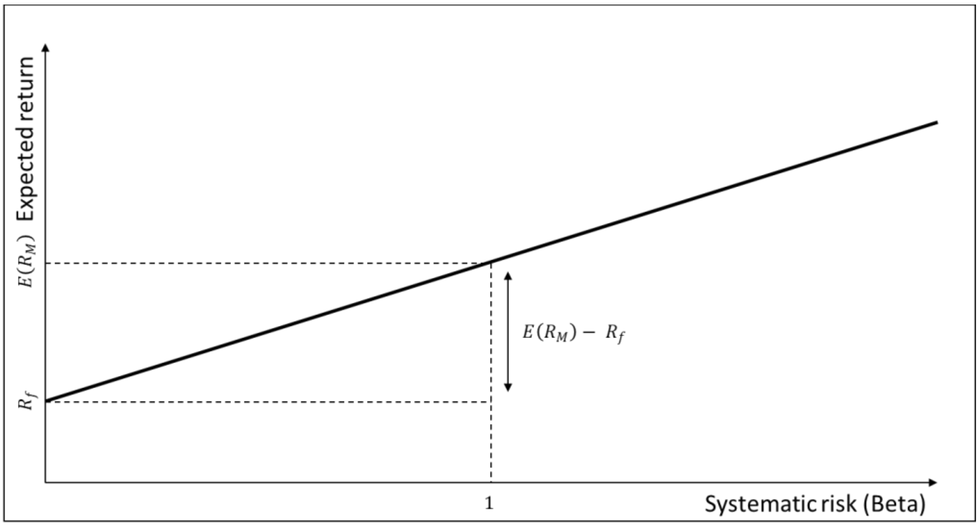

Figure 4 - Security market line (Ross et al., 2008)

From the plotted SML it becomes evident that the market portfolio (R_M) equals a beta of 1. This holds since a beta of 1 indicates that a security is equally volatile as its market; the numerator, $covariance\ (R_i, R_M)$, and denominator, $variance\ (R_M)$, are identical. The risk-free security equals a beta of 0 as its constant expected return cannot covary with the market. The SML clarifies the idea that an investor is rewarded for incurring additional, systematic risk. Additionally, as discussed, the SML illustrates that the market, as explained by Sharpe (1964), "presents him (the investor) with two prices: the price of time, or the pure interest rate (shown by the intersection of the line with the vertical axis) and the price of risk, the additional expected return per unit of risk borne (the slope of the line)."

The capital asset pricing model, with its security market line, and beta as a measurement of a security's systematic risk are crucial components of modern portfolio theory. Still today the method is widely used, as Graham and Harvey (2001) claim that nearly 75% of United States' corporate financial officers use the technique to calculate their companies' expected rate of return on investments. In Europe, CFO's of large firms most often use present value techniques in combination with CAPM in order to assess the feasibility of an investment opportunity (Brounen, De Jong & Koedijk, 2004). Despite its commonality, empirical research on CAPM and its implications has shown deficiencies. Starting with Roll (1977), who claims that the capital asset pricing model is "inherently untestable", because a true market portfolio in Roll's view should include all securities and is unobservable. Known as Roll's critique, Roll (1977) states that the only economic prediction of CAPM is that the market portfolio is mean-variance (return-risk) efficient. In addition, the main critical point to the capital asset pricing model, besides the debate on the efficient market hypothesis, is the collection of risks in a single factor. This can be useful for the analysis of well-diversified portfolios, however, the explanation of the variance of return of individual securities is considered inadequate. Research shows that other, more specific components of risk, also have a significant impact on the variance of return. Fama and French (1992) found both a size- and book-to-market effect in their empirical research on asset pricing theory. Many additional critiques by various researchers summarise in the finding that the capital asset pricing model operates under rigid input and assumptions, in which securities are assumed to carry distinct values for beta (Fama & French, 1993, Dempsey, 2013). As an alternative, Ross (1976) proposed the Arbitrage Pricing Theory.

2.4 Arbitrage pricing theory

The arbitrage pricing theory (APT) was first introduced by Ross (1976). APT is considered to be a multi-factor pricing model; the model tends to explain the variance of return with multiple risk factors. APT explains the previously discussed risk-return trade-off, of which the theory assumes to be a positive relationship: equally to the capital asset pricing model, an increase in risk results in an increase in expected return. With the use of APT, practitioners aim to take additional risk factors, beyond a security's market risk, into account in order to improve the explanation in securities' return (Hillier et al., 2012). This translates in the multi-factor Arbitrage Pricing Theory equation as follows:

$$E(R_i) = R_f + \beta_{i1} R_{i1} + \beta_{i2} R_{i2} + \cdots + \beta_{in} R_{in} + \varepsilon_i$$

where,
$E(R_i)$ = expected rate of return of security i;
R_f = rate of return of risk-free security;
β_{in} = sensitivity of the security i to systematic risk factor n;
R_{in} = systematic risk factor n; and,
ε_i = error term of regression, associated with unsystematic risk of security i.

The arbitrage pricing theory equation clearly illustrates that under the methodology the expected rate of return of a security is positively linked to multiple, infinite number of variables. The various beta coefficients in the model factor the variance of return of the analysed security explained by its related risk factor. The error term of regression, or unsystematic risk, is assumed to be uncorrelated with the risk factors included in the model and, when a portfolio of securities is subject of calculation, across the portfolio's securities.

There is a lack of consensus among researchers about both the number and the category of risk variables that should be included in the model. Also, the manner in which risk factors are identified differs in academics. Chen, Roll and Ross (1986) empirically test multiple macroeconomic variables to explain the variance of return of securities. The authors conclude with the identification of four variables that are significantly 'priced' in securities; these four variables significantly explain the securities' variance of return. They are the spread between long and short interest rates, expected and unexpected inflation, industrial production and the spread between high- and low-grade bonds. As noted, later Fama and French (1992, 1993) empirically constructed the well-known three-factor model, that included a macroeconomic factor market risk and two firm-specific risk factors. The first is SMB, which stands for Small Minus Big, and measures the historic excess return of smaller sized companies over larger sized companies in terms of market capitalisation. The second is HML, which stands for High Minus Low, and measures the historic excess return of companies with a 'high' book-to-market ratio over companies with a 'low' book-to-market ratio. As an extension of the Fama French three-factor model, Carhart (1997) identifies a fourth risk factor, momentum; the bias of a security price to move in its current direction. In a practical sense, Menike (2010) tests four macroeconomic variables on security prices in emerging Sri Lankan market using a multivariate regression and Rjoub, Türsoy and Günsel (2009) test six such factors on the Istanbul security market. Factors included in both studies were the interest rate, exchange rate, inflation rate and money supply. Rjoub et al. (2009) additionally tested the unemployment rate and the risk premium.

The three variables included in this thesis are, in alphabetical order, the return of European carbon prices, European interest rates and returns of European crude oil prices. Each variable will be discussed in detail in the following paragraphs together with a review of recent literature on the relation between the variable and stock performance. Each paragraph will be concluded with a hypothesis related to the variable discussed in that paragraph and its relation with stock returns of European clean technology companies. The three macroeconomic variables will be included in the arbitrage pricing model in subsequent chapters of this thesis.

2.4.1 Interest rate

An interest rate is the proportion of a loan that is charged as interest to the borrower expressed as a percentage of a principal. The total interest on a certain principal lent or borrowed results from (1) the principal sum, (2) the interest rate, (3) the compounding frequency, and (4) the duration period of the transaction. Hence, an interest rate is the rate that banks or other creditors charge borrowers.

An interest rate is the vital tool of a governmental monetary policy. For the European Central Bank (ECB), the primary objective of its monetary policy is to maintain price stability in the Eurozone, and thereby contributing to sustainable economic growth and job creation (Lisbon Treaty, 2007). The ECB states that its monetary policy operates by steering short-term interest rates that in turn influence economic developments, in order to sustain price stability and inflation in the Eurozone at around 2% (ECB, 2018).

In theory, the policy of monetary authorities can either be expansionary or contractionary (Thorbecke, 1997). An expansionary policy aims to stimulate economic activity, by increasing an economy's money supply. This policy mainly operates by lowering interest rates to stimulate financing of (borrowing by) companies, individuals and banks, but it can also involve quantitative easing where the Central Bank acquires financial assets (usually bonds) from banks, thereby increasing banks' capacity to finance (credit) companies and individuals. An expansionary policy, illustrated in Figure 5, intents to increase inflation.

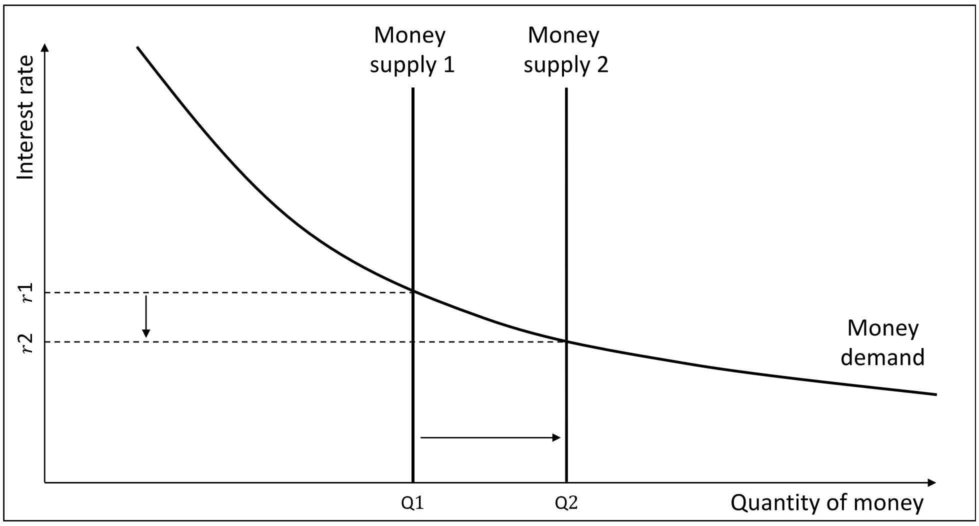

Figure 5 - Expansionary monetary policy (Thorbecke, 1997)

At the other end of the theoretic spectrum of monetary policy lies a contractionary policy. A contractionary policy aims to restrain economic activity, by decreasing an economy's money supply. This policy mainly operates by increasing interest rates, which in turn discourages financing of (borrowing by) companies, individuals and banks. A contractionary policy, illustrated in Figure 6, intents to decrease inflation.

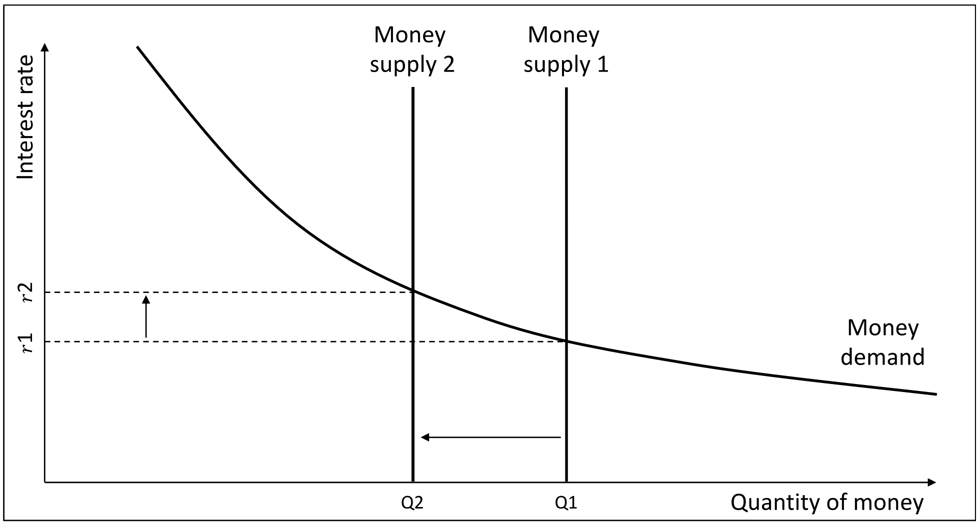

Figure 6 - Contractionary monetary policy (Thorbecke, 1997)

In theory, lower interest rates, with a consequent increase in money supply, stimulate demand for, and investments in, equity. Investors tend to switch to equity over fixed-return bonds because lower interest rates yield lower returns on risk-free investments. The switch to equity over fixed-return bonds and the stimulus in companies' investments by increasing money supply results in higher equity prices.

As stated above, the European Central Bank is responsible for steering short-term interest rates in the Eurozone. The monetary authority sets the key interest rates for the euro area. These key interest rates are (ECB, 2018):

1. The interest rate on main refinancing operations (MRO), which provide the bulk of liquidity to the banking system;
2. The interest rate on the deposit facility, which banks may use to make overnight deposits with the Eurosystem; and,
3. The interest rate on the marginal lending facility, which offers overnight credit to banks from the Eurosystem.

The interest rate on main refinancing operations (MRO) is the interest rate which financial institutions face when borrowing directly from the European Central Bank when liquidity is needed. In addition, to increase its liquidity, banks tend to lend from other banks in the interbank market; a central hub for complex institutional networks, connecting all financial organisations in the banking industry (Temiszoy, Iori & Montes-Rojas, 2015). The reference rate used for European interbank lending, and subject of this thesis, is the Euro Interbank Offered Rate, or Euribor. The Euribor is considered to be the most important reference rate in the Eurozone (Upper, 2012; Bernoth & Hagen, 2004). The Euribor rate is based on the average of the quoted interest rates at which forty-three contributing panel banks borrow money from one another (EBF, 2017). The Euribor is set at different maturities, ranging from one week to one year, of which a 3-month maturity is common practice. Historically, the Euro Interbank Offered Rate response to adjustments in the interest rate on main refinancing operations is strong, which illustrates the significance of the implemented monetary policy by the ECB (Bernoth & Hagen, 2004).

Figure 7 illustrates the adjustments made to the interest rate on main refinancing operations by the European Central Bank over the past years, together with the 3-month Euro Interbank Offered Rate over the same period.

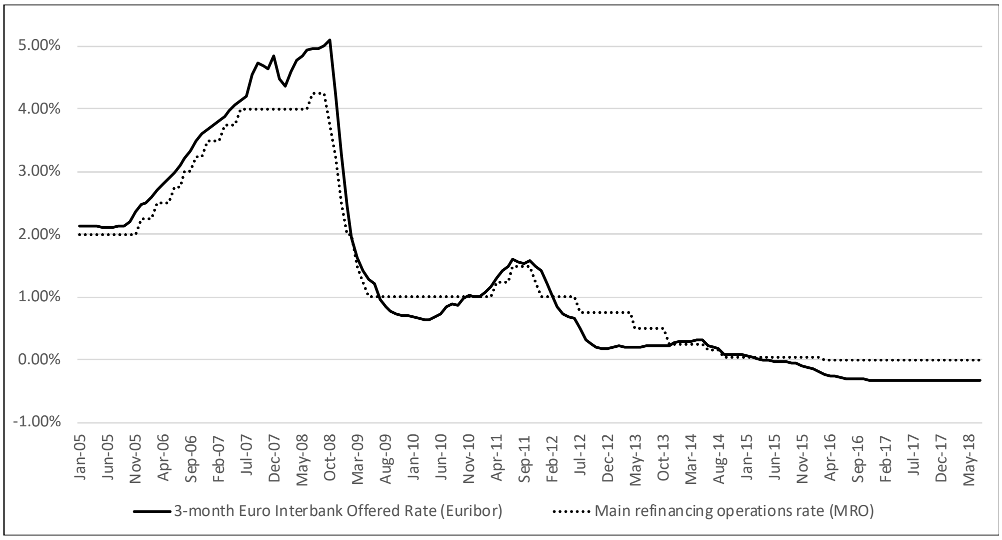

Figure 7 - Interest rate on main refinancing operations and 3-month Euribor (ECB)

The relationship between interest rates and stock prices is often researched in both theoretical and empirical studies. Due to the nature of the industry and sensitivity to changes in interest rates, the majority of existing research focuses on the financial industry. A financial institution's income and expenses, and thereby its stock performance, is for a large part directly influenced by interest rates (Flannery & James, 1984).

As this thesis focuses on stock performance of nonfinancial corporations, it is interesting to see, in theory, in what way this performance is related to adjustments in interest rates. First, adjustments to interest rates directly alter companies' debt service payments and therefor either increase or decrease corporate profits and stock performance. Second, adjustments to interest rates may act as a driver behind investors switching from fixed-return bonds to equity or vice-versa, thereby increasing or decreasing stock demand and performance. Third, adjustments to interest rates indirectly alter the market value of companies' financial assets and liabilities, thereby influencing stock performance. Fourth and final, adjustments to interest rates are of importance in asset-pricing models as they alter companies' cost of capital and thereby stock performance. Rising interest rates increase companies' cost of capital. Its future cash flows generated from its business activities (e.g. investments) a reduced in value because of the rising cost of capital. As a result, stock performance will decline.

The theoretical relationship between interest rates and stock performance has been the subject of an extensive amount of empirical research. As stated, the majority of this research concerned the relationship based on stock performance of financial institutions. These studies conclude that *financial* institutions' stock performance is correlated to changes in interest rates. Flannery and James (1984) found that for commercial banks, changes in interest rates are significantly negatively correlated to stock price movements using an ordinary least square regression model. In addition, a number of studies conclude that interest rates are one of the most significant explanatory variables in explaining *nonfinancial* organisations' stock performance. By using a two-factor excess return model, in which one-week US treasury bills rate are included as a proxy of interest rates, Choi and Jen (1991) concluded that interest rates have a significant negative effect, but limited impact, on financial performance of both small- and large-sized firms. The Greek economist Papapetrou's (2001) researched the relationship among oil prices, stock prices, interest rates, economic activity and employment for Greece. In her study she acknowledged that real stock returns, being continuously compounded return on the Greek stock market index corrected for the inflation rate, respond negatively to movement in the Greek 12-month interest rate.

Some researchers studied the relationship between, among others, interest rates and stock performance of clean technology companies. For example, Managi and Okimoto (2013) included interest rates in their Markov-switching vector autoregressive model and found a significant negative response of clean energy *prices* in the global stock market to changes in interest rates. Henriques and Sadorsky (2008) conclude that interest rates have some power in explaining the movements of the stock *prices* of alternative energy companies – negative effect – whereas, in contrary, studying the German market, Madaleno and Marvao Pereira (2015) find interest rates to be irrelevant in explaining the movements of stock *prices* of German alternative energy companies. Although previously mentioned articles study the relationship of interest rates and stock *prices* instead of return they are applicable to this thesis as it is assumed that a price movement of any asset – in this hypothesis European interest rates and clean technology stocks – implicates a (positive or negative) return of that asset.

As a result, interest rates are essential in business' capital structure and investments- and dividend policy and thereby have its effect on stock performance. In line with the theory of monetary policy and business' investment policy discussed in the previous sections, in this thesis it is hypothesised that an increase in interest rates encourage investments in and the use of (clean technology) equity. As a result, clean technology stock returns are hypothesised to be positive affected. This leads to the following hypothesis:

H1: European interest rates (3-month Euribor) have a positive effect on European clean technology stock returns.

2.4.2 Return of oil prices

Crude oil is an unrefined petroleum that can be found in certain geological locations across the globe. The liquid is comprised of hydrocarbon deposits, organic compounds and small amounts of metal. It is a dark greenish brown, viscous mineral oil, found deep in earth's crust (Demirbas, Alidrisi & Balubaid, 2014). As a type of fossil fuel, crude oil can be refined into, among others, gasoline, diesel, jet fuel, heating oil and other lubricants. Crude oil is a nonrenewable resource and therefore limited in its quantity and non-replaceable by nature (EIA, 2018b).

In 2017, 48% of global crude oil production came from Russia, Saudi Arabia, United States, Iraq and Iran (EIA, 2018c). Crude oil extracted from different geological locations on earth have different qualities, i.e. crude oil extracted from an oil field in Russia has different qualities to crude oil extracted from an oil field in Saudi Arabia. The quality varies in terms of its chemical composition, density, viscosity, its sulfur content. The latter is the most important characteristic of crude oil that affects its market price, where a low sulfur content is preferred since this requires less processing in the refinement process (Demirbas et al., 2014). Since crude oil from various geological locations differ in quality and composition, it carries different market values.

To implement these differences in pricings, and by means of comfort for traders, it is common practice to implement a benchmark in the price formation of the traded oil. Today, there are four primary benchmarks in the world (EIA, 2018d):

1. Brent Blend: Brent is the most widely used benchmark. The benchmark is historically based on crude oil extracted from the North Sea. Since this benchmark is primarily used in, among others, Europe, it is of great importance in this research. Brent is quoted in dollar per barrel;
2. West Texas Intermediate (WTI): WTI is recognized as the United States' benchmark as this crude oil is produced in, or imported into, the United States. WTI is quoted in dollar per barrel;
3. Dubai Crude: Dubai Crude is used for crude oil extracted from the Persian Gulf and the Middle East. This benchmark is primarily used in Asian markets and is quoted in yen per kiloliter; and,
4. OPEC Reference Basket (ORB): ORB represents a weighted average of crude oil supply extracted by the members of the Organisation of Petroleum Exchange Countries (OPEC). OPEC members currently extract ca. 40% of global oil supply. ORB is quoted in dollar per barrel.

As a subject in this research, in Figure 8, Brent crude oil spot prices are plotted in Euro (instead of dollar) per barrel over the period August 2005 until August 2018.

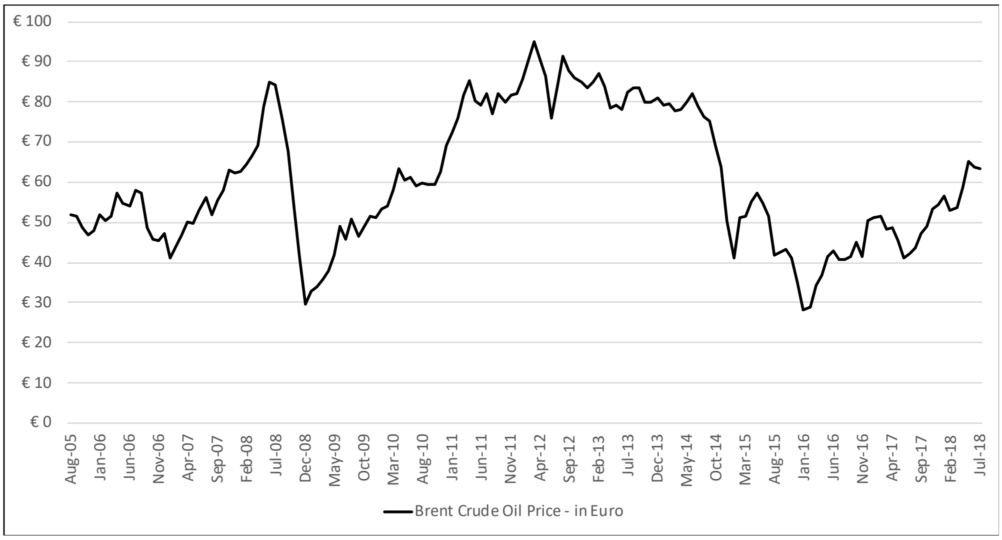

Figure 8 - Historical Brent crude oil spot prices (United States Energy Information Administration)

Over the past years, crude oil prices showed intense fluctuations. As the importance of oil exceeds its economic significance and impacts life in general, its pricing fluctuations are studied by many researchers and analysts.

From the beginning of the 21st century to the year 2008, the oil price rose up to a spike of €85 per barrel of crude oil in June 2008; in late December of that same year the price dropped to €29. During the intervening time, United States investment bank Lehman Brothers filed for bankruptcy in September, triggering a global financial crisis. Although it is complex to assess what occurrence preceded the other, the relation between fluctuating oil prices and economic state is present, since during the phase of economic recovery, oil price surged back to approximately $100 (over €90) after this precipitous fall (Bhar & Malliaris, 2011). The presence of this relationship alone, indicates the importance and significance of the crude oil price as an economic indicator, and explains the interest of many researchers to study the subject. In the aftermath of the described drop in oil price, researchers identified a variety of determinants not related to the financial crisis. Among these determinants were overproduction of oil in the United States with related mismatch between supply and demand, oversupply by OPEC countries to compete with higher-cost producers and, last, appreciation of the US dollar (Hamilton, 2009).

Eight years later, in the year 2014, oil prices illustrated a new, similar drop. After a period of nearly five years in which oil prices stabilised at approximately €80 per barrel of crude oil, it dropped to €40 in January 2015 and bottomed at approximately €30 in February 2016. Again, researchers and analysts differ in reasoning for the decline in oil price. Baumeister and Killian (2016) trace the decline to a negative demand shock as a result of a slowing global economy. Noguera-Santaella (2016) refers to threatened violence in the Middle East, sequential to the Arab Spring that began in December 2010 in Tunisia, but that did not persist in major oil-exporting countries, as a determinant for the decline in oil prices. As can be seen, researchers and analysts differ in their identification of driving forces behind these pricing fluctuations, but the model of supply and demand often recurs in conclusions and discussions.

Besides determinants of oil price fluctuations, the linkage between (return of) crude oil prices and stock performance is often studied, both theoretically and empirically. This linkage is important in this thesis. Global oil companies are directly impacted by crude oil price volatility in terms of profitability and value creation, as levels of revenue, profit margin and net income of these companies fluctuate and show correlation with oil price shocks. Accordingly, on a firm-level, oil companies' public stock performance declines with drops in the oil price, thereby diminishing the creation of shareholder value (Gupta, 2016). For non-oil companies, fluctuations in crude oil prices affect companies' costs and can therefore impact its stock performance. For consumers, these fluctuations impact their spending-capacity either positive or negative, which will indirectly alter their spending and thus companies' profit margins. This will impact stock performance (Kilian, 2007).

A much-cited study by Sadorsky (1999) confirms the theoretical relationship between fluctuations in oil prices and stock performance. The researcher uses a regression model, which includes oil prices, short term interest rates, industrial production and stock market returns, for the period 1947-1996. Sadorsky concludes that oil price fluctuations have a negative impact on stock returns. As an explanation Sadorsky states that oil price fluctuations affect economic activity (e.g. industrial production). By doing so it will affect the earnings of companies for which oil is a cost of production and decreasing its earnings. In an efficient stock market increasing oil prices will therefore decrease stock return. Later, using a multivariate vector autoregression model, Park and Ratti (2008) confirm the findings of Sadorsky by concluding that oil price shocks negatively affect stock performance in the United States and selected European countries. An exception is found for stock performance in Norway, which is stated to be an oil-exporting country. Conversely, Huang, Masulis & Stoll (1996) find no significant linkage between oil prices and general stock performance in the United States, as reflected by the S&P 500.

Some researchers studied the relationship between, among others, crude oil prices and stock performance of clean technology companies. For example, Henriques and Sadorsky (2008) use a four-variable vector autoregression model to investigate the empirical relationship between alternative energy stock prices, technology stock prices, oil prices and interest rates. Their results show that oil prices 'Granger cause' stock prices of alternative energy companies and can therefore be used to forecast future stock performance. Henriques and Sadorsky adhere an investment policy theory as they claim that rising oil prices stimulate a shift form petroleum based energy production, investments and usage to alternative (e.g. clean) energy based production, investments and usage. In their paper, in which they analyse the relationship among oil prices, clean energy stock prices and technology stock prices, Managi and Okimoto (2013) find a positive relationship between oil prices and clean energy stock prices for the period after 2007. As this opposes findings of prior studies and fundamental theory, the researchers explain this result as a suggested move from conventional energy to clean energy, partly driven by rising oil prices. Their research states that rising oil prices have stimulated technological improvement in alternative energy. As a result, while conventional energy becomes more expensive, clean energy becomes relatively inexpensive. Later, Inchauspe et al. (2015) implement a multi-factor asset pricing model with multiple energy prices and stock market indices as independent variables to explain volatility of excess returns of renewable energy stocks and find a relationship between crude oil prices and the volatility of excess return.

Again, empirical research focuses on the relation between oil *prices* and stock *prices* instead of the return of oil prices and stock return. By theory, return of an asset is determined by price movement of that asset, in which increasing (decreasing) asset prices increase (decrease) the return of that asset. For this reason, the studies mentioned before are applicable to the return of the assets in this hypothesis, being European crude oil and European clean technology stocks.

In line with the theory and prior empirical research discussed in previous sections, in this thesis it is hypothesised that an increase in return of crude oil prices encourages investments in clean technology assets. As a result, the return of clean technology stock prices are hypothesized to be positive affected. This leads to following hypothesis:

H2: Return of European crude oil prices have a positive effect on European clean technology stock returns.

2.4.3 Return of carbon prices

Carbon pricing refers to the exercise of levying carbon- and/or greenhouse gas emissions. In general, carbon pricing policies can be either price-based, by applying a carbon tax, or quantity-based, by means of cap-and-trade. In the first policy, a carbon tax is levied on, and linked to the level of, the distribution, sale or use of fossil fuels. A carbon tax increases the cost of fossil fuels and so tends to encourage the implementation of less carbon-intensive alternatives (OECD, 2015). The second policy is a quota-based policy, referred to as cap-and-trade. Under this policy, allowable levels of carbon dioxide and other greenhouse gas emissions are determined, or 'capped'. Hereafter, an emission market is created in which participants can buy and sell, 'trade', emission-allowances that are originally allocated or auctioned among participants. The cap-and-trade policy tends to ensure 'emissions are cut where it costs least to do so' and it, again, encourages the implementation of less carbon-intensive alternatives (EU, 2015).

Despite the fact that, in the far past, these approaches have rarely proved feasible (Baumol & Oates, 1971), forty-five national and twenty-five subnational administrations levy carbon emissions in 2017 (World Bank Group, 2018). Together these policy initiatives cover, in 2017, 11 gigatons of carbon dioxide ($GtCO_2e$), equalling ca. 20% of global greenhouse emissions, compared to 8 $GtCO_2e$ or 15% in 2016. The largest carbon pricing policy, and of importance in this thesis, is the European Union cap-and-trade system, the foundation of the Union's policy against climate change (EU, 2015).

On the 1st of January 2005, the European Commission launched The European Union Emission Trading Scheme (EU ETS). EU ETS primary goal was to support European Member States in their commitment to carbon emission reduction under the Kyoto Protocol, an international treaty that commits signees to reduce greenhouse emissions. The European Union Emission Trading Scheme caps carbon emissions with the introduction of European Union Allowances (EUA). Each European Union Allowance allows its owner to emit one tonne of CO2 (EU, 2015). Within the predetermined emissions cap, a maximum amount of EUA's can be traded among market participants, thereby ensuring that the allowances carry value. At year's end, participants must be in possession of EUA's that cover their emissions.

By now, the year 2018, The European Union Emissions Trading Scheme is organised in four phases:

1. The first trading period, phase one, from 2005 to 2007, is considered to be the pilot phase. Referred to as ‘learning by doing’ (EU, 2016), during this phase EU ETS was established as the world’s largest carbon market. The price of one European Union Allowance increased to ca. €30 in April 2006, after which it fell to approximately zero (Source: ICE) in 2007 as a result of a surplus number of allowances compared to actual carbon emissions;
2. In the second trading period, phase two, from 2008 to 2012, the policy was expanded with the participation of three non-EU countries, Norway, Iceland and Liechtenstein. In response to the surplus of allowances during the first phase, the number of tradable allowances was reduced by 6.5% during phase two (EU, 2016). At first the price of one EUA increased to over €20 during the phase, after which it decreased to €10 (Source: ICE), partly as a result of the global recession which in turn reduced carbon emissions;
3. The third trading period, phase three, from 2013 to 2020, commenced by the introduction of Croatia to the program. A major change to the policy is the implementation of yearly reductions of 1.74% on carbon emissions (EU, 2016). In January 2013, European Allowances traded at approximately €4, and prices increase to over €17 in July 2018 (Source: ICE); and,
4. The fourth trading period, phase four, planned for the period from 2021 to 2030, will implement multiple additions and changes to the policy as it was implemented during the third phase. The major change will be an increase in the linear annual cap reduction from 1.74% to 2.20% (EU, 2016).

Figure 9 shows historical prices for European Union Allowances future contracts ending December 2018.

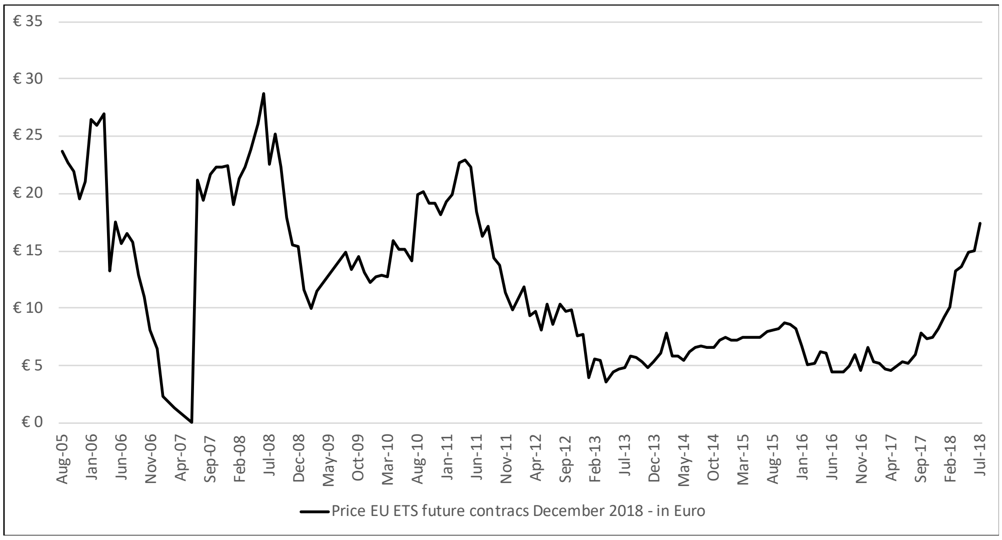

Figure 9 - Historical prices EU ETS future contracts (Intercontinental Exchange (ICE))

The concept of carbon pricing can be redirected to Pigou's 'externality'; an indirect (negative) impact of an activity (Pigou, 1932). According to Pigou, externalities can be corrected by levying activities that cause them. A so-called Pigouvian fee or tax on greenhouse emission, either price- or quantity-based, is considered to be the economically optimal policy to address climate change affairs (Jenkins, 2014). In the Pigouvian tradition, an externality-causing activity should be levied to the degree of its social impact; the levy on a certain activity (causing greenhouse emissions) is equal to the marginal social damage created by this activity (Pigou, 1932). In theory, a tax on carbon dioxide would increase the cost of electricity that is generated by means of production that cause (high) carbon emissions. Thereby, in theory, energy-generating activities causing carbon emissions are stimulated to be replaced by energy-generating activities causing less carbon emissions.

Little empirical research has been conducted to test this theory and researchers that did study the topic found contradicting results. By using a vector auto-regression model in which prices of technology stocks, oil prices and prices of carbon allowances are regressed on stock prices of clean energy firms, Kumar, Managi and Matsuda (2012) fail to demonstrate a significant relationship between carbon prices and stock prices of clean energy firms. In their study that focused on a company level of the German market, again using of a vector auto-regression model, Madaleno and Marvao Pereira (2015) do find a positive relation between a price on carbon emissions and investments in clean energy firms that produce solar energy.

Previous mentioned studies researched the linkage of carbon emission prices with clean technology stock prices instead of *return* of carbon emission prices and clean technology stock *returns*. The latter remains understudied, especially in the European case. In their study, Dutta, Bouri and Noor (2018) researched daily return and volatility linkages between the European Union Allowance prices and clean energy stock returns. Their research concluded that variations in EUA prices positively affect clean energy stock returns, however in most cases not statistically significant.

A price movement of any asset – in this hypothesis carbon allowances and clean technology stocks – implicates a (positive or negative) return of that asset. For that reason, in line with previous research and the theory discussed in the previous sections, in this thesis it is hypothesised that return of carbon prices encourages development of and investments in less carbon-intensive alternatives. This hypothesis is driven by an increased adoption of clean technology methods of generating energy stimulated by 'more expensive' (higher return) methods of generating energy capped by European Union Allowances. Return of stock prices of the clean technology sector increase as its demand increases. This leads to the following hypothesis:

H3: Return of European carbon emission prices have a positive effect on European clean technology stock returns.

3 Methodology and data

This thesis will research the relation between three macroeconomic variables and return of European clean technology companies' stock prices. The three variables included in this thesis are, in alphabetical order, the return of carbon prices, the interest rate and the return of oil prices. In this chapter the methodology and the data will be discussed that is used to test the various hypotheses.

The research question discussed in chapter 1 in this thesis is formulated as follows:

What is the influence of returns of European carbon prices, European interest rates and returns of European crude oil prices on index returns of European clean technology companies in the period 2008 – 2018?

The following hypotheses will be tested to answer the research question:

Table 1

Summary of the hypotheses that will be tested in this research

	Dependent variable
	Return of European clean technology stock prices
List of independent variables	Effect
European interest rates	+
Return of European oil prices	+
Return of European carbon prices	+

Table 1 - Summary of hypotheses

3.1 Multiple regression model

To examine the relation between macroeconomic variables and stock price development, various researchers use a variety of regression models. Park and Ratti (2008), Henriques & Sadorsky (2008) and Managi & Okimoto (2013) all use vector autoregressive models to test their hypotheses, whereas Keppler & Mansanet-Bataller (2010) use Granger causality tests to analyse the extent to which past variations of energy variables explain subsequent variations of other energy variables. Since this thesis studies a possible relationship between macroeconomic variables and stock performance, it implements a variant of the proposed multi-factor asset pricing model developed by Inchauspe et al. (2015) in their aim to study the dynamics of stock returns of renewable energy companies.

Following Managi & Okimoto (2013), Henriques & Sadorsky (2008) and (partly) Inchauspe et al. (2015), in order to reduce heteroskedasticity of all variables in the data to acceptable levels, all variables except interest rates have been transformed into natural logarithms as follows:

$$r_t = Ln\left(1 + \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)\right)$$

Where,
r_t = Return of any given variable at time week t;
P_t = Price of any given variable at time week t.

By transforming return of specific variable into logged return of that variable, return is expressed as continuously compounded return.

3.1.1 Multiple regression model

The multi-factor regression equation below follows Inchauspe et al. (2015) and is used to examine the relationship of the return of European carbon prices, European interest rates, return of European applicable crude oil prices and return of European clean technology companies' stock performance:

$ECTI_t = \beta_1\ EURIBOR_t + \beta_2\ EUETS_t + \beta_3\ OIL_t + \beta_4\ ECTI_{t-x} + \beta_5\ TECH_t + \varepsilon$

where the dependent variable is:
$ECTI_t$ = Natural logarithm of weekly return of European clean technology index
at time week t.

Where the independent variables are:
$EURIBOR_t$ = Weekly 3-month Euro Interbank Offered Rate (Euribor)
at time week t;
$EUETS_t$ = Natural logarithm of weekly return of European Union Allowances future prices
at time week t;
OIL_t = Natural logarithm of weekly return of Brent Blend Spot Prices
at time week t.

Where the control variables are:
$ECTI_{t-1}$ = Natural logarithm of weekly return of European clean technology index
at time week t-x;
$TECH_t$ = Natural logarithm of weekly return of SPDR MSCI Europe Technology ETF
at time week t;
β_1 until β_5 = coefficients of the various variables; and,
ε = error term of regression at time t.

In their research on stock performance, various researchers include lagged independent variables in their regression models. Among others, Menike (2010) uses two month lagged values of the independent variables money supply and inflation rate to test a possible relationship with stock prices in emerging markets. In this thesis the relation between European clean technology companies' stock performance is also examined with various three, six and twelve month lagged macroeconomic variables.

The statistical analysis software platform IBM SPSS is used to execute the OLS multiple regression in order to test the various hypotheses and to execute additional tests that are discussed in the following section that are needed to examine the various assumptions prior to OLS linear regression.

3.2 Dependent variable

3.2.1 European clean technology companies

As described, subject in this thesis is the WilderHill New Energy Global Innovation Index (Ticker: NEX). This index has been used in multiple previous studies on renewable and/or clean technology stock performance. The geographic focus of this thesis differs from the WilderHill NEX, since the index includes global companies, whereas this thesis focuses on European clean technology companies. To focus on European clean technology companies only, a value-weighted index by market capitalisation of European companies was constructed, which will be referred to as the European clean technology index. The index is re-weighted weekly on Wednesdays, as on this day in the week there are less chances for stock market closures because of holidays. All companies in the European clean technology index are tracked by the WilderHill NEX, thereby operating according to the WilderHill NEX objectives, and all were active during the sample period. The European clean technology index is comprised of 20 companies illustrated in Appendix A.

The return of European clean technology index is calculated on a weekly basis. Again, weekly returns are determined as per the next Wednesday closing prices.

The index is denoted in Euro (€). For companies originating outside the Eurozone, financial data of these companies are denoted in Euro against reflecting historic exchange rates. The financial data used to construct the European clean technology index is retrieved from Yahoo! Finance and is adjusted to possible stock splits and dividend payments.

3.3 Independent variables

3.3.1 Interest rate

The first independent variable that is included in this thesis is the interest rate. In line with Wang and Cai (2008), Managi and Okimoto (2013), Sadorsky (1999) and various other studies, a 3-month yield is used as the applied interest rate in the form of a 3-month Euro Interbank Offered Rate (Euribor). The historical data is retrieved from The European Central Bank.

3.3.2 Carbon price

The second independent variable that is subject in this thesis is the return of European carbon price. When studying stock return of European clean technology companies, the return of European carbon prices is the adequate reference price to take into account. As described, the European Commission levies carbon prices in their program The European Union Emission Trading Scheme (EU ETS). In line with Kumar et al. (2012) and Keppler and Mansanet-Bataller (2010), in this thesis European Union Allowances future contracts are used. The historical data is retrieved from the Intercontinental Exchange (ICE), via data-provider Quandl.
The return of European carbon prices is calculated on a weekly basis. Weekly returns are determined as per the next Wednesday closing prices.

3.3.3 Oil price

The third and final independent variable that is tested in this thesis is the return of crude oil prices. As described in the literature review, the price of crude oil is commonly constructed using a benchmark. The most widely used benchmark, and applicable to European companies, is Brent Blend. For this reason, it is the right benchmark to test the hypothesis in this thesis. Similar to El Sharif, Brown, Burton, Nixon and Russell (2005) and Madaleno and Marvao Pereira (2015), Brent Blend Spot Prices are used. The historical data is retrieved from the United States Energy Information Administration, a provider of independent statistics and analysis on energy related issues.
The return of crude oil prices is calculated on a weekly basis. Weekly returns are determined as per the next Wednesday closing prices.

3.4 Control variables

Apart from prior discussed macroeconomic independent variables, several control variables are included to test the various hypotheses in relation to European clean technology companies' stock performance. Although, these variables are not the focus of this thesis, including these control variables improves the accuracy of the hypotheses tests of the relationship between interest rates, return of carbon prices, return of oil prices and return of European clean technology stock prices.

3.4.1 Lagged index performance

As outlined in the literature review, the Efficient Market Hypothesis (EMH) suggests that stock prices change in accordance with new information that results from the process of supply and demand among investors. As a result, under the hypothesis, stock prices are priced independent of historic prices, as in price series subsequent price changes represent random departures from previous prices since historic information is already reflected in past prices. This is the concept of random walk. However, as various stock market crashes and investors that consistently 'beat the market' show, the concept of random walk is often violated. For this reason, in this thesis it is assumed to be necessary to control for this phenomenon to rightfully study the various hypotheses. In order to control for the violation of the concept of random walk, a lagged dependent variable is included as a control variable in the procedure to test the hypotheses. This (independent) control variable is the lagged (previously constructed) European clean technology index. As stated, financial data used to construct the European clean technology index is retrieved from Yahoo! Finance.

3.4.2 European technology companies

In their aim to study renewable or clean technology stock performance, various researchers include a technology stock index in their research (Kumar et al., 2012; Managi & Okimoto, 2013; Bondia et al. 2016; Henriques & Sadorsky, 2008). The general consensus among these researchers agrees upon the fact that investors view alternative energy and clean technology companies to have similarities to high technology companies. In their view, this was illustrated during the Dot-com collapse in 2000. At the time, return of stock prices of technology companies fell as the Dot-com bubble burst and, as a consequence of investor's (poor) notion of clean technology companies, the fall dragged along the stock prices of these clean technology companies. To control for this driver of clean technology stock performance a stock market index of technology companies is included in the model. In line with previously mentioned research that used the US focused Arca Tech 100 Index, in this thesis its European counterpart, the MSCI Europe Information Technology Index (Ticker: M7EU0IT), is included. This index is comprised of 21 European leading technology companies as of July 31, 2018. Constituents of the MSCI Europe Information Index are not included in the constructed European clean technology index. The financial data is retrieved from Yahoo! Finance in the form of the SPDR MSCI Europe Technology ETF (Ticker: STK.PA), an exchange traded fund traded on the Paris stock exchange that tracks the MSCI Europe Information Technology Index.

3.5 Gauss Markov Theorem

The data used in this thesis must adhere to various assumptions stated by the Grauss Markov Theorem. The Grauss Markov Theorem states that once various assumptions concerning the data used in the analysis are met, the ordinary least squares estimate for regression coefficients equals the *best linear unbiased estimate (BLUE)* possible (Gujarati & Porter, 2004). In the following paragraphs these assumptions will be discussed together with the appropriate tests that will be conducted on the data in this thesis.

3.5.1 Normality

Under the Theorem, the assumption of normality of residuals states that the data should be normally distributed. Although under the central limit theorem, the sample size used in this thesis is sufficiently large to assume normality of residuals (n > 30), P-P plots and histograms were studied to assess whether the residuals are normally distributed (De Veaux et al., 2016; Field, 2004).

3.5.2 Homoscedasticity

Under the Theorem, the assumption of homoscedasticity or homogeneity of variance states that the variance of the error term must be equal for all independent variables; the variance of the error term does not depend on the values of the independent variables (Field, 2004). A violation of this assumption, meaning the data is heteroscedastic, can result in biased estimates of the coefficients of the various variables and therefor unreliable hypotheses testing. Scatterplots of the standardised residuals on the standardised predicted values were studied to examine whether the data is homoscedastic.

3.5.3 Independence of residuals

Under the Theorem, the assumption of independence of residuals states that there must be no correlation between the different error terms, which excludes all forms of autocorrelation. Violation of this assumption will result in invalid significance tests (Field, 2004). The Durbin-Watson statistic is often used to detect possible autocorrelation and is applicable in this research.

3.6 Multicollinearity

Not part of the Gauss Markov Theorem, but important in linear regression models is the concept of multicollinearity. Perfect collinearity between two independent variables exists when on independent variable is a perfect linear combination of other independent variables; they have a correlation coefficient of 1 (Field, 2004). When multicollinearity exists, it can result in wrongfully (statistical) insignificance of independent variables as it is difficult to assess what an independent variable's coefficient means in the multiple regression, since it is possibly a result of collinearity with a second independent variable. To detect possible multicollinearity a correlation matrix of the various independent variables is included in further segments of this thesis. Additionally, the variance inflation factor (VIF) analysis is conducted. The VIF is widely used as a measure of the magnitude of multicollinearity. Since no method exists to determine whether VIF is too large, and therefor multicollinearity may be present, a rule of thumb is introduced by, among others, Menard (2002) and Hair, Anderson, Tatham and Black (1995).

Whenever the variance inflation factor values are higher than 10, serious multicollinearity exists. In the regression model that is used in this thesis two control variables are included that, by their nature, will be collinear. Since this thesis does not focus on these control variables but includes them merely to control for the concept of random walk (lagged index performance) and investor's (poor) notion (European technology companies), collinearity between these control variables and corresponding high VIF values can be neglected.

3.7 Sample period and size

This thesis studies the relation between macroeconomic variables and European clean technology companies' stock performance for the period starting April 7, 2008 and ending June 30, 2018. This period is chosen as it covers the start date of the launch of the second trading period of The European Union Emissions Trading Scheme, and includes the most recently available data.

In line with Wang and Cai (2018), Kumar et al. (2012), Managi and Okimoto (2013), Henriques and Sadorsky (2008) and various other researchers, the data set includes weekly observations. The sample size that is used in the procedure of testing the various hypotheses sums up to 536 observations for the entire sample period. Similar to prior research, Wednesday closing prices were used in the hypotheses testing to maximize sample size, as in general there are fewer holidays on Wednesdays then Fridays. If however, again similar to prior research, observations in the data are missing due to for example holidays, these data are replaced by their nearest, subsequent daily closing values.

The first part of the sample period covered disturbing times and a period of general economic and financial decline in both the financial crisis of 2008 and the latter Euro-crisis. To gain additional knowledge about the relation between the various tested variables and their association during this deviating period, the sample period is divided in two sub-periods. The first sub-period lasts from April 7, 2008 until December 31, 2012 and includes the crises. The second sub-period lasts from January 1, 2013 until June 30, 2018 and includes economic recovery.

4 Results

In this chapter the results of the statistical tests to examine the relation between interest rates, carbon prices, oil prices and the return of clean technology companies' stock prices will be presented. The first section will discuss the descriptive statistics of the various variables and the results of the various tests that are conducted to test the assumptions stated by the Gauss Markov Theorem and the concept of multicollinearity. Hereafter, the empirical results of the constructed multi-factor regression are presented.

4.1 Descriptive statistics

Table 2 provides the descriptive statistics of the various variables for the entire sample period. Appendix B includes descriptive statistics of the various variables for the separate time spans within the sample period.

Table 2

Descriptive statistics - number, minimum, maximum, mean, standard devaition, skewness and kurtosis of the logged return of European clean technology index, European interest rates, logged return of European carbon prices, logged return of European oil prices, 1-month lagged logged return of European clean technology index and logged return of the European technology index. Corrected for data points outside of 1,5 times the inter-quartile range of the first and third quartile.

	n	Min	Max	M	SD
Logged return of European clean technology index (LnINDEX)	507	-0.0386	0.0362	0.0005	0.0141
European interest rates (RATE)	495	-0.0033	0.0231	0.0034	0.0060
Logged return of European carbon prices (LnCARB)	502	-0.0596	0.0534	0.0002	0.0208
Logged return of European oil prices (LnOIL)	513	-0.0495	0.0434	-0.0009	0.0171
1-month lagged return of LnINDEX (1M LnINDEX)	503	-0.0386	0.0362	0.0005	0.0141
Logged return of European technology index (LnTECH)	511	-0.0268	0.0293	0.0017	0.0109

Table 2 - Descriptive statistics

To correct for outliers in the data, all variables are corrected for observations outside of 1.5 times the inter-quartile range of the first and third quartile.

Following Henriques and Sadorsky (2008), as table 2 shows, the average annual return of the European clean technology index obtained by multiplying the average weekly continuously compounded return by a factor of 52, was 2.44%. For European interest rates this was 0.34%, for the return of European carbon prices 1.28%, for the return of European oil prices –2.91% and for the return of the European technology index 9.24%. Possible deviations result from rounding numbers to three decimal points.

The results for the clean technology index differentiate from Henriques and Sadorsky who found an average annual return for the WilderHill Clean Energy Index of 0.84%. Although the results are not comparable as Henriques and Sadorsky focused on the American market in a different time span, prior to the time horizon in this research, it does imply a more recent shift from investors to clean assets. The minimum weekly return of – 3.87% was noted in June 2015, whereas the maximum weekly return of 3.62% was noted in March 2016. Henriques and

Sadorsky find minimum and maximum weekly compounded returns of -13.79% and 18.18% respectively, but they do not correct for outliers. Based on weekly observations, Kumar, Managi and Matsuda (2012) find weekly compounded excess returns for the WilderHill Clean Energy Index of 0.03. When multiplied by 52 the average annual return equals 1.73% (rounded), which is closer to the annual return found in this research. Kumar et al. focus on the time span between April 2005 and November 2008, prior to the time span from this research. Again, this can be explained by a shift from investors to clean asset investing.

From the variables used in this research, the return of European carbon prices is perceived to yield the highest risk given the highest standard deviation 2.08%. Kumar et al. (2012) find a standard deviation of 5.84%, by which they imply the asset to be yielding a higher risk. They, however, again, do not correct for outliers.

Although, this research and Inchauspe et al. (2015) focus on different time horizons and use different proxies for oil prices (e.g. European vs. American), the perceived riskiness of the oil denoted variable is approximately similar. In this research the standard deviation equals 1.71% and in the research of Inchauspe et al. this is 1,00%.

The average annual return of the European technology index equals 9.24%, thereby yielding the highest return of the variables that are included in this research. Kumer et al. (2012) include a different proxy (i.e. the Arca Tech 100 Index) for this control variable in their research and find an average annual return of –3.12%. The researchers focus on the years 2005 till 2008, in which returns on investments of technology assets crashed during the financial crisis which can be an explanation of the negative return. By comparison, Henriques and Sadorsky (2008), who focus on the years 2001 till 2007, find an annual average return of 1.52% for the Arca Tech 100 Index.

Figure 10 shows a time series plot of the weekly compounded return of the European clean technology index, interest rates, the weekly compounded return of carbon prices, the weekly compounded return of oil prices and the weekly compounded return of the European technology index. For the ease of comparison, each series is set equal to 100 on April 8, 2008. The plotted results are controlled for outliers, for which reason the development of the interest rate shows a flat pattern over time. The plotted results make clear that the return of the European technology index is highest over time, whereas the return of oil prices fall from late 2014 onwards, see also figure 8.

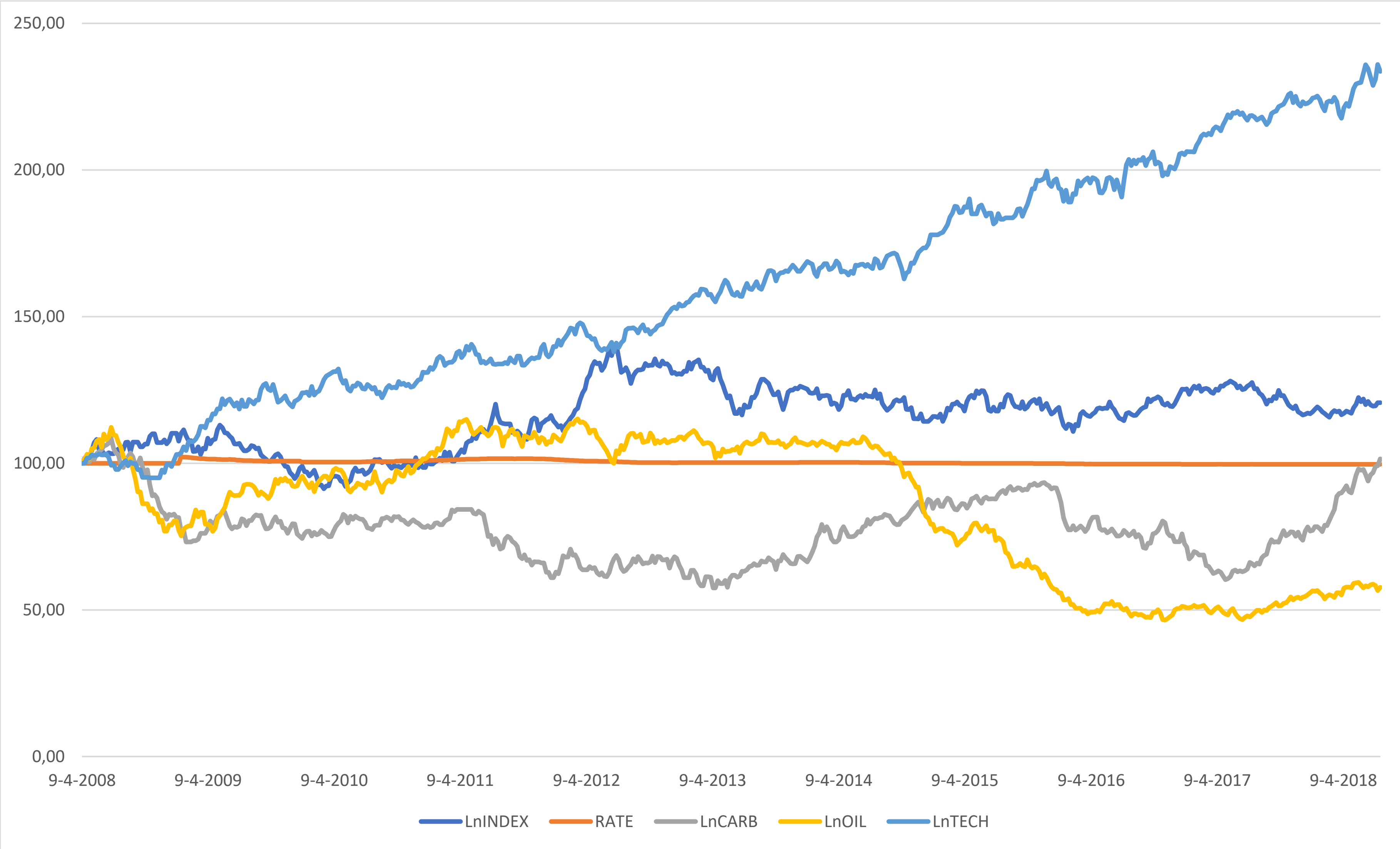

Figure 10 - Time series plot of weekly compounded return of various variables

4.2 Gauss Markov Theorem and multicollinearity

4.2.1 Normality

The assumption of normality of residuals indicates that the data should be normally distributed. As described earlier, although under the central limit theorem, the sample size used in this thesis is sufficiently large to assume normality of residuals ($n > 30$), P-P plots and histograms also confirm normality.

4.2.2 Homoscedasticity

The assumption of homoscedasticity or homogeneity of variance indicates that the variance of the error term must be equal for all independent variables. Scatterplots suggest heteroscedasticity of the data.

4.2.3 Independence of residuals

Under the Theorem, the assumption of independence of residuals indicates that there must be no correlation between the different error terms, which excludes all forms of autocorrelation. Durbin-Watson statistics of the various regression tests included in table 4 indicate that the assumption of independence of residuals is met. The Durbin-Watson test statistic can vary between 0 and 4, with a value of 2 meaning that the residuals are not correlated. A value toward 0 indicates positive autocorrelation and a value toward 4 indicates negative autocorrelation. Values less than 1 or greater than 3 are a definite cause for concern in terms of autocorrelation (Field, 2014).

4.2.4 Unit root test

Following Henriques and Sadorsky (2008), the augmented Dickey and Fuller test is conducted to investigate the integration properties of the data. The augmented Dickey and Fuller test tests whether the data of a time series is non-stationary and can thereby not be included in a forecasting model. It is also called a unit root test, in which a time series that include a unit root has a systematic pattern that is not predictable. The augmented Dickey and Fuller test is performed using Stata. Test results are included in Appendix C and imply that all variables are stationary.

4.2.5 Multicollinearity

An important assumption in linear regression models is the absence of multicollinearity. To detect possible multicollinearity, a correlation matrix of the various variables is shown in Table 3 and the results of the variance inflation factor (VIF) analysis are included in Appendix D. Perfect multicollinearity exists once the correlation between two independent variables equals 1 or -1. In practice, this is rarely the case. Multicollinearity becomes an issue in linear regression models, once there is a high degree of collinearity between two independent variables. As a rule of thumb, high degree of collinearity is present once the correlation coefficient between two independent variables is greater than 0.8 (Midi, Sarkar & Rana, 2010; Field, 2014). Additionally, as stated, the variance inflation factor analysis is conducted. As a rule of thumb, whenever a variance inflation factor value is higher than 10, serious multicollinearity exists (Menard, 2002; Hair et al., 1995).

Table 3
Pearson's correlations

	LnINDEX	RATE	LnCARB	LnOIL	1M LnINDEX	LnTECH
LnINDEX	1					
RATE	0.105**	1				
LnCARB	-0.004	-0.101**	1			
LnOIL	0.056	0.083**	0.193***	1		
1M LnINDEX	0.051	0.085**	-0.039	0.018	1	
LnTECH	0.001	0.024	0.017	0.198***	0.061	1

Table 3 - Pearson's correlation results

, ** or * indicate significance at the 10%, 5% or 1% level respectively.*

The results in the correlation matrices show correlation coefficient values among the various independent variables of less than the critical value 0.8. The highest correlation coefficient exists between return of the European technology index and return of European oil prices (0.198) and is well below the stated critical value. A can be seen, there are two combinations significantly correlated at the 1% significance level, which are 1) the return of European carbon prices and the return of European oil prices and 2) the return of European oil prices and the return of the European technology index. Both combinations follow Kumar et al., 2012, that also find positive correlations between the different set of variables.

The results of the variance inflation factor analysis included in Appendix D show values of less than the critical value 10 and no possible VIF values (i.e. higher than 8) that may cause concern in terms of multicollinearity.

It must be stressed that in terms of multicollinearity, collinearity between control variables can be neglected as this thesis does not focus on these control variables but includes them merely to control for the concept of random walk (lagged index performance) and investor's (poor) notion (European technology companies). Since all indicators of possible multicollinearity illustrate that multicollinearity does not cause for concern, this assumption is met.

4.3 Regression results

In this section, the resulting coefficients from the regression analysis are presented and discussed. It will start with the presentation and discussion of the regression results of the full period sample, covering the full sample period of 7-4-2008 until 30-6-2018, whereafter it will continue with the regression results of sub period 1 (i.e. 7-4-2008 until 31-12-2012) and sub period 2 (i.e. 1-1-2013 until 30-6-2018).

4.3.1 Full period: April 7, 2008 – June 30, 2018

Table 4

OLS regression results, in which logged return of the European clean technology index is the dependent variable and European interest rates, logged return of European carbon prices and logged return of European oil prices are independent variables. 1-month lagged logged return of the European clean technology index and the logged return of the European technology index are control variables.

	Full period 7-4-2008 - 30-6-2018				
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.000	-0.000	0.000	-0.000	0.001
	(-0.230)	(-0.092)	(0.421)	(-0.130)	(0.917)
RATE	0.230*				
	(1.932)				
LnCARB	-0.001				
	(-0.037)				
LnOIL	0.041				
	(0.960)				
1M RATE		0.245**			
		(2.009)			
1M LnCARB		-0.032			
		(-0.971)			
1M LnOIL		0.003			
		(0.071)			
3M RATE			0.144		
			(1.195)		
3M LnCARB			-0.033		
			(-0.951)		
3M LnOIL			0.060		
			(1.394)		
6M RATE				0.191	
				(1.624)	
6M LnCARB				-0.038	
				(-1.121)	
6M LnOIL				-0.027	
				(-0.636)	
12M RATE					0.086
					(0.701)
12M LnCARB					-0.008
					(-0.231)
12M LnOIL					0.108**
					(2.423)
1M LnINDEX	0.044	0.049	0.042	0.045	0.054
	(0.859)	(0.932)	(0.795)	(0.872)	(1.015)
LnTECH	-0.017	-0.012	-0.013	-0.023	0.017
	(-0.264)	(-0.182)	(-0.204)	(-0.337)	(0.246)
Adjusted R^2	0.003	0.004	0.000	0.002	0.008
Observations	405	403	395	388	361
Durbin Watson	2.010	1.953	2.034	2.053	2.086

*Table 4 - OLS Regression results full period. *, ** or *** indicate significance at the 10%, 5% or 1% level respectively. T-statistics are denoted in parenthesis.*

The results of the OLS regression for the full period from 2008 until 2018 show significant regression coefficients for variables in regression models 1, 2 and 5. In model 1, Euribor rates signal to be positive related to the return of the European clean technology index at the 10% level (0.230), whereas in model 2, one month lagged Euribor rates signal to be positive related to the return of the European clean technology index at the 5% level (0.245). The results in model 5 imply that the twelve month lagged return of European oil prices is positive related to the return of the European clean technology index at the 5% level (0.108). The results indicate that the return of European carbon prices are not significantly related to the return of the European clean technology index.

4.3.2 Sub period 1: April 7, 2008 – December 31, 2012

Table 5

OLS regression results, in which logged return of the European clean technology index is the dependent variable and European interest rates, logged return of European carbon prices and logged return of European oil prices are independent variables. 1-month lagged logged return of the European clean technology index and the logged return of the European technology index are control variables.

	Sub period 1 7-4-2008 - 31-12-2012				
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.003	-0.003	-0.001	0.000	0.006*
	(-1.252)	(-1.037)	(-0.322)	(0.149)	(1.843)
RATE	0.547**				
	(2.039)				
LnCARB	-0.008				
	(-0.139)				
LnOIL	0.018				
	(0.231)				
1M RATE		0.549*			
		(1.968)			
1M LnCARB		-0.001			
		(-0.010)			
1M LnOIL		-0.045			
		(-0.637)			
3M RATE			0.255		
			(0.958)		
3M LnCARB			-0.054		
			(-0.892)		
3M LnOIL			0.084		
			(1.180)		
6M RATE				0.197	
				(0.708)	
6M LnCARB				-0.038	
				(-0.625)	
6M LnOIL				-0.115	
				(-1.553)	
12M RATE					-0.317
					(-1.072)
12M LnCARB					-0.025
					(-0.345)
12M LnOIL					0.150*
					(1.798)
1M LnINDEX	0.052	0.016	0.068	0.037	0.056
	(0.639)	(0.190)	(0.827)	(0.446)	(0.616)
LnTECH	-0.022	0.001	-0.055	-0.055	-0.008
	(-0.212)	(0.005)	(-0.554)	(-0.512)	(-0.068)
Adjusted R^2	0.001	0.027	-0.006	-0.007	0.035
Observations	169	165	161	150	126
Durbin Watson	1.886	1.811	1.960	2.015	1.978

*Table 5 - OLS Regression results sub period 1. *, ** or *** indicate significance at the 10%, 5% or 1% level respectively. T-statistics are denoted in parenthesis.*

The results of the OLS regression for the sub period 1 from 2008 until 2012 show again significant regression coefficients for variables in regression models 1, 2 and 5. In model 1, Euribor rates signal to be positive related to the return of the European clean technology index at the 5% level (0.547), whereas in model 2, one month lagged Euribor rates signal to be positive related to the return of the European clean technology index at the 10% level (0.549). The results in model 5 imply that the twelve month lagged return of European oil prices is positive related to the return of the European clean technology index at the 10% level (0.150). The results indicate that the return of European carbon prices are not significantly related to the return of the European clean technology index.

4.3.3 Sub period 2: January 1, 2013 – June 30, 2018

Table 6

OLS regression results, in which logged return of the European clean technology index is the dependent variable and European interest rates, logged return of European carbon prices and logged return of European oil prices are independent variables. 1-month lagged logged return of the European clean technology index and the logged return of the European technology index are control variables.

	Sub period 2 1-1-2013 - 30-6-2018				
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.000	-0.000	0.000	-0.000	0.000
	(-.326)	(-0.080)	(0.220)	(-0.448)	(0.160)
RATE	-0.136				
	(-0.399)				
LnCARB	0.012				
	(-0.293)				
LnOIL	0.052				
	(1.013)				
1M RATE		-0.075			
		(-0.216)			
1M LnCARB		-0.050			
		(-1.243)			
1M LnOIL		0.036			
		(0.675)			
3M RATE			-0.025		
			(-0.068)		
3M LnCARB			-0.017		
			(-0.390)		
3M LnOIL			0.039		
			(0.707)		
6M RATE				-0.133	
				(-0.403)	
6M LnCARB				-0.035	
				(-0.874)	
6M LnOIL				0.026	
				(0.496)	
12M RATE					-0.031
					(-0.127)
12M LnCARB					-0.003
					(-0.080)
12M LnOIL					0.076
					(1.445)
1M LnINDEX	0.026	0.076	0.016	0.046	0.047
	(0.398)	(1.087)	(0.221)	(0.696)	(0.717)
LnTECH	-0.006	-0.025	0.021	0.012	0.036
	(-0.075)	(-0.297)	(0.239)	(0.143)	(0.433)
Adjusted R^2	-0.014	-0.008	-0.019	-0.015	-0.01
Observations	236	238	234	238	235
Durbin Watson	2.165	2.091	2.112	2.164	2.209

*Table 6 - OLS Regression results sub period 2. *, ** or *** indicate significance at the 10%, 5% or 1% level respectively. T-statistics are denoted in parenthesis.*

The results of the OLS regression for the sub period 2 from 2013 until 2018 show no significant regression coefficients. The results indicate that none of the independent variables is significantly related to the return of the European clean technology index in this time horizon.

4.4 Hypothesis 1

In this section, hypothesis 1 will be tested and discussed in line with the relevant coefficients. Hypothesis 1 is formulated as follows:

H1: European interest rates (3-month Euribor) have a positive effect on European clean technology stock returns.

In this thesis it is hypothesised that, through the theory of monetary policy, in which an expansionary policy aims to stimulate economic activity by lowering interest rates and a contractionary policy aims to restrain economic activity by increasing interest rates, investors tend to switch to equity and fixed-return bonds respectively. This would lead to a negative relation between European interest rates and European clean technology stock prices.

The majority of the resulting coefficients fail to show a significant relation between European interest rates and the return of European clean technology stocks. Only regression model 1 and 2 indicate a positive relation between both variables in the full period from 2008 – 2018 and in sub period 1 from 2008 – 2012. In the full period (table 4, model 1), Euribor rates are positive related to the return of the European clean technology index at the 10% level (0.230) and (table 4, model 2) one month lagged Euribor rates are positive related to the return of the European clean technology index at the 5% level (0.245). In sub period 1 (table 5, model 1), Euribor rates are positive related to the return of the European clean technology index at the 5% level (0.547) and (table 5, model 2) one month lagged Euribor rates are positive related to the return of the European clean technology index at the 10% level (0.549). These results are opposed by Bondia et al. (2016), who find bi-directional (negative) causality between interest rates and stock prices of alternative energy companies, which they explain by the relation between stocks and bonds as investment alternatives. Although these researchers find support for this relation for both non-lagged and lagged interest rates, the relation between the latter and stock prices of alternative energy companies is assumed ‘stronger’. In line with Bondia et al., the resulting coefficients in this research indicate a stronger one month lagged relation between the two in the full period from 2008 – 2018 than the non-lagged relation. Also, Henriques and Sadorsky (2008) support a negative relation between interest rates and alternative energy stocks in their study on the United States market. Again, they find stronger support for lagged interest rates, and explain this by their statement that interest rates are a lagging economic indicator.

Contrary, but similar to most results in this thesis, Madaleno and Marvao Pereira (2015) fail to signal a significant relation between European interest rates and European clean technology stock prices. They justify their results by the low interest rates in recent years of their sample period and the impact of the crises on overall investments levels. This explanation upholds for the lack of relation among Euribor rates and return of European clean technology stocks in the second sub-period from 2013 – 2018, when interest rates where at the lowest in the sample period (figure 7). As investment levels increased after 2012 (figure 1), while interest rates decrease even further (figure 7), one would assume a significant negative relation in the second sub period (table 6) to occur. This is not the case.

4.5 Hypothesis 2

In this section, hypothesis 2 will be tested and discussed in line with the relevant coefficients. Hypothesis 2 is formulated as follows:

H2: Return of European crude oil prices have a positive effect on European clean technology stock returns.

In this thesis it is hypothesised that, through the theory of substitution, an increase in return of crude oil prices encourages investments in clean technology assets. This would translate in a positive relation between the return of European crude oil prices and the return of European clean technology stock prices.

The majority of the resulting coefficients fail to show a significant relation between European crude oil prices and European clean technology stock prices. Only regression model 5 indicates a significant positive relation between both variables in the full period from 2008 – 2018 and in sub period 1 from 2008 – 2012. In the full period (table 4, model 5), twelve month lagged return of European oil prices is positive related to the return of the European clean technology index at the 5% level (0.108) and in sub period 1 (table 5, model 5) it is positive related at the 10% level (0.150). Bondia et al. (2016) fail to prove a significant relation between oil prices and alternative energy stock prices in the long run. In their study on the international market in which they, contrasting to this thesis, apply the benchmark West Texas Intermediate as the appropriate oil price. They suggest that they were unable to signify such a relation since the adoption of alternative energy is not a result of increasing oil prices in the long run. This thesis applied Brent Blend spot prices, which is the applicable benchmark to test its relation with clean technology stock returns in a European setting, but still the majority of the results fail to show a significant relation. This thesis was therefore unable to refute Bondia et al. (2016) suggestion that the adoption of alternative energy is not a result of increasing oil prices.

However, the significant positive relation in the full period 2008 – 2018 that was identified in this thesis, is confirmed by a number of researchers. In their paper, in which they analyse the relationships among oil prices, clean energy stock prices and technology stock prices, Managi and Okimoto (2013) find a positive lagged relation between oil prices and clean energy stock prices for the period after 2007. Inchauspe et al. (2015) implement a multi-factor asset pricing model and find a positive relation between crude oil prices and excess return of renewable energy stocks. Both studies identified 2007 as a turning point, at which, according to the authors, structural changes affected the relationship between oil prices and clean energy market. After this year the relation between the price of crude oil and renewable energy stock prices became significant, which coincides with a spike in the crude oil price (figure 8), suggesting a positive short-term effect. As an explanation, Inchauspe et al. (2015) suggest that investors' perception of crude oil prices to be an important factor in their investments decisions in renewable energy took shape after this spike in the crude oil price. The empirical results from multiple regression model 5 used in this thesis confirm these findings and may possibly be caused by alternating investors' perception of the importance of crude oil prices.

4.6 Hypothesis 3

In this section, hypothesis 3 will be tested and discussed in line with the relevant coefficients. Hypothesis 3 is formulated as follows:

H3: Return of European carbon emission prices have a positive effect on European clean technology stock returns.

In this thesis it is hypothesised that, through the theory of substitution, in which substitute commodities are replaceable as a result of changing conditions such as an increase in costs, in theory, energy-generating activities causing carbon emissions are replaced by energy-generating activities causing less carbon emissions. This would lead to a positive relation between the return of European carbon prices and the return of European clean technology stock prices.

The resulting coefficients fail to indicate a relation between the return of European carbon emission prices and the return of European clean technology prices. This is in accordance with Kumar, Managi and Matsuda (2012), who fail to demonstrate a significant relationship between carbon prices and stock prices of clean energy firms. These researchers used a vector-auto regression model in which, among others, prices of carbon allowances are regressed on stock prices of clean energy firms and they provide two reasons for the absence of a relation in their research: (1) they regress European carbon prices on United States clean energy stocks and (2) carbon prices used in their research are low and therefore not instrumental to stimulate the switch from fossil fuels to clean technologies. Although this thesis includes geological similarity of both it fails to indicate a significant relation. In addition, Madaleno and Marvao Pereira (2015) also fail to demonstrate a significant relation, as they illustrate that carbon prices do not

Granger cause stock prices of clean energy firms, except for solar companies. These researchers also argue that the absence of a significant relation might be due to the fact that carbon prices are too low to stimulate the switch.

Although not significant, in this thesis, for the European case, it is demonstrated that return of carbon emission prices are negatively – but not significant – related to the return of clean technology stock prices as almost all coefficients snow negative values. The literature suggests two possible arguments, that are also applicable to these findings, for this circumstance: (1) the idea that, as Oberndorfer (2009) suggests, increasing carbon prices occur during economic prosperity in which fossil fuels are still preferred over clean technologies, which might result in decreasing investments (demand) in clean technologies, and (2), the fact that clean technology stock prices are known to underperform in economic downturn (Inchauspe et al., 2015).

5 Conclusion

In this chapter, the research question formulated in the introduction of this thesis will be answered. The research question is formulated as follows:

What is the influence of European interest rates, returns of European crude oil prices and returns of European carbon prices on index returns of European clean technology companies in the period 2008 – 2018?

To answer this research question various hypotheses have been tested using ordinary least squares multiple regression models that tested the relation between the non-lagged and lagged independent variables Euribor rates, return of European crude oil prices and return of European carbon prices, with the dependent variable return of European clean technology stock prices. The regression models were controlled for 1-week lagged influence of return of the European clean technology companies stock prices and return of European technology companies stock prices.

Hypothesis 1, in which European interest rates are considered to be positively related to the return of European clean technology stock prices, is partially supported by the empirical results. European interest rates, exemplified by a 3-month Euro Interbank Offered Rate (Euribor), are non-lagged and one month lagged positively related to the return of European clean technology stock prices in the full period 2008 – 2018 and in sub period 1 2008 – 2012. Hypothesis 2, in which the return of European crude oil prices are considered to be positively related to the return of European clean technology stock prices, is partially supported by the empirical results. Twelve month lagged return of European crude oil prices, exemplified by the benchmark applicable to the European case, Brent Blend spot prices, are positively related to the return of European clean technology stock prices during the full period 2008 – 2018 and sub period 1 2008 – 2012. Hypothesis 3, in which the return of European carbon emission prices are considered to be positively related to the return of European clean technology stock prices, is not supported by the empirical results. Return of European carbon prices, exemplified by capped carbon emissions under the European Union Emission Trading Scheme, are not significantly related to the return of European clean technology stock prices.

The empirical results from this thesis are of particular interest to two groups of people, (1) European (environmental) policy makers and (2) (sustainable) investors. In times of increased awareness about climate change and its consequences, the first group of people is interested in factors that drive renewable energy or clean technology adoption. This thesis provides insight in such relations between three variables and clean technology stock prices in the European market. For instance, the European Union introduced the European Union Emission Trading Scheme (EU ETS), under which carbon emissions are capped and priced in order to stimulate reduction of greenhouse emissions. One way to reduce emissions is the adoption of renewable energy or clean technology, however the results in this thesis clarify that, so far, the introduction of European carbon prices fails to stimulate this adoption and therefore should be reconsidered.

The second group, (sustainable) investors, seeks investments that provide both their required rate of return, but also promote a greener environment. These investors are therefore particularly interested in investment opportunities in renewable energy or clean technology. This thesis provides insight in these opportunities as it subjects the relation between three variables and the return of clean technology stock prices in the European market. Empirical results indicate that investors should closely monitor Euribor rates, which appear to have non-lagged and a one month lagged positive relation with the return of European clean technology stock prices. Besides, information regarding the return of Brent Blend oil prices, may possess valuable information.

5.1 Limitations and future research

Although the empirical results of this thesis stem from a robust econometric method as the OLS regression, some limitations did occur. These limitations, in random order, are:

1. Simplicity of an ordinary least squares (OLS) regression: Although frequently used because of its simplicity and applicability, OLS regression’s simplicity does has its limitations. OLS regression is rather static compared to more advanced stochastic process models such as a vector autoregression (VAR). In a VAR each variable that is included in the model is explained by its own lagged values and lagged values of the other variables included in the model, whereas OLS only depicts a one-way relationship. Future researchers are recommended to include these more advance models;
2. Survivorship bias: As a form of selection bias, survivorship bias is the error of concentrating on elements that survived selection criteria. In this thesis possible survivorship bias occurred in the construction of the European clean technology index, which may have resulted in skewed estimates. Since due to the limited scope of this thesis it was not possible to do so, future researchers are advised to overcome possible survivorship bias by closely monitoring the historic development of existing stock indices before constructing an applicable index; and,
3. Limited lagged influence: This thesis focused on the relation between Euribor rates, the return of European crude oil prices and the return of European carbon prices with the return of European clean technology stock prices, only on a maximum lagged level of 12 months. Because of the nature of the independent variables it is very well possible that a significant (valuable) relation occurs outside the scope of 12 months. As this thesis is limited in exploring these possible relations, future researchers are advised to implement ‘longer’ lagged variables to explore them.

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Appendix A. European clean technology index

1. Ricardo Plc.
2. Dialight Plc.
3. Gurit Holding AG
4. Encavis AG
5. Verbund AG
6. NIBE AB
7. Kingspan Group Plc.
8. Vestas Wind System A/S
9. Novozymes A/S
10. PNE AG
11. Albioma
12. Nordex SE
13. Falck A/S
14. Nel ASA
15. Siemens AG
16. Drag Group Plc.
17. REC Silicon ASA
18. CropEnergies AG
19. Verbio AG
20. Meyer Burger Technology AG

Appendix B. Descriptive statistics

Descriptive statistics - number, minimum, maximum, mean, standard devaition, skewness and kurtosis of the logged return of European clean technology index, European interest rates, logged return of European carbon prices, logged return of European oil prices, 1-month lagged logged return of European clean technology index and logged return of the European technology index. Corrected for data points outside of 1,5 times the inter-quartile range of the first and third quartile.

	7-4-2008 - 31-12-2012				
	n	Min	Max	M	SD
Logged return of European clean technology index (LnINDEX)	229	-0.036	0.036	0.001	0.016
European interest rates (RATE)	206	0.002	0.023	0.009	0.005
Logged return of European carbon prices (LnCARB)	234	-0.059	0.050	-0.002	0.021
Logged return of European oil prices (LnOIL)	235	-0.050	0.043	0.001	0.018
1-month lagged return of LnINDEX	225	-0.036	0.036	0.001	0.016
Logged return of European technology index (LnTECH)	225	-0.268	0.029	0.002	0.012

	1-1-2013 - 30-6-2018				
	n	Min	Max	M	SD
Logged return of European clean technology index (LnINDEX)	278	-0.039	0.036	0.000	0.013
European interest rates (RATE)	289	-0.003	0.003	-0.001	0.002
Logged return of European carbon prices (LnCARB)	268	-0.060	0.053	0.002	0.021
Logged return of European oil prices (LnOIL)	278	-0.048	0.042	-0.002	0.016
1-month lagged return of LnINDEX	278	-0.039	0.036	0.000	0.013
Logged return of European technology index (LnTECH)	286	-0.027	0.029	0.002	0.010

Appendix C. Augmented Dickey and Fuller

*Augmented Dickey and Fuller test results - *, ** or *** indicate significance at the 10%, 5% or 1% level respectively.*

	ADF
Logged return of European clean technology index (LnINDEX)	-21.388***
European interest rates (RATE)	-3.844**
Logged return of European carbon prices (LnCARB)	-19.315***
Logged return of European oil prices (LnOIL)	-20.165***
1-month lagged return of LnINDEX (1M LnINDEX)	-21.596***
Logged return of European technology index (LnTECH)	-23.443***

Appendix D. Variance inflation factor

Collinearity statistics - Variance inflation factor

	1			2			3			4			5		
	7-4-2008	7-4-2008	1-1-2013	7-4-2008	7-4-2008	1-1-2013	7-4-2008	7-4-2008	1-1-2013	7-4-2008	7-4-2008	1-1-2013	7-4-2008	7-4-2008	1-1-2013
	30-6-2018	31-12-2012	30-6-2018	30-6-2018	31-12-2012	30-6-2018	30-6-2018	31-12-2012	30-6-2018	30-6-2018	31-12-2012	30-6-2018	30-6-2018	31-12-2012	30-6-2018
RATE	1.028	1.039	1.011												
LnCARB	1.056	1.069	1.066												
LnOIL	1.093	1.150	1.076												
1M RATE				1.018	1.024	1.011									
1M LnCARB				1.048	1.040	1.078									
1M LnOIL				1.049	1.018	1.077									
3M RATE							1.030	1.041	1.018						
3M LnCARB							1.072	1.084	1.083						
3M LnOIL							1.061	1.050	1.065						
6M RATE										1.026	1.032	1.011			
6M LnCARB										1.034	1.038	1.055			
6M LnOIL										1.048	1.024	1.051			
12M RATE													1.036	1.063	1.017
12M LnCARB													1.053	1.106	1.063
12M LnOIL													1.071	1.073	1.048
1M LnINDEX	1.012	1.032	1.003	1.010	1.012	1.010	1.026	1.026	1.039	1.004	1.003	1.008	1.013	1.036	1.009
LnTECH	1.045	1.028	1.010	1.006	1.012	1.012	1.004	1.014	1.001	1.007	1.002	1.017	1.012	1.006	1.015