Residual Momentum in the Clean Technology Sector

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Abstract: As a result of humanity slowly depleting natural resources and using polluting processes our globe is facing numerous environmental problems. Given the enormous challenges, investing in cleantech is highly necessary and will most likely increase in the following years. Correspondingly, it is relevant to investigate how equity investing in a socially responsible and sustainable way can be profitable. To measure profitability in equity investing in the cleantech subsegment of the market, this thesis firstly evaluates the performance of 19 cleantech indices representative of the sector. This study claims that investing in cleantech market indices proves to be a poor decision from a profit perspective as most of the indices underperform the market. This is especially appropriate when looking at the risk adjusted results. What is more, clean technology indices tend to be more sensitive to market turmoil. Subsequently, using the equity pool of the indices I construct two profitable ways of investing in the sector. Using the momentum anomaly based on total return and residual return one can achieve substantial abnormal returns. Both strategies prove to be superior to the available cleantech indices or holding the whole sector. Finally, in line with existing literature, the residual momentum strategy beats the simple momentum strategy as it delivers higher risk adjusted returns and due to the lack of factor exposures exhibits significantly shorter and lower drawdown at market turmoil.

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1. Introduction

Our globe is currently facing several environmental issues such as decreasing biodiversity, air pollution, ocean pollution, deforestation, climate change and stratospheric ozone depletion just to mention a few. In the last several decades, humanity slowly exploited the planet. There is a vast amount of evidence that for instance the impacts of climate change are happening in a faster pace than initially expected. In 2019, the global average temperature was 1.1 °C above the 1850-1900 base line of pre-industrial levels, increasing in a range of 0.1 °C -0.3 °C per decade. One of the main drivers of climate change are the increasing levels of greenhouse gases in the atmosphere such as CO_2, CH_4 and N_2O which is the result of human production and consumption. The IPCC SR15 report shows that to limit the warming 1.5 °C above pre-industrial levels by 2050 we must decrease CO_2 emissions to zero. In addition, thermal expansion from ocean warming with the combination of melting icebergs leads to sea level increase. Moreover, CO_2 also alters ocean chemistry which leads to the pH change of the oceans. Not to mention that, although, the magnitude of plastic on the surface of the open ocean is still an open debate, its effect on the biodiversity is severe. In addition, the increased occurrence of wildfires is yet another indicator of problems our globe has to encounter.

To cope with the above-mentioned environmental challenges, -especially with climate change-, governments, corporations and multinational institutions must cooperate. Environmental concerns are a global challenge that requires a global response (Rezec et al. 2017). Climate change and global warming have been gaining increasing media coverage lately, finding a way into conventional knowledge and thereby increasing attention to all environmental issues (Svoboda, 2020). Accordingly, governments all around the world have started taking a series of initiatives to address these problems. Interestingly, in the US as early as the 1960s an upswing of interest in environmental matters led to the first laws controlling environmental resources and pollution. At this time environmentalists were not influential and governmental intervention was deemed as unnecessary. Many of these early laws followed the “polluter pays” principle with linking the companies and the pollution emitted. As a result, companies essentially treated these concerns as a technical compliance or cost burden (Hoffman et al., 1999). However, in the early 1980s, as environmental activists began to pressure the polluting industries directly, getting around governments, their influence increased. Correspondingly, by the late 1980s and early 1990s investor sentiment also started to shift, thus companies started to adapt voluntary programs. This time environmental management became redefined from "technical compliance" to "proactive management" (Hoffman et al., 2001). In addition, O'Rourke (2009) describes that in the late 20th Century besides the narrative of the classical entrepreneurship and technology fueled economy a different approach was emerging. Namely, societal concern started growing over the state of the environment. This was partially driven by some large environmental disasters which ultimately led to an increasing conventional knowledge about climate change, species extinction, the ozone hole, acid rains and other global and local problems.

The European Union introduced its sustainable development strategy in 2001 which aims to improve the quality of life by environmental protection and social cohesion. In line with this, the EU 2020 strategy is trying to show the way towards sustainable growth, with shifting the economy towards a resource-efficient, low-carbon economy. Accordingly, the EU in 2019 presented the European Green Deal package which intends to decrease greenhouse gas emission with an ambition of decarbonizing the EU's economy by 2050. Notably, the union by 2018 already cut greenhouse gas emission by 23% compared 1990 and it is committed to achieving 40% by 2030. In line with the above, the EU is said to preserve biodiversity and ecosystem through its EU Biodiversity Strategy. Moreover, the union has a Water Framework Directive to restore clean water, air quality strategy which aims to achieve less air pollution, the Environmental Noise Directive to decrease noise pollution as well as several other legislations and laws to achieve a more sustainable and environmental friendly future. EU and US legislations are just examples, as we see endeavor to sustainable environmental policies worldwide with the lead of developed countries (EURlex, 2020). However, this paper does not try to evaluate the success of these policies.

Besides legislative guidelines, free-market environmentalism argues that the best possible way to protect our environment is to leave it for the free market, clarify and protect property rights, use the tort law properly, internalize pollution and conserve resources. Promoters of free-market environmentalism believe in the pricing system of free markets. They argue that when resources become scarce, prices rise which in fact incentivizes entrepreneurs to find substitutions for these scarce resources, thus making these resources conserved. As an example, if the price of oil rises entrepreneurs will look for other ways to substitute it, and we might end up driving electric cars instead. Free market supporters also believe in the power of property rights. Accordingly, owners face strong incentive to protect their property and decide how much they want to use today and preserve for tomorrow. Owners want to grow the value of their property; thus they conserve it until they can retrieve the most out of it (Stroup, 1990). Some economist also argue that industries should internalize the costs of negative externalities, thus they would have to face to reduce them and in order to increase profitability they would be forced to find innovative ways to do so (Anderson et al., 2011).

Driven by legislations and free-market environmentalism with the combination of changing consumer and thereby investor preference, we see industries shifting towards a more sustainable future. The involvement of companies in preserving the environment is crucial as these entities are the primary users of natural resources (Sarmento et al, 2006). Notably, corporate responsibility has been continuously debated. As the economist Milton Friedman (1970) famously argued that public companies possess only minimal ethical obligations beyond maximizing profit and obeying the law. Since the world has changed and accordingly the dogma is that companies should take social and environmental factors into account besides the economic motives. Nonetheless, the development of economies and social well-being accord with more consumptions and more precisely more energy consumption. As a result, the energy sector has seen one of the biggest transformations towards cleaner production in the last decades. Besides, one of the most conspicuous transformation hitting headlines is the electrification of the auto industry.

To transform industries, new sustainable technology must be invented and used. Although, there are several definitions, clean technology or in short cleantech (CT) is defined as any process, product or service that reduces negative environmental impact through the sustainable use of resources, environmental protection activities or other energy efficient ways (Rezec et al, 2017). The investment in clean technology has been receiving increasing public and professional attention since gaining spotlight at the beginning of the 2000s. Puaschunder (2016) for instance claims that the aftermath of the 2008/09 financial crisis called for social responsible investing and shed new lights on the mainstream economic theories of unregulated markets. The recapitalization of the banking system in the US following the financial crisis created a new need for reconsideration of social responsibility in the new finance world. Barack Obama in 2009 famously called out for the "Era of Responsibility" (Washington Post, 2009). As a consequence, ESG (Environmental, Social and Governance) investing, a relatively new phenomenon, which grew out of investment philosophies such as Social Responsible Investing (SRI), focuses on non-financial factors to identify growth opportunities. The center of this paper is on the E (Environmental) part of ESG investing with the focus on clean technologies.

Because of the increasing attention and investor sentiment shifting towards sustainable investing, several cleantech equity indices have been constructed worldwide. These indices focus on the following clean technology sectors: 1) wind power, 2) solar power, 3) green buildings, 4) biofuels, 5) smart grid, 6) water filtration, 7) personal transportation and 8) other solutions (Ortas et al. 2015). The performance of these indices indicate how profitable sustainable equity investing is in the stock market. Although there is an increasing spotlight on sustainable investments, given the novelty of these instruments, there is relatively limited research evaluating the performance of these indices. Ortas and Moneva (2015) report that cleantech indices outperformed the market during stable economic periods but in return these indices have a higher risk profile as well. Interestingly, the authors also show that CT indexes experience a structural break at the time of financial market collapse in 2008 with the indices becoming generally riskier than the benchmarks during this period. In addition, Rezec et al. (2017) show that renewable energy equity indices indicate relatively poor risk-adjusted performance compared to the benchmark indices. The paper concludes that renewables is not a financially attractive portfolio investment yet.

Given the enormous environmental challenges investing in the cleantech sector is highly necessary and will most likely increase in the following years. Correspondingly, it is relevant to investigate how equity investing in the stock market in a socially responsible and sustainable way can be profitable. Accordingly, this paper firstly researches whether clean tech equity indices indeed underperform the market, and therefore the first research question is:

1. **How does clean technology indices perform compared to the market?**

Besides the evaluation of the performance of cleantech indices, there is even less academic research in the asset pricing literature on the risk-return relationship of equities in the cleantech industry. Accordingly, the explanatory power of traditional asset pricing anomalies is also yet to be tested in the clean technology sectors. Some anomalies remained inconsistent with any known rational asset pricing models. Such examples include the traditional momentum anomaly. There is a vast amount of literature on the fact that trading on the momentum anomaly is profitable in most markets, asset classes and geographical regions. However, as Moskowitz et al (2013) noted the strategy tends crash in panic states following market declines when market volatility is high and are contemporaneous with market rebounds. Their paper suggests that the changing beta of the momentum portfolio may partially drive momentum crashes. Interestingly, first Gutierrez and Pirinsky (2006) and then Blitz et al (2011) show that the residual momentum trading strategy seems to be a superior strategy compared to the traditional momentum as residual momentum exhibits significantly smaller exposures to the Fama and French factors and thereby exhibits relatively stable performance during market crashes as well. Given the similar behavior of the momentum strategy and the cleantech indices, implementing a residual momentum strategy in the clean technology sector might lead to superior performance. As sustainable investing is a growing trend examining asset pricing anomalies in the sector is becoming increasingly significant. Therefore, the primarily focus of this thesis is on investigating the momentum anomaly and compare it to an improved version of it in the cleantech space. According to the above mentioned I intend to answer the following questions:

2. **Does implementing the simple momentum and residual momentum strategies using cleantech equities improve the profitability of cleantech investing?**
3. **Is the residual momentum strategy superior to the simple momentum strategy in the clean technology sector?**

This thesis contributes to the literature on investing in the relatively novel clean technology segment and in a broader term to Socially Responsible Investing (SRI) and Environmental, Social and Governance (ESG) investing. Moreover, it contributes to the existing literature in asset pricing and more precisely focused on the momentum and residual momentum anomalies.

Correspondingly, this thesis is structured as follows: Section 2 reports the most relevant literature in the clean technology sector and likewise the literature on the momentum anomaly. Following, data and methodology is presented in Section 3. Moving on to Section 4, first I report the analysis of the cleantech equity indices. Subsequently, using the equity pool from these indices I construct a buy-and-hold cleantech portfolio, a simple momentum portfolio and a portfolio based on the residual momentum strategy. In Section 5 several robustness checks are conducted. In Section 6 limitations and possible follow up researches are discussed. Section 7 concludes.

2 Literature overview

In the past, many relatively simple investing strategies have challenged the efficient markets theory by vastly outperforming the market. Momentum is one of most researched anomalies. Contrarily, the residual momentum literature is relatively small. Likewise, the literature on the clean technology segment is not too extensive. Accordingly, this section firstly discusses the relevant literature on the clean technology sector. Then, it outlines the most relevant literature on the well-established momentum anomaly.

2.1 Clean technology:

As clean technology is a relatively new asset class there is no ultimate definition perfectly describing the sector. Haldar et al. (2018) defines cleantech as the technology which minimizes undesirable effluents, emissions and waste from products and processes. According to Muralikrishna et al (2017) clean technology refers to avoiding environmental damage already at the source, through the use of materials, processes in order to ideally eliminate or more realistically reduce the creation of wastes or pollutant substances. Based on Doble et al (2007) clean technology is made up of several principles such as renewable energy, renewable raw materials, life-cycle assessment, heterogeneous catalyst, and biotechnology approach, just to mention a few. What is common in all these technologies is that it is based on pure science such as physical chemistry, chemical engineering, or synthetic organic chemistry. Thus, the segment requires engineers and scientists cooperating to create a clean environment and prevent humanity from completely depleting the flora and fauna trough the dumping of toxic chemicals. O'Rourke (2009) argues that clean technology represents the convergence of two powerful narratives of industrial development in the early 21th Century: innovation driven economic growth and at the same time environmental degradation. Clean technology symbolizes a new wave of entrepreneurial activity with the combination of innovation serving to create a more sustainable economic system. Moreover, not only is cleantech an environmental solution, but also it enables to produce efficiently.

Accordingly, this relatively new asset class caught the attention of investors as well. In a broader sense clean technology investing is the part of Socially Responsible Investing and Environmental, Social and Governance investing. SRI seeks to consider both financial return and social/environmental good. As part of SRI, investors encourage corporate practices to promote environmental change, consumer protection and human rights. SRI has evolved into means to promote environmentally sustainable development since the late 1990s. Correspondingly, many investors recognized climate change and in a wider sense all the other environmental global issues as a significant business an investment risk (Richardson et al., 2008). Based on a 2016 report by the US SIF Foundation, more than one out of every five dollars under professional management in the US was invested in SRI (FRR, 2016). ESG investing is the successor of SRI. While SRI typically used value judgements, such as financial return besides the social and environmental good, ESG looks only at the positive impacts of an investment in the three areas of environmental, social and governance factors.

Noticeably, several institutions consider the social implications of their investment decisions and it has become one of the most significant principles guiding investment strategies (Hartzmark et al, 2019). Based on 2020 Deloitte report globally ESG investing jumped from 45% in 2017 to 75% in 2019. In agreement with this, government-controlled funds such as pension funds who are often prominent large players on the market are being pressured by environmental activists as well as by citizens. One novel example is the Government Pensions Fund of Norway with approx. $1tn under management as of 2018, which is dedicated to avoiding violation of fundamental human rights or sever environment damages (Gordon et al, 2010). Furthermore, turning to mutual funds and ETF’s we see the same pattern, as over the five-year quarter period ending in 03/31/2020 sustainable investment expanded by 447% reaching $2.1 trillion under management (SustainableResearch, 2020). Cao et al. (2019) argues that this ESG preference of institutional investors led to recent mispricing and violation of market efficiency. They show that as socially responsible institutions focus more ESG factors they tend to react less to direct signals of firm value. As a consequence, these investors are less likely to buy underpriced stocks with low ESG scores or sell overpriced stocks with high ESG scores. Alongside, Hartzmark et al. (2018) shows that there is a reverse relation between fund performance and sustainability rating. Contrasting these findings, Edmans et al. (2011) argues that the 100 best companies to work for in the US exhibit higher alpha in the future as the market undervalues the intangible assets on the firms’ balance sheet. Another fascinating finding of Hong and Kacperczyk (2009) is that “sin” industries earn significantly higher abnormal returns compared to firms in other industries.

Besides pension funds, mutual funds and ETF’s holding the equities of clean technology firms already listed on the stock exchange, another way of investing in this asset class is through

Venture Capital (VC) and Private Equity (PE) funds. O'Rourke (2009) argues that the venture capital industry appraised the clean technology industry to where it stands today as cleantech emerged initially within the North American venture capital community. By 2007 clean technology was a necessity in every VC's portfolio. Accordingly, for an investor who intends to invest in clean technology in the early growth phase of cleantech firms before the venture gets listed on the stock exchange VSs and PEs are the investing vehicles. Venture Capital firms provide the initial capital needed for an idea that later might turn into a clean technology solution. Private Equity firms usually help at the later stages to expand operations. One interesting way of investing is through mezzanine debt, that is between debt and equity. These vehicles are typically not backed by the companies' assets and firms are expected to pay it back from the firm's cash flows. Private Equity firms often use this type of financing in leveraged buyouts. However, this thesis focuses only on equity investing when the clean technology firms are in a more mature phase and are already listed on the stock exchange.

To evaluate equity investing and examine the stock performance of the clean technology segment, investigating market indices is the best course of action as the right collection of market indices potentially covers the required segment of the financial market. Focusing strictly on clean technology investing the literature is relatively limited. Ortas et al (2013) when measuring the performance of 21 cleantech equity indices in the period of 2002-2011, covering primarily the energy markets worldwide find that during market stability clean technology indices outperform the market in terms of returns, but their outperformance is mainly driven by higher risk levels associated with the indices. They also find structural change in the risk return relationship during the financial crisis as clean technology indices turn even riskier during bear markets. Similarly, Rezec et al. (2017) investigate a subset of clean technology investing and they show that renewable energy equity indices display relatively poor risk-adjusted performance compared to the benchmark indices. The paper concludes that renewables is not a financially attractive portfolio investment yet. The authors also argue that renewable energy equity indices can be regarded as an example of market environmentalism. Dutta et al (2019) focuses on how equity investors can mitigate this downside risk. The authors address the issue by considering the role of commodity market volatility indices of crude oil, gold and silver. They use a dynamic conditional correlation model which shows that clean technology indices and commodity volatilities move in the opposite directions. Based on the effectiveness all three volatility indices of oil, gold and silver prove to be a good hedge.

Summarizing the literature on clean technology equity investing, there is evidence that the ESG preference of institutions led to recent mispricing and distortion of market efficiency. ESG investors are less likely to buy underpriced stocks with low ESG scores or sell overpriced stocks with high ESG score. This might be one of the drivers behind what Ortas et al. (2013) and Rezec et al. (2017) find when examining clean technology equity indices. That is, cleantech indices tend to underperform the market on a risk return basis. However, this needs further research and this thesis is mostly focused on the other findings of the authors. Namely, the structural change in the risk return relationship during the financial crisis, as clean technology indices turn even riskier during bear market. Therefore, this thesis after evaluating the performance of clean technology indices aims to structure a possible profitable investing strategy in the clean technology sector. Dutta et al. (2019) use commodity market volatility indices of crude oil, gold and silver to hedge against this downside risk. Nonetheless, this thesis recommends the residual momentum strategy.

2.2 Momentum strategy

Momentum is one of the most researched and well-established empirical facts in the asset pricing literature. Its presence and robustness have been stable over time. What is more, along with the size and value factors, the momentum factor has become one of the central questions in the market efficiency debate. Moreover, Fama and French (1996) referred to the momentum anomaly as the ‘main embarrassment of the three-factor model’.

The predominant momentum strategy established by Jegadeesh and Titman (1993, 2001) is based on past returns predicting the cross section of future returns, that is buying stocks that have performed well in the past and selling stocks that have performed poorly in the past. This generates economically significant returns over a 3- to 12-month holding periods. However, they also find that part of the abnormal return generated disappears in the next two years. What is more, as first documented by De Bondt and Thaler (1985), the momentum effect even inverts resulting in a contrarian strategy of buying past losers and shorting past winners. As a result, the momentum portfolio must be rebalanced frequently to prevent this reversal effect. Following Jegadeesh and

Titman laying out the foundation of the anomaly, many subsequent researches confirm the validity of their findings over different time periods, assets classes, markets and regions. Carhart (1997) when studying the persistence of mutual fund performance was the first who included the momentum factor in his four-factor asset pricing model, adding it to the original Fama and French (1993) three factor model. According to his findings, the four-factor model performs better than the CAPM in explaining mutual fund returns. Rouwenhorst (1998) documents that in line with the findings of Jegadeesh and Titman (1993) in the U.S. markets, the momentum factor is also present in the European markets. Chui, Titman, and Wei (2000) find similar results for the Asian markets with the outstanding exception of Japan and Korea. Later, in 2010 Chui, Titman, and Wei confirmed the absence of the momentum effect in Japan. Moskowitz and Grinblatt (1999) and Grundy and Martin (2001) investigate the industry and factor components of momentum profits.

While it has been researched massively, the jury is still out on what explains the momentum phenomenon. The ongoing academic debate ranges from compensation for risk to arguments based on investor behavior. In the latter, there are two main competing hypotheses: underreaction and delayed overreaction. According to the overreaction theory, winner (looser) stocks are overvalued (undervalued) and investors chasing returns drive prices even further away from its fundamental values until subsequently it is reversed. Jegadeesh and Titman (1993, 2001) in their original research paper argue that momentum profits are partially driven by delayed overreactions about the long-term future of the firm that are eventually reversed. Barberis, Shleifer, and Vishny (1998) discuss that delayed overreactions are due to the so called representative heuristic bias, namely when investors conclude that firms which exhibited extraordinary performance in the recent past will continue to do so in the future. Moreover, Daniel, Hirshleifer, and Subramanyam (1998) and Hong and Stein (1999) explain the delayed overreaction by the self-attribution bias. Investors due to their cognitive biases, attribute the positive performance of stocks in their portfolio to their exceptional selection skills. Consequently, investors become overconfident and push the prices even further up. This is in line with the findings of DeLong et. al. (1990) who show how positive feedback traders move prices away from their fair prices. Furthermore, Grinblatt et. al. (2001) argue that the overreaction is attributable to investors' herding behavior.

Based on the underreaction hypothesis, information diffuses slowly into prices, thus moving it just slowly to its intrinsic value. Accordingly, the slow information incorporation causes momentum. The early work of Ball and Brown (1968) show that investors tend to underreact to earnings information. Jegadeesh and Titman (1993, 2001) besides their overreaction explanation, also argue that momentum is partially driven by underreaction about the short-term information regarding the firm. This is in line with Merton (1987) who documents the limited processing ability and attention constraints of investors. Barberis, Shleifer and Vishny (1998) attribute the underreaction to conservatism bias as investors tend to underweight new information when adjusting their prior beliefs. Hong and Stein (1999) show how due to underreaction, momentum traders can profit by trend chasing. Furthermore, Grinblatt and Han (2005) document that underreaction is driven by the prospect theory with the combination of mental accounting. Namely, investors look at individual stock performance in their portfolio and make risk averse or risk loving decisions on an individual level. This results in Odean's (1998) and Barber and Odean's (2000, 2001) disposition effect, the tendency of investors selling winning investments too soon and holding loosing investments too long. Grinblatt and Han (2005) and Frazzini (2006) find similar link between the disposition effect and momentum.

Besides the over- and underreaction behavioral explanations there is a growing literature on the limits of arbitrage opportunities. Many studies examine whether implementing a momentum strategy is profitable after accounting for transaction costs. Among others, Moskowits and Grinblatt (1999), Grundy and Martin (2001) and Lesmond et al. (2004) argue that the high portfolio turnover streaming from frequent rebalancing when forming the momentum strategy offsets the profitability of the strategy. Korajczyk and Sadka (2004) find similar results when studying large investment funds.

Although most of the literature is focused on the behavioral explanations of momentum, the supporters of the efficient market theory argue that the momentum premium is simply a compensation for risk. Asness (1997) documents that momentum is more amplified among stocks with larger growth opportunities and risker cash flows. Alongside, Berk, Green and Naik (1999) also show that risk factors have an impact when firms face possible growth opportunities resulting in momentum. Pastor and Stambaugh (2003) find that liquidity risk factor accounts for about half of the momentum premium. In parallel with these findings, Sadka (2006) argues that substantial part of the momentum premium can be regarded as compensation for market-wide liquidity risk. Zhang (2004) uses time-varying risk factors to explain momentum, based on which the beta risk is changing over time, resulting in higher (lower) beta risk with higher (lower) expected returns to well (poorly) performing assets. Ahn, Conrad, and Dittmer (2003) and Chordia and Shivakumar

(2002) also find that the momentum premium might be driven by time-varying risk and macroeconomics risk. In addition, in a recent paper Stefan Ruenzi and Florian Weigert (2017) and Stefan Ruenzi, Florian Weigert and Fousseni Chabi-Y (2016) found that market crash sensitivity of individual stocks is plausible risk measure explaining the momentum premium.

To summarize, momentum is a robust well-researched anomaly in the asset pricing literature. Although a vast amount of research is trying to provide explanation for the momentum premium, the justification is still subject to debate.

2.3 Residual momentum strategy

Contrary to the conventional momentum strategy, which ranks the portfolio based on total returns, the residual momentum strategy divides the portfolio based on the residual returns of those stocks. Subsequently, it follows the same pattern, that is buying the last winners and selling past losers. As opposed to the traditional momentum literature, the residual momentum literature is relatively small. Grundy and Martin (2001) show the dynamic factor exposure of the momentum strategy. They model and document the natural and significant correlations between the momentum premium and the momentum strategy's factor loadings. The authors conclude that the momentum profits are driven by momentum in the stock-specific components of returns. During the construction period of the momentum strategy, it loads positively or negatively on systematic factors when these factors produce positive or negative returns. Using a hypothetical strategy they try to hedge these exposures by adding costless hedge portfolios. However, this only results in marginal performance improvement.

Following, Gutierrez and Pirinsky (2006) when examining an agency-based explanation for the momentum effect, identify two types of momenta strategies. They differentiate between relative-return-momentum stocks and abnormal-return-momentum stocks. The former is defined as those stocks in the extreme deciles based on prior raw returns relative to other stocks, as it was established by Jegadeesh and Titman (1993). The latter one is identified as those with firm specific abnormal returns determined by the stock's own idiosyncratic return. The authors use the combination of the residual return ($\dot{\varepsilon}$) and the variance (σ^2) of the residual in order to determine abnormal returns. They use the CAPM, the Fama and French (1993) three-factor model and a two-factor model including the market portfolio and the appropriate industry portfolio to identify the residual return ($\dot{\varepsilon}$). Variance is estimated over the residual return based on the prior five years. In their model, a stock is considered as a winner if its cumulative residual return is greater than or equal to the square root of its cumulative variance during the period ($\dot{\varepsilon} \geq \sigma^2$) and conversely a stock is consider as a loser if its cumulative abnormal return is smaller than the negative square root of its cumulative variance ($\dot{\varepsilon} \leq -\sigma^2$). Their research is motivated by the fact that the profits of relative-return-momentum stocks reverse in the long term, while returns in the abnormal-return momentum streaming from firm specific characteristics, such as corporate events, earning reports, stock splits etc. continue for a longer period without reversion. Although both momentum portfolios generate economically significant and robust premia, they perform completely differently. The relative-return-momentum reverses strongly following the first year in line with the overreaction hypotheses, whereas abnormal-return-momentum persists for approx. at least for four years in line with the underreaction theory.

Based on the seminal work of Gutierrez and Pirinsky (2007), Blitz et al. (2011) find that compared with the conventional momentum strategy, the residual momentum strategy yields superior risk-adjusted profits mainly due to lower return variance. They conclude that the reason for the superior performance is related to the fact that the momentum strategy exhibits substantial time-varying exposures to the Fama and French factors as firstly documented by Grundy and Martin (2001). By construction, however, the residual momentum has lower loadings on these factors, and thereby the volatility of the strategy is also lower. Furthermore, the authors also find that at bear market the residual momentum is superior to the traditional momentum strategy. The reason is that while the simple momentum strategy loads towards the low beta segment of the market during early recession, this effect is less pronounced for the residual momentum.

The approach of the authors is similar to that of in the empirical literature. Stocks are ranked based on their total raw returns and residual returns standardized by their standard deviation. To construct the residual momentum, Blitz et al (2011) use the Fama and French three-factor model. Their work extends the research of Gutierrez and Pirinsky (2007) by taking risk into account. Whereas Gutierrez and Pirinsky (2007) document no significantly different performance in the first year between the traditional momentum and the residual momentum strategies, by adjusting for risk, Blitz et al. (2011) observe a substantially different result between the two strategies. They claim that their findings are in line with the underreaction hypothesis which states that information diffuses only gradually into the price.

One interesting beneficiary of the residual momentum is the Japanese market. First Chaves (2016) and then Chang et al. (2018) demonstrate that as opposed to the traditional momentum strategy of Jegadeesh and Titman (1993), which since its publication fails to work on the Japanese market, residual momentum seems to be profitable in Japan. Chang et al. (2018) notes that residual momentum profits over the short-term horizon but remain insignificant over a long-term period. They conclude that investor underreaction is a plausible underlying reason of the residual momentum.

To summarize, residual momentum proves to be a superior trading strategy to the simple momentum strategy. The residual momentum generally has lower loadings on FF3 factors, and thereby the volatility of the strategy is also lower. What is more, at the time of market turmoil residual momentum proves to be relatively stable given the different market beta loadings of the strategy.

3 Data and methodology

This section describes the data and methodology used in this analysis. The first part defines the data and methodology used to analyze the performance of the clean technology indices representative of the clean technology segment. The second part depicts how the momentum and residual momentum trading strategies are applied in the sector. Furthermore, the effectiveness of residual momentum and momentum strategies are compared when constructed in the clean technology segment.

3.1 Measuring the clean technology sector performance

The sample is based on twenty years of daily data collected from Datastream and the Bloomberg databases and, whenever available, from the index provider for the period between 01/01/2001 and 01/01/2020. This research analyses 19 international indices covering 1) wind power, 2) solar power, 3) green buildings, 4) biofuels, 5) smart grid, 6) water filtration, 7) personal transportation and 8) other solutions sectors in line with Ortas et al. (2015). The indices serve as a fair, impartial and transparent performance of the clean technology sector worldwide. All indices are compared to two market benchmarks, the MSCI World and the S&P Global 1200 indices. These benchmarks provide a global investment alternative. The free-float weighted MSCI World Index captures large- and mid-cap companies across 23 developed countries. With approximately ~1,600 constituents the index covers around 85% of the market capitalization in each county. The S&P Global 1200 is also a free-float weighted stock market index, which includes 1,200 companies of 31 countries which is approximately 70% of global stock market capitalization. Thus, these indices are considered as commonly used benchmarks to measure market performance.

First, I calculate mean excess returns, standard deviations, and Sharpe ratios to measure index performance. Implicitly, when reported in Table 1, excess returns and standard deviations are in an annualized form. The annualized excess return is calculated using the three-month US treasury bill. The standard deviation is the standard deviation of the daily excess returns. Moreover, Sharpe ratio is a commonly used measure which helps to understand returns compared to risk. However, without context no far-reaching implications should be made solely on the Sharpe ratio. As Michael and Bert (2017) and Rezec (2017) point out, Sharpe ratios are not stable over time and change due to the altering underlying fundamentals. The Sharpe ratios are calculated using the below formula:

$$Shr_i = \frac{r_i^a - r_f}{\sigma_i} \quad (1)$$

where, r_i^a is the annualized mean return for asset *i*, *rf* represents the-risk free rate using the three-month US treasury bill, and σ_i is the standard deviation of index returns. It is important to mention, that not all indices were available for the full period of 01/01/2001 and 01/01/2020. For more details please refer to the Appendix. Therefore, when comparing a technology index to the benchmarks, the corresponding individual periods are compared.

To assess further the performance of clean tech indices, I turn to regression analysis. Relative performance of the clean tech equity indies is calculated using a simple linear regression of excess returns over the benchmark indices for each indices individually. That is:

$$r_{i,t}^{,exc} = \alpha_i + \beta_i r_t^{BM} + \varepsilon_{i,t} \quad (2)$$

where, $r_{i,t}^{,exc}$ is the excess return of each indices for a given time over the risk-free rate, r_t^{BM} is the benchmark excess return over the risk-free rate for the same period, α_i is Jensen's alpha, $\varepsilon_{i,t}$ is the error term and the β_i coefficient measures systematic risk of the indices. Correspondingly, to measure if the clean technology indices provide superior returns compared to the market benchmarks, first, I examine Jensens's alpha. Consequently, my first hypothesis is that alpha is equal to zero (H_0: $\alpha_i = 0$). To further assess risk, I look at the beta coefficient. The hypothesis is that beta equals to one (H_0: $\beta_i = 1$). If $\beta_i>1$, then the clean technology index is considered to be riskier than holding the market portfolio, and contrary if $\beta_i<1$ then the index is regarded to have lower systematic risk.

As Rezec et al (2017) rightly point out based on De Roon et al (2001) in terms of the classical mean-variance spanning test, the clean technology indices put more emphasis on a larger set of clean technology equities and thereby exclude other assets. Investors investing in cleantech indices therefore ideally exclude these other non-clean technology assets because they become better off in the classical mean-variance dimensions. Hence, testing the joint hypothesis of H_0: $\alpha_i = 0$ and $\beta_i = 1$ is important to understand the performance of the clean technology indices in terms of the mean-variance frontier. Accordingly, this means that if the joint coefficient Wald-test is not rejected then investors are indifferent between the clean technology indices and the market benchmarks, as there would be no difference in the mean-variance framework.

As a robustness check for index performance I conducted basically the same analysis for three different time periods. One starting from 01/01/2001 until the beginning of the great recession defined as 12/31/2007. The second during the great recession starting from 01/01/2008 until 06/30/2009, and the last one after the great recession until 01/01/2020. The time periods I use are defined by the National Bureau of Economics Research (NBER) business cycle indicator.

Additionally, other risk factors are added to the analysis. Namely, the size and value factors are included. These are downloaded from the Kenneth French database for the corresponding period. Accordingly, equation (2) is modified as follows:

$$r_{i,t}^{,exc} = \alpha_i + \beta_i r_t^{BM} + \gamma_i r_t^{SMB} + \delta_i r_t^{HML} + \varepsilon_{i,t} \quad (3)$$

where, the previously defined variables remain and r_t^{SMB} is the small cap-premium and $\delta_i r_t^{HML}$ is the value premium from the Kenneth French database. γ_i and δ_i are the coefficients of the small-cap premium and the value premium, respectively.

3.2 Constructing the momentum and residual momentum strategies

The data sample to construct the momentum and residual momentum portfolios is based on the 19 clean technology index constituents. These indices are considered to cover the whole clean technology sector and were created by seasoned professionals. Therefore, creating the momentum and residual momentum strategy using the equity pool of the indices will be representative of the whole clean technology sector. Data is collected using Bloomberg, Datastream and from the Wharton Research Data Services (WRDS). Accordingly, my sample consists of the monthly data of 322 companies from 21 different stock exchanges. As clean technology is most common in developed economies, my data is biased towards North-America, with 165 out of the 322 stocks situated in the USA or Canada. Also, based on the first two letters categorization of the 4 digit SIC codes the sample is biased towards the Chemicals and allied products, Electronic and other electrical equipment and components, Electric, gas, and sanitary services and industrial and commercial machinery and Computer equipment industrial segments. Notably, given that clean technology is a relatively new sector and some of the firms got listed later than others, my observations are between 151 and 283 each month through the period. When looking at the average market betas of the individual equites, using a 36-months rolling regression on the FF3 factors, 62.1% of the stocks have an average market beta greater than one. What is more, 27.0% exceeds even 1.5 and 80.9% is above 0.75. As a result, the sample is biased towards high beta stocks on average. Moreover, the sample also loads a bit more towards the small cap premium, and therefore slightly biased towards small cap firms. This is most likely the result of the immaturity of the whole sector.

In line with many researches, I exclude stocks during the period when their stock price is below $1 to reduce microstructure concerns. Consistent with most of the momentum literature (see, e.g. Jegadees and Titman, 1993, 2001; Chan et al., 1993; Grundy and Martin, 2001; Gutierrez and Pirinsky, 2007; Blitz et al., 2009), simple momentum strategy is formed using monthly excess returns over the preceding twelve months excluding the most recent month (12M-1M). As noted by Jegadees and Titman (1993) and Novy-Marx (2012) the most recent month is excluded because stocks tend to exhibit short-term mean reversion, as the best-performing stocks in the past month often yield contrarian performance to the subsequent months. Correspondingly, cumulative excess returns are calculated for the 12M-1M period for each company and period. Following, all firms are ranked in quintiles for each period. The top (bottom) quintile contains the top (bottom) 20% of stocks with the highest (lowest) 12M-1M total returns. Thus, winner portfolios constitute the highest returns, whereas loser portfolios comprise the lowest returns. The strategy is as follows: long the winners and short the losers. Consistent with most of the literature, equal weights are assigned to each quintile. Subsequently, portfolios are formed holding for K-months (1, 3, 6 and 9 months respectively). Based on this, the strategies hold a series of portfolios in each month.

When constructing the residual momentum strategy, a similar approach is used. Following the procedures proposed by Blitz et al. (2009) residual returns are estimated each month using the Fama and French three-factor model:

$$r_{i,t}^{exc} = \alpha_i + \beta_{1,i} r_t^{BM} + \beta_{2,i} r_t^{SMB} + \beta_{3,i} r_t^{HML} + \varepsilon_{i,t} \tag{4}$$

where $r_{i,t}^{exc}$ is the excess return of stock i in month t over the risk free rate, again, calculated by using the three-month US treasury bill, r_t^{BM}, r_t^{SMB}, r_t^{HML} are the market premium, the small-cap premium and the value premium, respectively, for month t, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$ are the coefficient parameters in the same order, α_i is Jensen's alpha, and $\varepsilon_{i,t}$ is the residual return of stock *i* in month *t*. In line with Blitz et al. (2009) in order to obtain accurate and complete return history a three-year rolling window is used to estimate the regressions, that is at the beginning of each month *t*, over the period from *t*-36 to *t*-1. Notably, Chang et al. (2018), besides the three-year window also applied a five-year window to replicate the residual momentum in the Japanese market, and their results remain virtually unchanged. Consequently, only stocks with appropriate 36-months return history are included in the analysis. Following, similarly to the simple momentum strategy stocks are ranked in quintiles, but this time instead of using the 12M-1M cumulative excess returns, the portfolios are ranked based on the 12M-1M cumulative residual returns. Notably, residual returns are standardized by the standard deviation of the residual return of the same portfolio formation period. Blitz et al. (2018) and Gutierrez and Pirinsky (2007) also standardize residual returns to obtain an improved measures as raw residual return can be a noisy estimate. Stocks ranked in the top quintile, based on their residual returns, are defined as winners and those ranked at the bottom 20% are defined as losers. The trading strategy follows the same approach as the simple momentum strategy, thus buying the winners and selling the losers each month. Again, the portfolios are equally weighted and formed for the same holding period of K (1, 3, 6 and 9 months), using the same overlapping approach as the simple momentum strategy. To test *t*-statistics adjusted for autocorrelation and heteroskedasticity and estimate correct standard errors, the Newey and West (1987) approach is used.

To contrast both the simple momentum and residual momentum strategies, investment in the MSCI World Index and in a portfolio constructed from all the constituents of the clean technology indices is used with a buy-and-hold (BAH) approach.

4. Main results

This section evaluates the performance of the clean technology indices representative for the whole clean technology sector. The second part shows the results of implementing the momentum and residual momentum strategies using the constituents of the clean technology indices.

Table 1. Clean Technology equity index performance vs. benchmark performance

Index (abbrev.)	Period	**Indices**			**BM: MSCI World Index**			**BM: S&P Global 1200 Index**		
		Mean RE	Std.dev	Sharpe Ratio	Mean RE	St.dev	Sharpe Ratio	Mean RE	St.dev	Sharpe Ratio
AGIGL	01/02/2001 - 12/31/2019	-0.021	0.267	-0.004	0.047	0.156	0.013	0.049	0.158	0.013
AGIEM	06/30/2005 –12/31/2019	0.034	0.293	0.293	0.066	0.157	0.018	0.068	0.160	0.018
AGINA	01/02/2001 - 12/31/2019	-0.045	-0.045	-0.006	0.047	0.156	0.013	0.049	0.158	0.013
SOLRX	12/31/2004 - 12/31/2019	-0.084	0.408	-0.009	0.062	0.155	0.017	0.064	0.158	0.017
DBCC	02/10/2010 –09/14/2012	-0.244	0.241	-0.050	0.096	0.179	0.022	0.096	0.181	0.022
GWE	12/16/2005 –12/31/2019	0.055	0.226	0.010	0.058	0.159	0.015	0.061	0.162	0.016
MSCIGC	09/01/2010 –12/29/2017	0.095	0.138	0.029	0.125	0.129	0.039	0.127	0.130	0.040
MSCIGSW	11/28/2008 –12/31/2019	0.125	0.180	0.028	0.132	0.146	0.037	0.133	0.148	0.036
MSCIGB	11/28/2008 –12/31/2019	0.162	0.194	0.034	0.132	0.146	0.037	0.133	0.148	0.036
CELS	11/17/2006 –12/31/2019	0.024	0.312	0.003	0.048	0.162	0.013	0.049	0.165	0.013
QGRD	09/22/2009 –12/31/2019	0.087	0.183	0.020	0.103	0.132	0.032	0.104	0.133	0.032
SPGTCLEN	11/21/2003 –12/31/2019	-0.040	0.275	-0.006	0.076	0.152	0.021	0.078	0.154	0.021
WEXP	12/31/2003 –12/31/2019	0.124	0.158	0.032	0.069	0.152	0.019	0.071	0.155	0.019
WAEX	12/31/2003 –12/31/2019	0.084	0.220	0.016	0.069	0.152	0.019	0.071	0.155	0.019
CTIUS	01/02/2001 –12/31/2019	0.096	0.242	0.016	0.047	0.156	0.013	0.049	0.158	0.013
ECO	01/02/2001 –12/31/2019	-0.077	0.310	-0.011	0.047	0.156	0.013	0.049	0.158	0.013
NEX	01/02/2001 –12/31/2019	0.021	0.216	0.004	0.047	0.156	0.013	0.049	0.158	0.013
RENIXX	01/02/2002 –12/31/2019	-0.074	0.311	-0.011	0.064	0.155	0.017	0.065	0.157	0.017
SOLEXD	12/31/2003 –12/31/2019	0.000	0.405	0.000	0.069	0.152	0.019	0.071	0.155	0.019

Notes: This table reports the summary statistics of the 19 clean technology indices and the MSCI World Index and S&P 500 Indices used as benchmarks in the appropriate periods. For the abbreviations please refer to Table A in the Appendix. Column 2 presents the periods in which each index is evaluated. All returns and standard deviations are in an annualized form. Standard deviations are annualized by multiplying if with the square root of 12. The Sharpe ratio is the ratio of the mean excess return divided by the standard deviation.

4.1 Evaluating index performance

Table 1 reports the summary statistics of the nineteen clean technology indices and their performance compared to the benchmark indices. Most of the clean technology indices are characterized by poor excess return performance as well as high volatility. Seven out of the nineteen indices displayed negative annualized excess return during the period examined. Seven showed single digit performance and only five indices had double digit annualized excess returns in the 10%-16% range. Interestingly, most of the clean technology indices with the double-digit excess return performance have a starting date after 2008. In addition, as shown in Appendix A the daily excess return of all cleantech indices are non-normally distributed as all Jarque-Bera normality tests are rejected. This is driven by the negative skewness and high kurtosis resulting in negative asymmetry and fat tails.

Although, looking at index returns individually paints a somewhat mixed picture, when compared to the benchmark indices the clean technology indices vastly underperform the market. Only four out of the nineteen indices seem to show higher annualized excess return when compared to both market benchmarks. Turning to volatility, it is salient immediately that clean technology indices show higher volatility than the market. The annualized standard deviation of these indices is in the range of 13% - 40%, but mostly situated in the 20% - 30% range. Whereas the market benchmarks move in the 13%-18% interval. Consequently, when comparing the Sharpe ratios of the clean technology indices to the benchmark indices in the corresponding period, the clean technology indices underperform the market seventeen out of nineteen cases. It is important to mention that negative Sharpe ratios do not provide additional information as it simply means that the risk-free rate has a higher return than the underlying indices.

Albeit, from the summary statistics it might already seem like clean technology indices underperform the market, it is important to put these indices in context. Table 2 shows the relative performance of the clean technology indices compared to the MSCI World and S&P 1200 Global benchmark indices in the appropriate time-period. When looking at the estimated alpha coefficients, using the OLS regression, it is striking immediately that the Wald-test on the null hypothesis (H_0: $\alpha_i = 0$) shows that Jensen alphas in most of the cases are not significantly different from zero. What is more, when the test shows significantly different alpha, it tends to be negative with both benchmarks. This implies that the indices do not significantly deviate from the market.

Table 2. Relative performance the energy indices. Regression analysis

Index (Abbrev.)	**BM: S&P 1200 Global** Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	Adj. R^2	**BM: MSCI World index** Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	Adj. R^2
AGIGL	-0.0006*	1.3676***	329.40***	0.6570	-0.0006*	1.3982***	379.74***	0.6630
AGIEM	-0.0003	1.2610 ***	69.87***	0.4731	-0.0003	1.3247***	110.99***	0.5043
AGINA	-0.0008*	1.5018***	379.84***	0.5883	-0.0008	1.5145***	375.82***	0.5777
SOLRX	-0.0013	1.6856***	230.26***	0.4249	-0.0013	1.7245***	250.16***	0.4295
DBCC	-0.0027***	1.1950***	44.59***	0.8097	-0.0027***	1.2213***	57.48***	0.8217
GWE	-0.0001	1.0683***	10.00***	0.5823	-0.0001	1.1134***	28.61***	0.6108
MSCIGC	-0.0002	0.9633**	7.02**	0.8320	-0.0002	0.9890	1.20	0.8648
MSCIGSW	0.0000	0.9508**	5.98**	0.6166	0.0000	0.9633**	3.21**	0.6139
MSCIGB	0.0001	1.0520***	6.44**	0.6510	0.0001	1.0858***	17.95***	0.6728
CELS	-0.0003	1.4801***	270.07***	0.6100	-0.0003	1.4923***	266.27***	0.5986
QGRD	-0.0003	1.2179***	149.47***	0.7842	-0.0003	1.2385***	187.02***	0.7970
SPGTCLEN	-0.0010**	1.3915***	249.59***	0.6085	-0.0010**	1.4292***	297.63***	0.6197
WEXP	0.0004*	0.7708***	231.11***	0.5496	0.0004	0.7734***	210.53***	0.5496
WAEX	0.0001	1.0166	0.58	0.5106	0.0001	1.0194	0.74	0.4958
CTIUS	0.0002	1.3085***	361.17***	0.7320	0.0002	1.3264***	382.06***	0.7262
ECO	-0.0010**	1.4916***	358.82***	0.5806	-0.0010**	1.5012***	349.56***	0.5678
NEX	-0.0002	1.1199***	56.11***	0.6723	-0.0002	1.1530***	92.49***	0.6881
RENIXX	-0.0010	1.0093	1.24	0.2603	-0.0010	1.0327	1.96	0.2635
SOLEXD	-0.0008	1.6608***	213.93***	0.4028	-0.0008	1.6999***	233.55***	0.4075

Note: The table presents the results of the OLS regressions ran on the 19 clean technology indices using the S&P 1200 Global and MSCI World benchmark indices. For the abbreviations used please refer to Table A in the Appendix. Equation (2) is used to determine the results presented. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. The first columns of each benchmark blocks reports the alpha coefficients and tests whether each coefficient is significantly different from 0. Column 3 and 7 show the estimated beta coefficients and tests whether the coefficients are different from 1. Column 4 and 8 reports the Chi-square values of the Wald 's join coefficient tests. *,**,*** respectively, indicate the significance levels of 10,5, and 1 percent.

Turning to the estimated beta coefficients, the Wald-test rejects the null hypothesis, that is H_0: $\beta_i = 1$. In 14 out the 19 cases beta is significantly greater than one for both benchmark indices. The beta coefficients exceeding one indicate that the clean technology indices have a significantly higher relative risk compared to the market benchmarks. As shown in Table 2 only a few indices display lower or equal beta coefficients.

When examining index performance in the efficient frontier framework with the Wald joint significance test on the null hypothesis of H_0: $\alpha_i = 0$ and $\beta_i = 1$, 16 and 17 out of the 19 tests are rejected for the MSCI World Index and the S&P 1200 Global respectively. As shown previously, the rejection is mostly driven by the beta coefficients exceeding one. Thus, the higher risks of clean technology indices do not seem to result in higher returns as well.

Based on the above results we can conclude that investors, who invest in clean technology indices, do not report significantly different returns from the market benchmarks. However, they do endure significantly higher risks for similar returns. When examining the results in the efficient frontier framework, it can be concluded that investing in clean technology indices cannot be replicated by using the market benchmarks. These finding are in line with Rezec et al. (2017) and Michael and Bert (2017), but in contrast with the findings of Cummins et al. (2014) who, as claimed by Rezet et al. (2017), use a more heterogenous and smaller sample.

To evaluate robustness of my findings and gain more insight into the return and risk characteristics of the clean technology indices, the size and value risk factors are added to the analysis. As Table B in the Appendix shows, Jenses alphas remained not significantly different from zero in most of the cases. Moreover, the beta coefficients are significantly greater than one 18 out of the 19 cases for both benchmark indices. What is more, the joint hypothesis of H_0: $\alpha_i = 0$ and $\beta_i = 1$ is rejected in all cases. Concluding, adding the Fama and French factors to the regression confirms the previous results.

To shed more lights on the return and risk characteristics of the clean technology indices I conducted virtually the same analysis, but this time for different time periods. For further information please refer to Table C in the Appendix. The NBER business cycle indicator is used to define crisis and normal periods. The data is divided for the time intervals of 12/01/2001 – 12/31/2007, 01/01/2008 – 06/30/2009 and 07/01/2009 – 01/01/2020, that is the expansion period before the financial crisis, the financial crisis and the expansion after the crisis, respectively. As expected, due to the increased systematic risk on the market, in most of the cases betas are elevated during the financial crisis compared to that of during the expansion periods for both benchmark indices. This indicates that clean technology indices are considered as riskier investments during crisis period compared to the general market. These findings confirm the results of Ortas et al. (2015) who show that cleantech indices experienced a structural break during the time of the financial market collapse in 2008. Turning to Jensen alphas, none of the indices have significantly different value from zero at the time of the financial crisis. Interestingly, however, their value is slightly positive and significant in the pre-crisis period. The positive pre-crisis Jensen alphas also confirm the findings of Ortas et al (2015). Nonetheless, alphas turn negative in the post-crisis period.

Based on the above, it seems like clean technology investing proves to be a rather poor decision as most of the clean technology indices show underperformance when compared to the market benchmarks. What is more, clean technology indices tend to be more sensitive to market turmoil. Consequently, if clean technology indices representing the sector seem to underperform the market, would investment strategies based on the momentum anomaly and more precisely on residual momentum be profitable?

4.2 Constructing the simple and residual momentum strategies

Table 3 shows the results of implementing the simple momentum and residual momentum strategies in contrast to holding the market portfolio or holding the clean technology sector. Returns, standard deviations, Sharpe ratios and alphas are all in an annualized form.

Table 3. Constructing the simple momentum and residual momentum strategies

	Returns	**Standard deviation**	**Sharpe**	**Alpha**	**MktRF**	**SMB**	**HML**	**Adj R^2**
Panel A: Benchmark portfolios								
Buy-and-hold CT	0.039	0.151	0.259	-0.058***	1.215***	0.571***	0.118	0.902
MSCI World	0.051	0.193	0.265	-0.031***	1.016***	-0.139**	-0.010*	0.950
Panel B: Simple momentum								
1M	0.107	0.184	0.581	0.129***	-0.288**	-0.069	-0.336	0.108
3M	0.066	0.112	0.585	0.068*	-0.078*	0.028	0.086	0.121
6M	0.051	0.082	0.625	0.049*	-0.012	-0.025	0.154	0.127
9M	0.041	0.067	0.624	0.039*	0.009	0.016	0.088	0.071
Panel C: Residual momentum								
1M	0.115	0.134	0.856	0.115***	-0.073	0.118	-0.153	0.014
3M	0.083	0.079	1.045	0.078***	0.033	0.300	-0.006	0.026
6M	0.060	0.054	1.100	0.056***	0.027	0.121	0.080	0.012
9M	0.045	0.048	0.936	0.042**	0.026	0.096	0.021	0.003

Note: This table reports the results of the simple momentum strategy versus the residual momentum strategy constructed in the clean technology sector. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum return strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Portfolios are equally weighted and formed for the holding period of K (1, 3, 6 and 9 months respectively) using the overlapping approach. Panel A reports the simple buy-and-hold strategy in the clean technology sector, and the MSCI World benchmark index. Panel B and C reports the simple momentum and residual momentum strategies, respectively. All results are reported in an annualized form. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

The results of Pane A of Table 3 indicate that although with a buy-and-hold strategy one can achieve slightly higher returns than holding the market portfolio, on a risk-adjusted basis, using the standard deviation of the portfolio returns, there is no significant difference. However, what is immediately conspicuous when looking at the market betas is that the clean technology sector has a beta of 1.2 which is significantly greater than one. Not surprisingly, the MSCI world index is not significantly different from one when ran against the market factors from the Fama and French library. The beta exceeding one for the clean technology sector portfolio is in line with the first findings of this thesis, when looking at the market indices from which the clean technology portfolio has been constructed. Correspondingly, all the buy-and-hold clean technology portfolio and the momentum strategies are constructed from high beta equites on average. In addition, when looking at the other two FF3 factors, namely the small cap premium and value premiums, the buy-and-hold clean technology portfolio is significantly different from the market benchmark. What is interesting, is that the clean technology sample is slightly biased towards small cap firms as it loads significantly with a 0.58 coefficient on the small cap factor. However, the value factor does not seem to have significant explanatory power on the returns of the buy-and-hold strategy in this subsegment of the market.

Turning to the strategies constructed on the momentum anomaly, Panel B and C of Table 3 indicate that both the simple momentum and residual momentum strategies with different holding periods outperform the buy-and-hold clean technology portfolio in terms of returns. Using the example of the one-month holding period, the residual momentum shows an annualized return of 11.5%, the simple momentum 10.7%, while a buy-and-hold strategy in the clean technology sector only has a 3.9% annualized return for the researched period. Comparing the performance based on the alpha measure, both momentum strategies again significantly outperform the buy-and-hold strategy. While the buy-and-hold portfolio achieves negative alphas, those are significantly positive around 12% for both momentum strategies.

Evaluating the performance of the strategies on a risk adjusted basis, Sharpe ratios are also superior for both strategies constructed on the momentum anomaly. The residual momentum strategies and simple momentum strategies have a Sharpe ratio in the 0.98 and 1.10 and 0.58-0.63 intervals respectively, while this ratio is around 0.26 for the buy-and-hold clean technology portfolio. What is more, while the traditional simple momentum strategy indicates a significant -0.3 market coefficient, the market beta for the residual momentum strategy is not significantly different from zero. This is in turn a significant improvement from the 1.2 market beta of the clean technology sample, and thus makes both momentum strategies less risky.

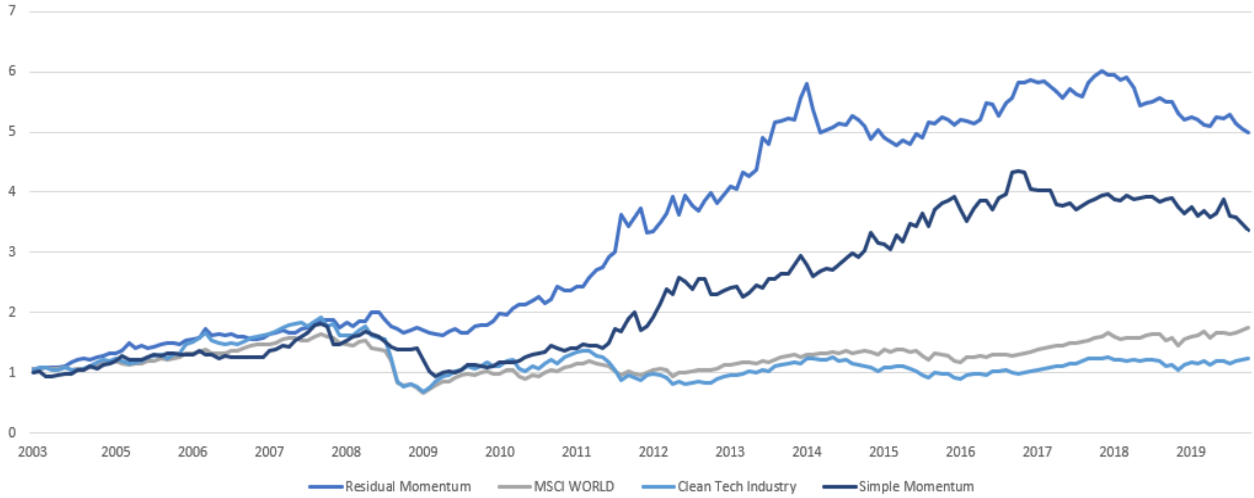
When comparing the two momentum strategies, as mentioned in the previous paragraph, both in terms of returns and Shapre ratios the residual momentum strategy is superior to the traditional simple momentum strategy. When looking at the standard deviation separately, the residual momentum again proves to be superior to the simple momentum strategy. For example, staying with the one-month holding period, the annualized standard deviation of the simple momentum strategy is 18.4% compared to 13.4% for the residual momentum. Moving forward with longer holding periods, this remains true, hence as Blitz et al (2009) also note ranking stocks on their residuals decreases risk and it remains true in the clean technology sector as well. While Blitz et al. (2009) report strong exposure to the Fama and French factors for the simple momentum strategy in the US market, when applied only on the global clean technology sector the common factors seem to somewhat lose relevance. Only the strategy with the one-month and three-months holding periods seem to show correlation with the common market factor. When turning to the residual momentum strategy, none of the FF3 factors seem to be relevant. This is similar to what Blitz et al. (2009) find when comparing the residual and simple momentum strategies. Namely, the residual momentum strategy exhibits a somewhat smaller factor exposures than the simple momentum strategy. In addition, although, also similarly to Blitz et al. (2009) the R-squared values show a slightly stronger relation for the simple momentum strategies, the explanatory power of the regressions for both strategies are quite low. As a result, comparing the alphas to the raw returns of the strategies, there is no significant difference. Consequently, although ranking stocks on their residual momentum is an effective approach to somewhat reduce factor exposure of the conventional momentum strategies in the clean technology sector, the traditional momentum strategies also exhibit lower exposures to these factors in this subsequent of the market.

To use the same benchmark as for the index performance evaluation in the first part of the thesis, I ran the same test against the MSCI World Index instead of the market factor from the Fama and French library. The result remains essentially the same. For further details please refer to Table D in the Appendix.

In addition, to investigate the performance of both momentum strategies from a different aspect, I investigate the long and short elements of those. As shown in Table E in the Appendix, the annualized return realized on the short positions of the simple momentum strategy with a one-month holding period averaged around 4.5%, which is a substantial amount out of the aggregate 10.7% return. However, this is only 2.1% out of the total 11.5% for the residual momentum strategy. This difference remains significant for longer holding periods as well. Thus, investing only in the long position of the simple and residual momentum strategies would yield an annualize return of 5.8% and 9.2% respectively, which remains more than the BAH strategy in the cleantech sector. However, looking at a risk-adjusted basis only the long position of the residual momentum strategy seems to outperform the buy-and-hold strategy with a Sharpe ratio of 0.42. Regressing the long and short positions on the Fama and French three factors, the long simple momentum strategy yields negative alphas, while the residual momentum strategy yields significantly no different results from zero. Nonetheless, the short positions of both strategies seem to contribute significantly more alphas to the aggregate strategies than the long positions, with the alphas of 17% and 12% for the short positions of the simple and residual momentum strategies, respectively. Concluding, for both the simple momentum and residual momentum strategies, applying both the long and short side of the strategy at the same time significantly improves performance.

Summarizing, both momentum strategies are superior to the traditional buy-and-hold strategy or any of the here listed equity indices in the clean technology sector. Furthermore, the residual momentum strategy proves to be the better choice in the clean technology sector, as although it yields similar returns to the traditional momentum strategy, ranking stocks based on the residuals reduces risk through lower standard deviation and exhibiting a somewhat lower exposure to the market factor. Notably, however, in the clean technology sector even the traditional momentum strategy has lower exposure to Fama and French factors than using the same strategy in general. Moreover, trading both the short and long side of both momentum strategies at the same time makes the strategies effective.

Figure 1. Cumulative returns of the different strategies

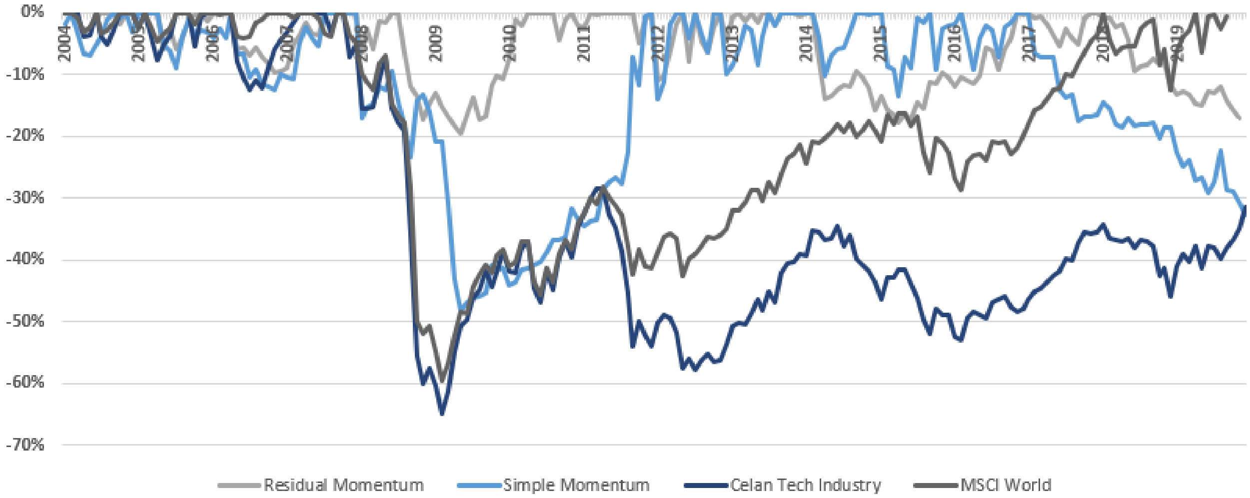


Note: This figure shows the cumulative return of the simple momentum strategy, the residual momentum strategy, the buy-and-hold clean technology portfolio and the MSCI World market benchmark. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Accordingly, the returns of the portfolio cover the period December 2003 to December 2020. Portfolios are equally weighted and formed for a one month holding period.

4.3 Performance difference over time

To better understand the performance of the momentum strategies, it is important to investigate how the performance differential evolve over time. Figure 1 shows the cumulative performance of investing in the buy-and-hold clean technology portfolio, in the simple momentum strategy and in the residual momentum strategy, with both momentum strategies constructed from the same stocks as BAH portfolio and held for one month after formation. The cumulative performance of the MSCI World Index is also included as a benchmark. Both the simple momentum and residual momentum strategies outperform the market and the BAH strategy in the clean technology sector. What is more, as it was already implied when evaluating the different cleantech indices, the BAH strategy in the cleantech sector underperforms even the MSCI World index. In other words, if one had invested $1 in the residual momentum strategy or the simple momentum strategy at the end of 2003, that investment would have been worth ~$5 or ~$3.5 respectively, not including transaction costs, by 2020. Whereas, a $1 investment in the clean technology BAH strategy would have been around ~$1.3, the same way not including transaction costs, by 2020.

Figure 2. Drawdown of the strategies

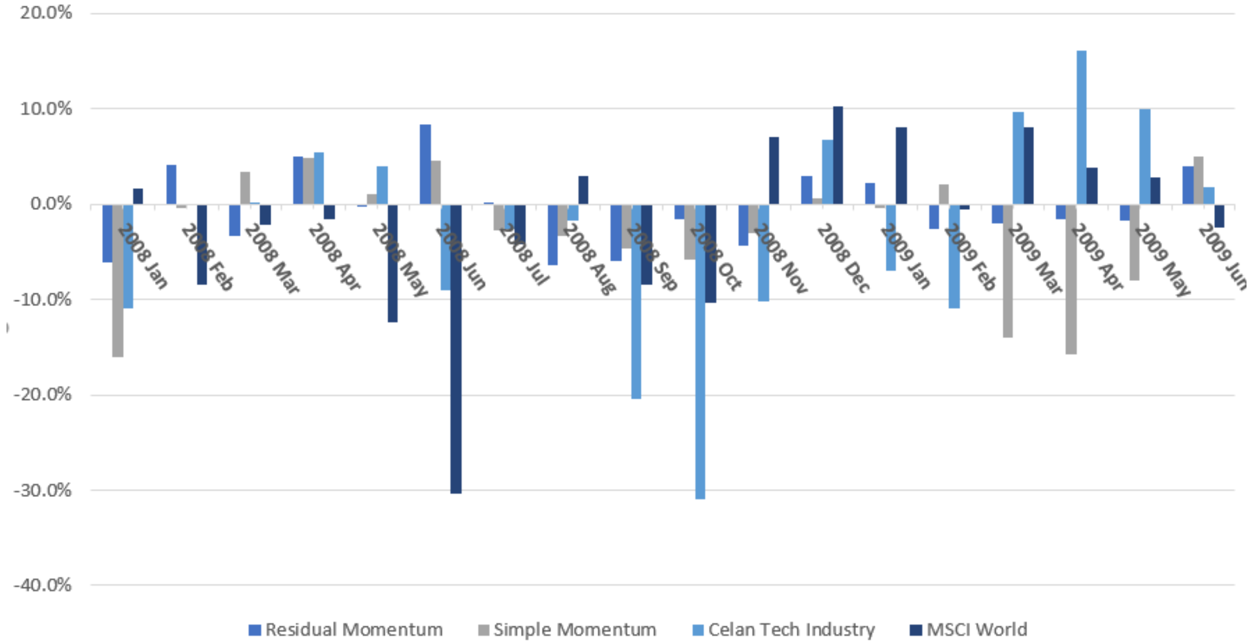


Note: This figure shows the drawdowns of the simple momentum strategy, the residual momentum strategy, the buy-and-hold clean technology portfolio and the MSCI World market benchmark. Drawdown at time t is defined as the ratio between the cumulative return until time t and the all-time high cumulative return until time t minus one. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Accordingly, drawdowns cover the period December 2003 to December 2020. Portfolios are equally weighted and formed for a one month holding period.

Figure 2 tracks the drawdowns of the strategies against the MSCI World Index used as the benchmark again. Drawdown at time *t* is defined as the ratio between the cumulative return until time *t* and the all-time high cumulative return until time *t* minus one. What is visible immediately, is that, in line with the findings of Blitz et al. (2009), returns generated by the residual momentum strategy are the most consistent over time. As an example, during the financial crisis when the market benchmark MSCI World Index suffers a maximum drawdown of around -60%, the BAH cleantech strategy exceeding this exhibits approx. -65%. Concurrently, the worst drawdowns suffered by the simple momentum and residual momentum strategies are around -48% and -20% respectively. Not only the magnitude, but also the length of these drawdowns is the least severe for the residual momentum strategy.

To shed further light on the behavior of the strategies during the greatest drawdown I investigate when the return differences between the momentum strategies are the greatest in details. That is in the period of 01/01/2008 – 06/30/2009, which is defined as the crisis period based on the NBER indicator. Figure 3 reports the monthly returns of the MSCI World Index, the BAH cleantech portfolio, the simple momentum and residual momentum strategies. Both momentum portfolios are held for one month after formation and were constructed from the same pool as the BAH cleantech portfolio.

Figure 3. Monthly performance of the strategies during the financial crisis



Note: This figure shows the detailed monthly return performance of the simple momentum strategy, the residual momentum strategy, the buy-and-hold clean technology portfolio and the MSCI World market benchmark during the 2008-2009 financial crisis. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Portfolios are equally weighted and formed for a one month holding period.

The late recession period starting in 2009 is characterized by strong market return reversals. Accordingly, both the MSCI World Index and the cleantech portfolio reversed and yielded significantly positive returns. Conversely, however, this is the period when the simple momentum strategy crashes and exhibits substantial negative returns. Blitz et al (2009) and Moskowitz et al (2013) argue that this is driven by the massive negative market returns in the buildup period of the momentum strategy which pushes the simple momentum strategy towards the low (negative) beta segment of the market. Following, when the market recovers the momentum strategy suffers large losses driven by this negative market beta.

Based on Figure 3 the clean technology portfolio suffered substantial losses of -20% and -30% in 2008 September and October respectively. This tilted the simple momentum strategy in the clean technology sector towards the low beta segment and when the sector reversed in the early months of 2009 the momentum strategy crashed. In contrast to the simple momentum strategy, the residual momentum strategy is claimed to be less negatively exposed to the market and thus during the late recession period it suffers limited losses. As Figure 3 represents and in line with the findings of Blitz et al. (2009) when the clean technology sector reverses in the period of March 2019 and May 2019 the residual momentum suffers limited losses.

To conclude, although on the long term both momentum strategies formed in the clean technology sector seem to show similar annualized returns, when examining the returns of the strategies in a more detailed way, it is obvious that the residual momentum strategy is superior, as the simple momentum strategy exhibits larger and longer drawdowns during crisis periods driven mostly by the negative market exposure when the market it reverses.

4.4 Business cycle effects

After showing that core return difference between the momentum and residual momentum strategies in the clean technology sector is driven by the different market exposure during the formation period, I further investigate the behavior of the strategies during the stages of the market cycles. Using the same NBER business cycle indicator as used for the index analysis, a crisis and expansion period is defined. Data from the period of 12/01/2001 – 12/31/2007 and 07/01/2009 – 01/01/2020 is considered as the expansion periods, while 01/01/2008 – 06/30/2009 is defined as the crisis period. Table 4 reports the detailed results of contrasting the returns of the buy-and-hold strategy with the momentum strategies. For comparison, the annualized returns of the Fama and French factors are also shown. The last three columns report the annualized returns of the buy-and-hold, the simple momentum and the residual momentum strategies in this order.

Panel A of Table 4 reports that in the expansion period the traditional momentum strategy is considered to perform the best in terms of returns with 15.6% as opposed to the 13.5% and 7.9% for the residual momentum and the buy-and-hold strategies, respectively. However, moving to the recession period the simple momentum strategy reacts more heavily to the market crash as it was already concluded in the previous section. The simple momentum strategy crashes with a return of -30%, while the loss for the residual momentum strategy in recession is only 6%.

Furthermore, Panel B of Table 4 reports the results during the early and late stages of expansions and recessions. Panel B confirms the previous findings, namely that the losses of the simple momentum strategy are concentrated in the second half of the recession. Late recession the simple momentum strategy suffers around 41% loss whereas it is only around 6% for the residual momentum strategy. The clean technology portfolio suffers the greatest loss early recession. In essence, the residual momentum strategy exhibits a quite stable performance over the business cycle, as during recession it averages around -6%.

Table 4. Strategies over the NBER business cycle

	MktRF	**SMB**	**HML**	**RF**	**Return BAH CT**	**Return Momentum**	**Return residual momentum**
Panel A: Full expansion and recession							
Expansion	0.112***	0.010	0.018	0.013***	0.079*	0.156***	0.135***
Recession	-0.23***	0.03	-0.02	0.01***	-0.287	-0.300***	-0.060***
Panel B: Early and late stage expansion and recession							
Early expansion	0.170***	0.031	0.038	0.003***	0.078**	0.211***	0.263***
Late expansion	0.096**	-0.010	-0.015	0.021***	0.080*	0.091**	0.046**
Early recession	-0.299***	-0.031	0.070	0.021***	-0.380***	-0.179***	-0.058***
Late recession	-0.146***	0.097	-0.111	0.002*	-0.180***	-0.415***	-0.063***

Note: This table shows the return performance of the simple momentum strategy, the residual momentum strategy and the buy-and-hold clean technology portfolio over the economics expansion and recession periods defined by the NBER in the period of January 2001 to December 2020. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Portfolios are equally weighted and formed for a one month holding period. To contrast the results of the strategies the returns of the Fama and French three factor model are added. All results are in an annualized form. Panel A focuses on the full expansion and recession periods, while Panel B extracts the periods into an early and late phase. In line with Blitz et al. (2009) early and late phases are defined by simply dividing the expansion and recession periods into halves. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

These findings in the clean technology sector are parallel with the general findings of Blitz et al. (2007) who argue that the reason why the residual momentum strategy exhibits lower losses is due to the significantly lower exposure to the Fama and French factors. Moreover, as also discussed in the previous section, the authors attribute the significantly negative performance to the fact that during large economic contractions the simple momentum strategies in the formation period move towards the low beta segment of the market, and consequently, during large reversals that typically take place during late recession, the simple momentum moves opposite the market. Given the lower loading of the residual momentum strategy on the market factor, this has a less pronounced effect on the residual momentum strategy. This is proven by the -0.29 and -0.14 market betas calculated for the simple momentum and residual momentum strategies respectively for the late recession period.

Summarizing, analyzing the stages of the business cycles, although, in expansion both the simple momentum and residual momentum strategies formed in the clean technology sector perform similarly, it became evident that the traditional momentum crashes in the late recession phase when the market tends to revert. Contrary, the residual momentum strategy shows more stable performance over the different stages of the business cycle.

4.5 Small-cap exposure

Jagadeesh and Titman (1993) when constructing the simple momentum strategy claim that the top and bottom deciles of the strategy are heavily concentrated in the small-cap high beta segment of the market. What is more, the authors show that the firm specific risk of the portfolios in the extremes tend to be higher as well. Campbell and Taksler (2003) argue, for instance, that these firm specific risk characteristics are in positive correlation to bond yields. Moreover, Agarwal and Taffler (2008), Avramov et al. (2007) and Su-Lien et al. (2014) all claim that the simple momentum strategy is significantly concentrated in the highest credit-risk segment of the market. On the contrary, Blitz et al. (2009) in their paper on the residual momentum strategy show that the portfolios ranked based on their residual returns have minor differences between the deciles in terms of market cap or betas. Accordingly, to further compare the characteristics of the simple momentum and residual momentum strategies in the clean technology sector I conduct virtually the same analysis.

Table 5 reports the findings of this analysis. Consistent with what Jagadeesh and Titman (1993) and Blitz et al. (2009) report, the extremes, in this case quintile one and five, of the simple momentum portfolio in Panel A, have higher market betas and lower market caps. Moreover, the standard deviation of the first and last quintile is also significantly higher compared to the other quintiles in the middle. Therefore, the characteristics of the simple momentum strategy are in line with what is reported in the literature.

Moving to Panel B of Table 5, the residual momentum shows different results. Accordingly, market betas through the quintiles are more consistent. What is more, the two extreme quintiles are not as heavily concentrated in the small-cap segment of the cleantech market as the simple momentum strategy. Moreover, standard deviations are also more equable across quintiles.

What is slightly different from the findings of Blitz et al. (2007), is that market betas in general are higher across quintiles. Also, the concentration in the small-cap segment of the market is less pronounced. This is primarily attributable to the difference between the general market characteristics and the US sample used by Blitz et al. (2007) and that of for the clean technology sector, a subsegment of the market. The cleantech sector as represented in Tables 2 and 3 is more tilted towards a higher beta market segment.

To conclude, the residual momentum strategy is less risky compared to the simple momentum strategy in the cleantech segment. For the reason, that the two extreme quintiles of the residual momentum strategy from which the strategy is constructed, contain less high-beta and small-cap stocks than those of in the case of the simple momentum strategy.

Table 5. Characteristics of the quintile portfolios based on the simple momentum and residual momentum strategies

	Returns	**Standard deviation**	**Sharpe**	**Alpha**	**MktRF**	**SMB**	**HML**	**Adj R^2**
Panel A: Simple momentum								
Q1 (losers)	-0.045	0.279	-0.160	-0.173***	1.552***	0.710***	0.203	0.715
Q2	0.041	0.203	0.204	-0.060***	1.218***	0.557***	0.230**	0.839
Q3	0.042	0.173	0.244	-0.045***	1.085***	0.384***	0.071	0.889
Q4	0.056	0.176	0.315	-0.031*	1.068***	0.335***	0.079	0.828
Q5 (winners)	0.058	0.219	0.263	-0.044*	1.265***	0.642***	-0.134	0.766
Q5-Q1	0.107	0.184	0.581	0.129***	-0.288***	-0.069	-0.336	0.109
Panel B: Residual momentum								
Q1 (losers)	-0.021	0.217	-0.095	-0.120***	1.251***	0.480***	0.262	0.761
Q2	0.011	0.194	0.058	-0.081***	1.162***	0.616***	0.170*	0.831
Q3	0.033	0.186	0.177	-0.057***	1.135***	0.397***	0.187	0.843
Q4	0.044	0.180	0.242	-0.043**	1.082***	0.525***	0.166	0.837
Q5 (winners)	0.092	0.203	0.454	-0.005	1.178***	0.596***	0.109	0.776
Q5-Q1	0.115	0.134	0.856	0.115***	-0.073	0.118	-0.153	0.014

Notes: This table reports the characteristics of the quintile portfolios ranked based on the total and residual returns of the stocks. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using equation (4) over a 36 months period. Portfolios are equally weighted and formed for a one month holding period. Column 2,3 and 4 reports annualized returns, standard deviations, and Sharpe ratios respectively. The market factor (MktRF), the small firm premium (SML) and the value premiums (HML) are determined using Equation (4). Panel A reports the quintile portfolios based on the simple momentum strategy, while Panel B focuses on the quintile portfolios based on the residual momentum strategy. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

5. Robustness check

After concluding that constructing the simple momentum or residual momentum strategies investors can improve profitability in the clean technology sector, and that the residual momentum strategy remains superior to the simple momentum strategy in the cleantech space as well, I extend the analysis to assert these further in this section.

5.1 Alternative momentum definitions

Table 6 present my first sensitivity check. In line with the literature all simple momentum and residual momentum strategies were previously formed on a twelve-months run up period excluding the most recent month. The reason for exclusion is driven by the fact that stocks tend to exhibit short-term mean reversion, as the best-performing stocks in the past month often yield contrarian performance the subsequent month (Jegadees et al. (1993) and Novy et al. (2012).

However, as Blitz et al. (2009) note, many researchers have used alternative momentum definitions. Accordingly, I observe these alternative momentum definitions to further investigate two research questions of this thesis, namely, whether implementing the simple momentum and residual momentum strategy in cleantech equities potentially improve the profitability of investing in the cleantech sector, and whether the residual momentum strategy remains superior to the simple momentum strategy in this sector.

Table 6. Different *(J,K)* momentum portfolios

		Simple momentum				Residual momentum			
		J=3	J=6	J=9	J=12	J=3	J=6	J=9	J=12
K=1	Return	0.025	0.050	0.059	0.086	-0.012	0.052	0.110	0.111
	Standard deviation	0.151	0.158	0.163	0.171	0.102	0.102	0.117	0.116
	Sharpe	0.165	0.315	0.362	0.502	-0.117	0.509	0.935	0.957
K=3	Return	0.041	0.063	0.078	0.062	0.020	0.071	0.072	0.073
	Standard deviation	0.071	0.087	0.094	0.098	0.058	0.059	0.067	0.072
	Sharpe	0.578	0.723	0.825	0.637	0.341	1.208	1.075	1.020
K=6	Return	0.047	0.064	0.061	0.044	0.035	0.066	0.062	0.052
	Standard deviation	0.061	0.067	0.072	0.073	0.044	0.046	0.051	0.053
	Sharpe	0.775	0.965	0.852	0.603	0.799	1.429	1.215	0.989
K=9	Return	0.044	0.045	0.049	0.030	0.034	0.049	0.042	0.035
	Standard deviation	0.051	0.057	0.062	0.063	0.036	0.041	0.043	0.046
	Sharpe	0.852	0.791	0.797	0.477	0.942	1.206	0.985	0.770

Notes: This table presents the simple momentum and residual momentum portfolios formed in the cleantech section on different *(J,K)* momentum strategies originally defined by Jegadees and Titman (1993), where $J=(3,6,9,12)$ and $K=(1,3,6,9)$. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past J-months returns this time not excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past J months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using equation (4) over a 36 months period. Portfolios are equally weighted and formed for K-months holding period. All values are in an annualized form. The first block reports the different simple returns strategies, while the second block presents the different portfolios for the residual momentum strategy.

Consequently, portfolios are formed according to the *(J,K)* momentum definitions of Jegadeesh and Titman (1993). That is, equity portfolios are composed based on their J-months lagged returns, but this time not excluding the preceding month, and held for K-months, where

J=(3,6,9,12) and *K=(1,3,6,9).* As previously, simple momentum and residual momentum strategies are composed as a zero-investment strategy with the top-minus-bottom quintile portfolios approach. Annualized returns, standard deviations and Sharpe ratios are compared again.

Firstly, I address whether the portfolios still improve profitability in the cleantech sector. As a reminder, the largest Sharpe ratio achieved by any of the indices examined was 0.293, while the buy-and-hold strategy in the sector yielded a ratio of 0.259 for the examined period. Looking at Table 6, most of the *J-K* portfolio combinations outperform these values. The only exception is the short formation period of *J=3,* when held for *K=1* for both momentum strategies. This is attributable to the beforementioned short-term reversal effect.

When comparing the profitability of the simple momentum and residual momentum strategies, using the alternative definitions, the residual momentum strategy remains superior to the simple momentum strategy on a risk-adjusted basis in most of the cases, with an exception for, again, the short formation period of *J=3,* when held for *K=1 and 3* periods. Thus, the residual momentum strategy performs better in the cleantech sector due to the significantly lower standard deviation of the strategy, and therefore yields higher Sharpe ratios when alternative approaches are used. This parallel with what Blitz et al. (2009) finds.

To conclude, using alternative momentum strategy definitions, the strategies outperform the clean technology sector. In addition, the residual momentum strategy remains superior to the simple momentum strategy.

5.2 Alternative estimation window

Another way to examine the profitability of the two momentum strategies in the clean technology segment is to find out whether the residual momentum strategy is sensitive to the length of the rolling window used when estimating the residuals.

Correspondingly, instead of using the 36-months rolling regression when estimating the residuals, 20-months and a 60-months regression windows were considered. Table F reports the findings of this analysis. The results of the regression are highly similar to the findings of Table 1. The residual momentum strategy outperforms the simple momentum strategy on a risk adjusted basis, regardless of the length of the rolling window.

Table 8. Constructing the residual momentum based on the FF5 model

	Returns	Standard deviation	Sharpe	Alpha	Mkt-RF	SMB	HML	RMW	CMA	Adj R^2
Panel A: Benchmark portfolios										
Buy and hold CT	0.039	0.151	0.259	-0.354**	1.132***	0.478***	0.185*	-0.277*	-0.475 **	0.908
MSCI World	0.051	0.193	0.265	-0.233***	0.997***	-0.159***	0.052	-0.019	-0.124	0.950
Panel B: Simple momentum										
1M	0.107	0.184	0.581	0.350	0.046	0.156	-0.662*	1.097**	0.701	0.123
3M	0.066	0.112	0.585	0.313	0.077	0.148	-0.164	0.266*	0.328	0.101
6M	0.051	0.082	0.625	0.262	0.081	0.038	-0.009	0.130	0.178	0.179
9M	0.041	0.067	0.624	0.184	0.081	0.043	-0.037	0.149	0.085	0.165
Panel C: Residual momentum (FF5)										
1M	0.122	0.124	0.983	1.062***	-0.168*	0.373*	-0.039	0.564	-0.107	0.109
3M	0.077	0.068	1.130	0.536***	-0.013	0.298*	0.140	0.282	-0.145	0.064
6M	0.055	0.044	1.242	0.364***	0.015	0.117	0.119	0.215	0.020	0.013
9M	0.035	0.041	0.852	0.216**	0.023	0.104	0.040	0.147	0.078	0.025

Note: This table reports the results of the simple momentum strategy versus the residual momentum strategy constructed in the clean technology sector. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF5 factors using Equation (5) over a 36 months period. Portfolios are equally weighted and formed for the holding period of K (1, 3, 6 and 9 months respectively) using the overlapping approach. Panel A reports the simple buy-and-hold strategy in the clean technology sector, and the MSCI World benchmark index. Panel B and C reports the simple momentum and residual momentum strategies, respectively. All results are reported in an annualized form. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

5.3 Five-factor model

Another widely accepted and used asset pricing model is the Fama and French five-factor model, which adds two more factors to the originally used market, size and value factors. Namely, the authors in their research paper use profitability and investment as additional factors. Accordingly, higher firm profitability may imply higher stock returns. Thus, the profitability factor is defined as the difference between the returns of a diversified robust profit stock portfolio minus a similar portfolio with weak profitability. The investment factor implies that high investment firms tend to underperform the market. The investment factor is constructed the same way as the profitability factor, that is, the difference between the return of a diversified portfolio of low investment stocks and a portfolio of high investment stocks (Fama and French, 2015).

Consequently, to further confirm the previous findings of this thesis, particularly that the simple momentum and residual momentum strategies improve profitability when investing in the cleantech space and that the residual momentum strategy is superior to the simple momentum strategy, I conduct the same analysis as previously, using the Fama and French five-factor model. Correspondingly, to construct the residual momentum strategy the following model is used:

$$r_{i,t}^{exc} = \alpha_i + \beta_{1,i} r_t^{BM} + \beta_{2,i} r_t^{SMB} + \beta_{3,i} r_t^{HML} + \beta_{4,i} r_t^{RMW} + \beta_{5,i} r_t^{CMA} + \varepsilon_{i,t} \tag{5}$$

where, the variables defined in Equation (4) remain, and variable r_t^{RMW} and r_t^{CMA} are the profitability and investment factors respectively, and $\beta_{4,i}$ and $\beta_{5,i}$ are the coefficients of the factors in the same order. The three-year rolling window is used again to estimate the regressions, that is at the beginning of each month *t*, over the period from *t*-36 to *t*-1. Subsequently, portfolios are ranked based on their 12M-1M cumulative residual returns and standardized by the standard deviation of the residual return of the same portfolio formation period. Again, stocks ranked in the top quintile based on their residual returns are defined as winners and those ranked at the bottom 20% are defined as losers. The trading strategy follows the same approach of buying the winners and selling the losers each month. Portfolios remain equally weighted and formed for the same holding period of K (1, 3, 6 and 9 months) using the same overlapping approach.

The results in Table 5 remain virtually unchanged from those of in Table 3. Panel C indicates that the residual momentum strategy remains superior to both the buy-and-hold clean technology portfolio and the simple momentum strategy. The residual momentum strategy constructed on the FF5 factors outperforms both strategies again on a risk-adjusted basis with Sharpe ratios averaging between 0.85 and 1.24. Similar to Table 3, both momentum strategies constructed in the cleantech sector exhibit a relatively low exposure to the model factors when tested against the five-factor model. Interestingly, however, in the case of the simple momentum strategies with a holding period of one- and three- months the newly added profit and investment factors seem to pick up the exposure from the market factor when ran against the FF3 model.

Summarizing, the residual momentum strategy remains superior to the simple momentum strategy in the cleantech sector when constructed with the Fama and French (2015) five-factor model instead of the three-factor model. Also, in line with the previous findings, when using the Fama and French (2015) five-factor model, both the simple momentum and residual momentum strategies exhibit lower factor exposures than what Blitz et al (2009) shows for the broader general US market.

6. Limitations and follow up research

This study has potential limitations. Accordingly, in this section I describe these limitations, which include the oft-repeated transaction cost problem when constructing the momentum strategies, potential sample biases, the time frame issue, and the lack of existing literature.

An often-quoted critique of the momentum anomaly is that profits evaporate if we consider trading costs. For instance, Stein et al. (1999) argue that one possible explanation for the momentum strategy is trading costs. The authors claim that it seems plausible if trading costs increase, momentum traders choose to hold their position longer, thus leading to mispricing. Among others Moskowits and Grinblatt (1999), Grundy and Martin (2001) and Lesmond et al. (2004) argue that the high portfolio turnover streaming from frequent rebalancing when forming the momentum strategy offsets the profitability of the strategy. Korajczyk and Sadka (2004) find similar results when studying large investment funds. In addition, Li et al. (2009) using data from the UK demonstrate that costs of selling the loser firms when in the momentum strategy is around double the costs of buying winners. Correspondingly, one of the main limitations of this thesis is that transaction costs are not considered through the analysis. Thus, including transaction costs when constructing both momentum strategies in the cleantech sector might be an interesting follow up research.

Furthermore, Korajcyzk et al. (2004) using intraday data claims that the abnormal returns to a portfolio formed on the momentum strategy decline with portfolio size. Using a liquidity-weighed portfolio approach to reduce costs the authors create a maximum $5bn market capitalization portfolio which remains profitable. Moreover, Israelov et al. (2011) construct a strategy to create exposure to short-term momentum signals without imposing additional transaction costs. Thus, constructing a similarly liquidity-weighed portfolio or using the strategy of Israelov et al. (2011) in the clean technology sector to increase profitability would be an interesting topic for future research.

Interestingly, both De Groot et al. (2001) and Keim and Madhavan (1997) claim that market capitalization and stock volatility are important factors in explaining trading costs. Based on this as the residual momentum is neutral to both market capitalization and stock volatility Blitz et al. (2009) in their seminal work argue that trading costs have a lower impact on the profitability of the residual momentum strategy. However, this thesis finds that even when constructing the residual momentum strategy, the short positions have a significant role to achieve superior performance. Li et al. (2009) argue the costs of selling the loser firms when in the momentum strategy vastly exceeds the costs of buying winners, thus investigating the trading cost impact on the residual momentum strategy constructed in the cleantech sector might be also an interesting topic.

In addition, using the pool of the 19 clean technology indices might not reflect all the characteristic of equity investing in the cleantech sector, and therefore this thesis might be subject to sample bias. Driven by this the size of the sample might also not be representative for the whole cleantech sector. Notably however, the cleantech sector is still considered to be in a growing phase, and thus the number of listed equities is relatively limited. Also given this novelty of clean technology investing the examined twenty-year period might not be representative for future market behavior of the simple momentum and residual momentum strategies when all these firm are in a more mature phase of their life cycle.

Moreover, given the lack of literature on the segment also raises some questions when considering the methodology applied. In addition, as the popularity of sustainable investing increasing, other asset pricing anomalies should be tested in the clean technology sector as well. Accordingly, testing strategies based on the low-volatility, the size or the value anomalies, just to mention a few, are interesting candidates for future academic research.

7. Conclusion

As a result of humanity slowly depleting natural resources and using polluting processes our globe is facing several environmental issues including global warming, ozone depletion, acid rain, deforestation and a loss of diversity just to mention a few. Fortunately, however, there is a shift in conventional thinking towards a more sustainable future, as people are increasingly becoming more aware to use natural resources in a more sustainable manner. Therefore, governments and corporations all started to implement programs to preserve our environment. In line with this, numerous industries have started to transform with finding ways to pollute less and preserve more. At the same time, the concept of cleantech has appeared and sustainable technologies has potentially become the solution. Accordingly, investor sentiment has been also shifting towards more sustainable businesses. SRI and ESG investing have been gaining increasing popularity. Given the enormous challenges, investing in cleantech is highly necessary and will most likely increase in the following years. Correspondingly, it is relevant to investigate how equity investing in a socially responsible and sustainable way can be profitable. The jury is still out on whether sustainable investing is hurting market efficiency or not.

To measure profitability in equity investing in the cleantech subsegment of the market, evaluating cleantech market indices representative of the industry was the first step of this thesis. As a reminder, the first research question addressed was the following: *(1) How does clean technology indices perform compared to the mark*et? Parallel to existing literature, this study claims that investing in cleantech market indices proves to be a poor decision from a profit perspective as most of the indices underperform the market. This is especially appropriate when looking at the risk-adjusted results. What is more, clean technology indices tend to be more sensitive to market turmoil.

As simply holding cleantech indices does not prove to be profitable, the second part of the thesis investigates whether using the constituents of these indices and combining it with one of the most researched asset pricing anomalies, namely, constructing strategies based on the momentum anomaly, potentially increases profitability of investing in the clean technology segment. Moreover, as the literature claims that residual momentum strategy is superior to the momentum strategy, primarily I examine whether this holds in the cleantech segment. Accordingly, the other two research questions this thesis investigates are as follows: *(2) Does implementing the simple momentum and residual momentum strategies using cleantech equities improve the profitability of cleantech investing?* and *(3) Is the residual momentum strategy superior to the simple momentum strategy in the clean technology sector?*

I find that both the simple momentum and residual momentum strategies in the clean technology sector potentially increase profitability compared to holding cleantech indices or implementing a buy-and-hold strategy in the sector. Both strategies outperform the BAH strategy in terms of returns, alphas or risk adjusted returns. This holds for different business cycles, holding periods and alternative ways of constructing the momentum strategies.

When comparing the two momentum strategies, in line Blitz et al. (2009) I find that the residual momentum strategy significantly improves upon the simple momentum strategy in the clean technology segment as well. Although the residual momentum strategy yields similar returns, ranking stocks based on the residuals reduces risk through lower standard deviation and exhibiting a somewhat lower exposures to the market factor. Moreover, when looking in detail, the residual momentum strategy exhibits significantly shorter and lower drawdown during crisis periods. Although in expansion both the simple momentum and residual momentum strategies formed in the clean technology sector perform similarly, it became evident that the traditional momentum crashes in the late recession phase when the market tends to revert. Contrary, the residual momentum strategy shows more stable performance over the different stages of the business cycle. In addition, the residual momentum strategy in the cleantech segment is considered to be less risky than the simple momentum strategy, as the two extreme quintiles of the residual momentum strategy from which the strategy is constructed, contain less high-beta and small-cap stocks than those of in the case of the simple momentum strategy. These results hold when using alternative momentum strategy definitions, different rolling windows when estimating the residuals or using the Fama and French five-factor model (2015).

One somewhat different finding from Blitz et al. (2009) when comparing the two momentum strategies in the cleantech segment is that factor exposure seems to be less significant for both strategies.

This thesis contributes to the literature on investing in the relatively novel clean technology segment and in a broader term on Socially Responsible Investing and Environmental, Social and Governance investing. Moreover, it contributes to the existing literature on the momentum anomaly in asset pricing. In addition, the findings are in line with those of the seminal work of Blitz et al. (2009) on the residual momentum. The residual momentum also delivers higher risk-adjusted abnormal returns in the clean technology sector, and thus poses yet another serious challenge to the Efficient Market Hypothesis.

Appendix

Table A. Index details

Index (abbrev.)	Clean Technology Index	Start date	End date	Skewness	Kurtosis	Jarque-Bera Test
AGIGL	Ardour Global Alt. Energy Index	01/02/2001	12/31/2019	-0.369	6.831	3012.7***
AGIEM	Ardour Global Alt. Energy Europe	06/30/2005	12/31/2019	-0.582	7.538	3318.0***
AGINA	Ardour North America Alt. Energy Index	01/02/2001	12/31/2019	-0.230	3.891	199.1***
SOLRX	Ardour Solar Energy Index	12/31/2004	12/31/2019	-0.364	5.375	965.1***
DBCC	DB NASDAQ OMX Clean Tech Index	02/10/2010	09/14/2012	-0.245	1.779	47.1***
GWE	ISE Global Wind Energy	12/16/2005	12/31/2019	-0.754	9.427	6377.4***
MSCIGC	MSCI Global Climate Index	09/01/2010	12/29/2017	-0.657	4.955	423.9***
MSCIGSW	MSCI Global Sustainable Water	11/28/2008	12/31/2019	-0.275	3.233	41.2***
MSCIGB	MSCI Green Building Index	11/28/2008	12/31/2019	-0.639	11.489	8515.2***
CELS	NASDAQ Clean Edge Energy Index	11/17/2006	12/31/2019	-0.596	5.007	745.3***
QGRD	NASDAQ OMX Clean Edge Smart Grid Index	09/22/2009	12/31/2019	-0.343	3.138	52.4***
SPGTCLEN	S&P Global Clean Energy Index	11/21/2003	12/31/2019	-0.833	12.928	17014.7***
WEXP	SGI Global Environment	12/31/2003	12/31/2019	-0.815	6.679	2700.2***
WAEX	SGI World Alternative Energy Index	12/31/2003	12/31/2019	-0.408	4.003	278.8***
CTIUS	The Cleantech Index	01/02/2001	12/31/2019	-0.321	3.853	225.5***
ECO	WilderHill Clean Energy Index	01/02/2001	12/31/2019	-0.333	4.099	327.1***
NEX	WilderHill New Energy Global Innovation Index	01/02/2001	12/31/2019	-0.531	6.687	2913.9***
RENIXX	World Renewable Energy Index	01/02/2002	12/31/2019	-0.350	9.227	7365.9***
SOLEXD	World Solar Energy Index	12/31/2003	12/31/2019	-0.306	6.516	2123.8***

Notes: This table presents details on the 19 indices used in this thesis. Column 1 states the abbreviations used in other tables, column 2 lists the full names of the indices and column 3 and 4 defines the period in which each index is examined. Ideally, this period is between January 2001 and December 2019. However, some indices have a starting date later than January 2001 and also some are not available until December 2019.

Table B. Relative performance the energy indices. Regression analysis using the FF3 factors.

Index (Abbrev.)	BM: S&P 1200 Global (FF3) Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	Adj. R^2	BM: MSCI World index (FF3) Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	Adj. R^2
AGIGL	-0.0006*	1.5458***	533.27***	0.6874	-0.0006*	1.5743***	583.30***	0.6923
AGIEM	-0.0003	1.3355***	80.78***	0.4807	-0.0003	1.4116***	126.67***	0.5138
AGINA	-0.0007	1.6924***	533.78***	0.6268	-0.0007	1.6923***	500.23***	0.6129
SOLRX	-0.0013*	1.8989***	282.40***	0.4402	-0.0013*	1.9318***	298.03***	0.4439
DBCC	-0.0026***	1.2612***	60.13***	0.8241	-0.0026***	1.2862***	74.05***	0.8354
GWE	0.0000	1.1774***	48.51***	0.6006	0.0000	1.2293***	85.64***	0.6315
MSCIGC	-0.0002	1.0330**	5.46**	0.8574	-0.0002	1.0653***	26.84***	0.8953
MSCIGSW	-0.0001	1.0369**	2.43*	0.6310	-0.0001	1.0473*	3.86**	0.6285
MSCIGB	0.0001	1.1172***	23.87***	0.6702	0.0001	1.1585***	45.90***	0.6952
CELS	-0.0004	1.6506***	344.45***	0.6300	-0.0004	1.6470***	319.17***	0.6152
QGRD	-0.0002	1.2694***	185.15***	0.7943	-0.0002	1.2942***	234.68***	0.8095
SPGTCLEN	-0.0010*	1.5253***	331.24***	0.6226	-0.0010**	1.5600***	377.65***	0.6333
WEXP	0.0004*	0.7679***	171.12***	0.5714	0.0005*	0.7613***	170.14***	0.5552
WAEX	0.0000	1.1119***	18.42***	0.5215	0.0001	1.1026***	14.60***	0.5040
CTIUS	0.0002	1.4571***	590.73***	0.7589	0.0002	1.4675***	581.00***	0.7506
ECO	-0.0011**	1.7329***	582.17***	0.6158	-0.0011**	1.7292***	537.22***	0.5992
NEX	-0.0003	1.3377***	353.24***	0.7244	-0.0003	1.3737***	447.04***	0.7407
RENIXX	-0.0011*	1.1387***	11.32***	0.2688	-0.0011*	1.1602***	14.41***	0.2718
SOLEXD	-0.0008	1.8609***	264.31***	0.4169	-0.0008	1.8935***	279.61***	0.4207

Note: The table presents the results of the OLS regressions ran on the 19 clean technology indices using the S&P 1200 Global and MSCI World benchmark indices. For the abbreviations used please refer to Table A in the Appendix. Equation (3) including the FF3 factors is used to determine the results presented. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. The first columns of each benchmark blocks reports the alpha coefficients and tests whether each coefficient is significantly different from 0. Column 3 and 7 show the estimated beta coefficients and tests whether the coefficients are different from 1. Column 4 and 8 reports the Chi-square values of the Wald 's join coefficient tests. *,**,*** respectively, indicate the significance levels of 10,5, and 1 percent.

Table C/1. Comparing index performance during different business cycles using the MSCI World Index benchmark

Index (Abbrev.)	2001/12/01 – 2007/12/31 Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	2008/01/01 – 2009/06/30 Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$	2009/07/01 – 2020/01/01 Alpha H_0: $\alpha_i = 0$	Beta H_0: $\beta_i = 1$	Wald Joint Significance Test H_0: $\alpha_i = 0$ and $\beta_i = 1$
AGIGL	0.0004	1.4101***	148.63***	-0.0005	1.4829***	56.59***	-0.0009	1.2616***	114.82***
AGIEM	0.0025*	1.5331***	27.89***	-0.0008	1.4183***	25.00***	-0.0009	1.2179***	37.26***
AGINA	-0.0005	1.6040***	133.57***	-0.0009	1.4743***	34.11***	-0.0008	1.4010***	149.78***
SOLRX	0.0052***	1.6169***	22.68***	-0.0021	1.9387***	72.33***	-0.0028***	1.5777***	104.58***
DBCC							-0.0027***	1.2213***	57.48***
GWE	0.0035***	1.4569***	33.40***	-0.0003	1.1649***	8.85***	-0.0007*	1.0232	2.77*
MSCIGC							-0.0002	0.9890	1.20
MSCISW				-0.0004	0.7654***	9.97**	0.0000	1.0189	0.75
MSCIGB				-0.0005	1.1504*	1.90	0.0001	1.0678**	12.55***
CELS	0.0038**	1.5177***	20.39***	-0.0008	1.5409***	42.30***	-0.0006	1.4520***	170.22***
QGRD							-0.0003	1.2385***	187.02***
SPGTCLEN	0.0014*	1.5695***	115.47***	-0.0012	1.6967***	76.15***	-0.0016***	1.1904***	48.56***
WEXP	0.0013***	0.8014***	23.55***	-0.0009	0.8773***	9.67***	0.0004	0.6853***	249.24***
WAEX	0.0025***	1.1737***	9.65***	-0.0015	1.0904**	2.70*	-0.0005	0.9269***	8.91***
CTIUS	0.0004	1.4596***	116.69***	0.0002	1.2875***	52.30***	-0.0001	1.2302***	237.33***
ECO	0.0000	1.3904***	58.91***	-0.0022	1.5701***	48.50***	-0.0016***	1.4888***	181.54***
NEX	0.0014***	1.0142***	4.82***	-0.0007	1.2527***	30.41***	-0.0009**	1.1297	43.73***
RENIXX	0.0001	0.9945	0.01	-0.0021	1.3126***	10.51***	-0.0011*	0.8381***	16.03***
SOLEXD	0.0055***	1.6315***	29.22***	-0.0015	1.9055***	57.41***	-0.0028***	1.5559***	103.02***

Note: The table presents the results of the OLS regressions ran on the 19 clean technology indices NBER using the MSCI World benchmark index. The regression is ran for different business cycles defined by the NBER. For the abbreviations used please refer to Table A in the Appendix. Equation (2 is used to determine the results presented. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. The first columns of each time period blocks reports the alpha coefficients and tests whether each coefficient is significantly different from 0. Column 3,7 and 10 show the estimated beta coefficients and tests whether the coefficients are different from 1. Column 4, 8 and 11 reports the Chi-square values of the Wald 's join coefficient tests. *,**,*** respectively, indicate the significance levels of 10,5, and 1 percent.

Table C/2. S&P Comparing index performance during different business cycles using the S&P 1200 Global benchmark

	2001/12/01 – 2007/12/31			**2008/01/01 – 2009/06/30**			**2009/07/01 – 2020/01/01**		
Index (Abbrev.)	Alpha $H_0: \alpha_i = 0$	Beta $H_0: \beta_i = 1$	Wald Joint Significance Test $H_0: \alpha_i = 0$ and $\beta_i = 1$	Alpha $H_0: \alpha_i = 0$	Beta $H_0: \beta_i = 1$	Wald Joint Significance Test $H_0: \alpha_i = 0$ and $\beta_i = 1$	Alpha $H_0: \alpha_i = 0$	Beta $H_0: \beta_i = 1$	Wald Joint Significance Test $H_0: \alpha_i = 0$ and $\beta_i = 1$
AGIGL	0.0004	1.3760***	85.73***	-0.0007	1.4196***	41.19***	-0.0009	1.2483***	104.73***
AGIEM	0.0025*	1.4144***	17.53***	-0.0011	1.3286***	14.70***	-0.0009	1.1797***	25.11***
AGINA	-0.0006	1.5760***	125.93***	-0.0009	1.4463***	32.69***	-0.0008	1.3985***	153.58***
SOLRX	0.0052	1.5249***	18.17***	-0.0023	1.8640***	62.13***	-0.0028***	1.5716***	104.81***
DBCC							-0.0027***	1.1950***	44.59***
GWE	0.0035***	1.3645***	22.58***	-0.0005	1.1001**	3.06**	-0.0007	0.9969	1.81
MSCIGC							-0.0002	0.9633***	7.02***
MSCISW				-0.0004	0.7401***	13.31***	0.0000	1.0135	0.40
MSCIGB				-0.0004	1.0950	0.79	0.0002	1.0393***	4.09**
CELS	0.0037**	1.4655***	18.24***	-0.0008	1.5165***	42.29***	-0.0006	1.4520***	177.47***
QGRD							-0.0003	1.2179***	149.47***
SPGTCLEN	0.0014	1.4931***	85.67***	-0.0014	1.6278***	61.01***	-0.0016	1.1781***	43.78***
WEXP	0.0013***	0.7882***	27.82***	-0.0009	0.8582***	13.91***	0.0004	0.6952***	248.58***
WAEX	0.0024***	1.1582***	8.97***	-0.0015	1.0720	1.99	-0.0006	0.9362***	7.48***
CTIUS	0.0007	1.4901***	149.50***	0.0001	1.2558***	44.42***	-0.0001	1.2172***	211.29***
ECO	0.0000	1.3728***	56.21***	-0.0022	1.5463***	49.12***	-0.0016	1.4892***	189.44***
NEX	0.0041	1.0492**	4.79***	-0.0009	1.1972***	17.18***	-0.0009	1.1105***	32.11***
RENIXX	0.0000	0.9961	0.000	-0.0023	1.2482***	6.82***	-0.0011*	0.8255***	18.59***
SOLEXD	0.0055***	1.5616***	25.26***	-0.0016	1.8361***	50.23***	-0.0028 ***	1.5426***	100.08***

Note: The table presents the results of the OLS regressions ran on the 19 clean technology indices NBER using the S&P 1200 Global benchmark index. The regression is ran for different business cycles defined by the NBER. For the abbreviations used please refer to Table A in the Appendix. Equation (2 is used to determine the results presented. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. The first columns of each time period blocks reports the alpha coefficients and tests whether each coefficient is significantly different from 0. Column 3,7 and 10 show the estimated beta coefficients and tests whether the coefficients are different from 1. Column 4, 8 and 11 reports the Chi-square values of the Wald 's join coefficient tests. *,**,*** respectively, indicate the significance levels of 10,5, and 1 percent.

Table D. Simple momentum and residual momentum strategies

	Returns	Standard deviation	Sharpe	Alpha	Beta	Adj R^2
Panel A: Simple momentum						
1M	0.106	0.193	0.553	0.119**	-0.258*	0.129
3M	0.066	0.112	0.585	0.066*	-0.083*	0.146
6M	0.051	0.089	0.625	0.048*	-0.007	0.125
9M	0.042	0.067	0.624	0.038*	0.009	0.073
Panel B: Residual momentum						
1M	0.115	0.133	0.869	0.112***	-0.057	0.012
3M	0.083	0.079	1.045	0.079***	0.018	0.023
6M	0.060	0.054	1.100	0.057***	0.022	0.010
9M	0.044	0.048	0.936	0.043***	0.020	0.000

Note: This table reports the results of the simple momentum return strategy versus the residual momentum strategy constructed in the clean technology sector. Instead of the market factor the MSCI World index is used as the market factor. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple moemntum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Portfolios are equally weighted and formed for the holding period of K (1, 3, 6 and 9 months respectively) using the overlapping approach. Panel A and B reports the simple momentum and residual momentum strategies, respectively. All results are reported in an annualized form. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

Table E. Long and Short positions in the simple and residual momentum strategies

	Returns	Standard deviation	Sharpe	Alpha	MktRF	SMB	HML	Adj R^2
Panel A: Simple momentum Long and Short positions								
Long (1M)	0.058	0.279	0.208	-0.044***	1.265***	0.642***	-0.134	0.766
Short (1M)	0.045	0.219	0.206	0.173***	-1.553***	-0.710***	-0.203	0.715
Panel C: Residual momentum Long and Short Positions								
Long (1M)	0.092	0.217	0.424	-0.005	1.178***	0.596**	0.109	0.776
Short (1M)	0.021	0.203	0.104	0.120***	-1.251***	-0.479**	-0.262	0.761

Note: This table reports the results of long and short positions within the simple momentum strategy and the residual momentum strategy constructed in the clean technology sector. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum return strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 36 months period. Portfolios are equally weighted. All results are reported in an annualized form. To test t-statistics adjusted for autocorrelation and heteroskedasticity the Newey and West (1987) approach is used to correct standard errors. *, **, *** respectively, indicate the significance levels of 10, 5, and 1 percent.

Table F. Rolling window test

	Returns	**Standard deviation**	**Sharpe**
Panel A: Benchmark portfolios			
Buy and hold CT	0.039	0.151	0.259
MSCI World	0.051	0.193	0.265
Panel B: Simple momentum			
1M	0.107	0.184	0.581
3M	0.066	0.112	0.585
6M	0.051	0.082	0.625
9M	0.041	0.067	0.624
Panel C: Residual momentum, RW 20-months			
1M	0.098	0.116	0.847
3M	0.062	0.070	0.888
6M	0.050	0.047	1.065
9M	0.038	0.041	0.930
Panel D: Residual momentum, RW 60-months			
1M	0.104	0.111	0.936
3M	0.053	0.067	0.798
6M	0.031	0.050	0.630
9M	0.031	0.048	0.644

Notes: This table shows the results of the simple momentum strategy versus the residual momentum strategy constructed in the clean technology sector. Data is collected from Bloomberg, DataStream and WRDS databases between the period January 2001 and December 2020. Stocks are excluded during the period when their stock price is below $1. Simple momentum strategy is a zero-investment strategy with the top minus bottom quintile portfolio based on ranking equities on their past 12 months returns excluding the most recent month. The residual momentum strategy is also defined as a zero-investment strategy with the top minus bottom quintiles based on ranking the stocks on the past 12 months residual returns, standardized by the standard deviation of the residuals over the same period. Residual returns are estimated using the FF3 factors using Equation (4) over a 20- and 60-months periods. Portfolios are equally weighted and formed for the holding period of K (1, 3, 6 and 9 months respectively) using the overlapping approach. Panel A reports the simple buy-and-hold strategy in the clean technology sector, and the MSCI World benchmark index. Panel B reports the simple momentum. Panel C and D shows the residual momentum strategies using 20- and 60- months rolling windows, respectively. All results are reported in an annualized form

References

Agarwal, V., & Taffler, R. J. (2008). *Comparing the Performance of Market-Based and Accounting-Based Bankruptcy Prediction Models*. https://doi.org/10.1016/j.jbankfin.2007.07.014

Ahn, D.-H., Conrad, J., & Dittmar, R. F. (2003). Risk Adjustment and Trading Strategies. *Review of Financial Studies*, *16*(2), 459–485. https://doi.org/10.1093/rfs/hhg001

Analysis, S. R. and. (n.d.). *Rapid Growth in ESG Funds Calls for Adoption of Standards*. Retrieved July 14, 2020, from https://www.prnewswire.com/news-releases/rapid-growth-in-esg-funds-calls-for-adoption-of-standards-301064903.html

Anastasia Rose, O. (2009). *The emergence of cleantech—ProQuest*. https://search.proquest.com/openview/615c5d092a17227997240b9882e926cf/1?pq-origsite=gscholar&cbl=18750&diss=y

Anderson, T., & Leal, D. R. (2001). *Free Market Environmentalism*. Palgrave Macmillan US. https://doi.org/10.1057/9780312299736

Asness, C. S. (1998). *The Interaction of Value and Momentum Strategies* (SSRN Scholarly Paper ID 7687). Social Science Research Network. http://papers.ssrn.com/abstract=7687

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2007). Momentum and Credit Rating. *The Journal of Finance*, *62*(5), 2503–2520. https://doi.org/10.1111/j.1540-6261.2007.01282.x

Ball, R., & Brown, P. (2019). Ball and Brown (1968) after fifty years. *Pacific-Basin Finance Journal*, *53*, 410–431. https://doi.org/10.1016/j.pacfin.2018.12.008

Barber, B. M., & Odean, T. (2000). Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance*, *55*(2), 773–806. https://doi.org/10.1111/0022-1082.00226

Barber, B. M., & Odean, T. (2011). *The Behavior of Individual Investors* (SSRN Scholarly Paper ID 1872211). Social Science Research Network. https://doi.org/10.2139/ssrn.1872211

Barberis, N., Shleifer, A., & Vishny, R. (1998). A Model of Investor Sentiment. *Journal of Financial Economics*, *49*(3), 307–343.

Berk, J. B., Green, R. C., & Naik, V. (1999). Optimal Investment, Growth Options, and Security Returns. *The Journal of Finance*, *54*(5), 1553–1607. https://doi.org/10.1111/0022-1082.00161

Blitz, D., Huij, J., & Martens, M. (2009). *Residual Momentum* (SSRN Scholarly Paper ID 2319861). Social Science Research Network. https://doi.org/10.2139/ssrn.2319861

Bloc, W. E., Anderson, T., Dolan, E., Mcfetridge, D., D, M. R., Smith, D., Borcherding, T., Shaw, J., Chant, J., Stroup, R., Block, W., Anderson, T., Block, W., Borcherding, T., Chant, J., Dolan, E., Mcfetridge, D., Shaw, J., Stroup, R., … Smith, D. A. (n.d.). *John Baden*. Fraster Institute.

Bondt, W. F. M. D., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, *40*(3), 793–805. JSTOR. https://doi.org/10.2307/2327804

Campbell, J. Y., & Taksler, G. B. (2003). Equity Volatility and Corporate Bond Yields. *The Journal of Finance*, *58*(6), 2321–2350. https://doi.org/10.1046/j.1540-6261.2003.00607.x

Cao, J., Titman, S., Zhan, X., & Zhang, W. E. (2020). *ESG Preference, Institutional Trading, and Stock Return Patterns* (SSRN Scholarly Paper ID 3353623). Social Science Research Network. https://doi.org/10.2139/ssrn.3353623

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2016). *Crash Sensitivity and the Cross-Section of Expected Stock Returns* (Working Papers on Finance No. 1324). University of St. Gallen, School of Finance. https://econpapers.repec.org/paper/usgsfwpfi/2013_3a24.htm

Chang, R. P., Ko, K.-C., Nakano, S., & Ghon Rhee, S. (2018). Residual momentum in Japan. *Journal of Empirical Finance*, *45*(C), 283–299.

Chaves, D. B. (2016). Idiosyncratic Momentum: U.S. and International Evidence. *The Journal of Investing*, *25*(2), 64–76. https://doi.org/10.3905/joi.2016.25.2.064

Chordia, T., & Shivakumar, L. (2002). Momentum, Business Cycle, and Time-varying Expected Returns. *The Journal of Finance*, *57*(2), 985–1019. https://doi.org/10.1111/1540-6261.00449

Chui, A. C. W., Titman, S., & Wei, K. C. J. (2010). Individualism and Momentum around the World. *The Journal of Finance*, *65*(1), 361–392. https://doi.org/10.1111/j.1540-6261.2009.01532.x

Chui, A., Wei, K. C., & Titman, S. (2000). Momentum, Legal Systems and Ownership Structure: An Analysis of Asian Stock Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.265848

Clark, G., & Monk, A. (2010). The Norwegian Government Pension Fund: Ethics Over Efficiency. *Rotman International Journal of Pension Management*. https://doi.org/10.2139/ssrn.1618834

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, *53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

de Groot, H., Verhoef, E., & Nijkamp, P. (2001). Energy saving by firms: Decision-making, barriers and policies. *Energy Economics*, *23*(6), 717–740.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*(4), 703–738. JSTOR.

Demsetz, H. (1974). Toward a Theory of Property Rights. In C. Gopalakrishnan (Ed.), *Classic Papers in Natural Resource Economics* (pp. 163–177). Palgrave Macmillan UK. https://doi.org/10.1057/9780230523210_9

Doble, M., & Kruthiventi, A. K. (2007). CHAPTER 10—Conclusions and Future Trends. In M. Doble & A. K. Kruthiventi (Eds.), *Green Chemistry and Engineering* (pp. 297–312). Academic Press. https://doi.org/10.1016/B978-012372532-5/50011-0

Dutta, A., Bouri, E., Das, D., & Roubaud, D. (2020). Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability. *Journal of Cleaner Production*, *243*, 118669. https://doi.org/10.1016/j.jclepro.2019.118669

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, *101*(3), 621–640. https://doi.org/10.1016/j.jfineco.2011.03.021

Environment and climate change—EUR-Lex. (n.d.). Retrieved July 25, 2020, from https://eur-lex.europa.eu/summary/chapter/20.html

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Financial Social Responsibility. (2014, February 22). *Julia M. Puaschunder*. https://juliampuaschunder.com/financial-social-responsibility/

Frazzini, A. (2006). The Disposition Effect and Underreaction to News. *The Journal of Finance*, *61*(4), 2017–2046. https://doi.org/10.1111/j.1540-6261.2006.00896.x

Friedman, M. (2007). The Social Responsibility of Business Is to Increase Its Profits. In W. C. Zimmerli, M. Holzinger, & K. Richter (Eds.), *Corporate Ethics and Corporate Governance* (pp. 173–178). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-70818-6_14

Global Warming of 1.5 ºC —. (n.d.). Retrieved July 14, 2020, from https://www.ipcc.ch/sr15/

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, *78*(2), 311–339.

Grinblatt, M., & Keloharju, M. (2001). What Makes Investors Trade? *The Journal of Finance*, *56*(2), 589–616. https://doi.org/10.1111/0022-1082.00338

Grundy, B. D., & Martin, J. S. M. (2001). Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *The Review of Financial Studies*, *14*(1), 29–78. https://doi.org/10.1093/rfs/14.1.29

Gutierrez, R. C., & Pirinsky, C. A. (2006). *Momentum, Reversal, and the Trading Behaviors of Institutions* (SSRN Scholarly Paper ID 637281). Social Science Research Network. https://doi.org/10.2139/ssrn.637281

Haldar, S. K. (2018). Chapter 14—Environmental System Management of Mineral Resources and Sustainable Development. In S. K. Haldar (Ed.), *Mineral Exploration (Second Edition)* (pp. 291–311). Elsevier. https://doi.org/10.1016/B978-0-12-814022-2.00014-9

Hartzmark, S. M., & Sussman, A. B. (2019). *Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows* (SSRN Scholarly Paper ID 3016092). Social Science Research Network. https://doi.org/10.2139/ssrn.3016092

HOFFMAN, A. J., & VENTRESCA, M. J. (2016). The Institutional Framing of Policy Debates: Economics Versus the Environment. *American Behavioral Scientist*. https://doi.org/10.1177/00027649921954903

Hong, H., & Kacperczyk, M. (2009). The price of sin The effects of social norms on markets. *Journal of Financial Economics*, 22.

Hong, H., & Stein, J. C. (1997). *A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets* (Working Paper No. 6324; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w6324

Israelov, R., & Katz, M. (2011). *To Trade or Not to Trade? Informed Trading with Short-Term Signals for Long-Term Investors* (SSRN Scholarly Paper ID 1935015). Social Science Research Network. https://papers.ssrn.com/abstract=1935015

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance*, *56*(2), 699–720. JSTOR.

Jegadeesh, N., & Titman, S. (2011). *Momentum* (SSRN Scholarly Paper ID 1919226). Social Science Research Network. https://doi.org/10.2139/ssrn.1919226

Keim, D. B., & Madhavan, A. (1998). The Cost of Institutional Equity Trades. *Financial Analysts Journal*, *54*(4), 50–69. JSTOR.

Korajczyk, R. A., & Sadka, R. (2003). *Are Momentum Profits Robust to Trading Costs?* (SSRN Scholarly Paper ID 305282). Social Science Research Network. https://doi.org/10.2139/ssrn.305282

Lesmond, D., Schill, M., & Zhou, C. (2003). The Illusory Nature of Momentum Profits. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.256926

Li, X., Brooks, C., & Miffre, J. (2009). *Transaction Costs, Trading Volume and Momentum Strategies* (SSRN Scholarly Paper ID 1406475). Social Science Research Network. https://doi.org/10.2139/ssrn.1406475

Lu, S.-L., Lee, K.-J., & Yu, C.-C. (2014). Momentum strategy and credit risk. *Applied Financial Economics*, *24*, 753–762. https://doi.org/10.1080/09603107.2014.904487

Media coverage of climate change in 2019 got bigger—And better » Yale Climate Connections. (2020, March 10). Yale Climate Connections. https://www.yaleclimateconnections.org/2020/03/media-coverage-of-climate-change-in-2019-got-bigger-and-better/

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*(3), 483–510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance*, *54*(4), 1249–1290. JSTOR.

Muralikrishna, I. V., & Manickam, V. (2017). Chapter Thirteen—Industrial Wastewater Treatment Technologies, Recycling, and Reuse. In I. V. Muralikrishna & V. Manickam (Eds.), *Environmental*

Management (pp. 295–336). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-811989-1.00013-0

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, *103*(3), 429–453.

Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *The Journal of Finance*, *53*(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Ortas, E., & Moneva, J. (2013). The Clean Techs equity indexes at stake: Risk and return dynamics analysis. *Energy*, *57*, 259–269. https://doi.org/10.1016/j.energy.2013.03.046

Pastor, L., & Stambaugh, R. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, *111*(3), 642–685.

PQDT Open. (n.d.). Retrieved July 14, 2020, from https://pqdtopen.proquest.com/doc/305039537.html?FMT=ABS

Rezec, M., & Scholtens, B. (2016). Financing Energy Transformation: The Role of Renewable Energy Equity Indices. *International Journal of Green Energy*, *14*. https://doi.org/10.1080/15435075.2016.1261704

Richardson, B. J. (n.d.). Socially Responsible Investment Law: Regulating the Unseen Polluters. In *Socially Responsible Investment Law*. Oxford University Press. Retrieved July 14, 2020, from https://www.oxfordscholarship.com/view/10.1093/acprof:oso/9780195333459.001.0001/acprof-9780195333459

Rouwenhorst, K. G. (1997). *International Momentum Strategies* (SSRN Scholarly Paper ID 4407). Social Science Research Network. https://doi.org/10.2139/ssrn.4407

Ruenzi, S., & Weigert, F. (2017). *Momentum and Crash Sensitivity* (SSRN Scholarly Paper ID 3092546). Social Science Research Network. https://doi.org/10.2139/ssrn.3092546

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, *80*(2), 309–349.

Sarmento, M., Durão, D., & Duarte, M. (2006). Analysis of companies' environmental strategies for a green society. *Energy*, *31*(13), 2333–2340. https://doi.org/10.1016/j.energy.2006.01.015

SRI-Strategy-2013-2017.pdf. (n.d.). Retrieved July 14, 2020, from http://www.fondsdereserve.fr/documents/SRI-Strategy-2013-2017.pdf

The Economic Lens (Natural Gas in the Eastern Mediterranean Economic Impacts and Strategic Implications, pp. 16–37). (2013). Institute for National Security Studies; JSTOR. https://www.jstor.org/stable/resrep08960.4

WMO. (2020). *WMO statement on the state of the global climate in 2019*. https://library.wmo.int/doc_num.php?explnum_id=10211

Zhang, T. (2004). Statistical behavior and consistency of classification methods based on convex risk minimization. *The Annals of Statistics*, *32*(1), 56–85. https://doi.org/10.1214/aos/1079120130