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A Study on the Combination of Low-Volatility and Sustainability Investing Strategies- Evidence from the U.S.

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Abstract

The thesis reports an analysis on portfolios constructed on two mainstream investing factors, low-volatility and sustainability, and a combination of these. The investment objective is a portfolio composed of sustainable companies, which deliver great risk-adjusted performance. A portfolio bearing the two main characteristics of the two strategies, namely low volatility and sustainability concerns, while providing satisfying financial performance, is rather optimal (and sellable). A database of U.S. companies and their relative ESG scores form 2003-2014 is employed. Portfolios are constructed by ranking stocks on either volatility, ESG scores, or a combination of these factors based on two double-sorting methodologies. While no evidence of outperformance for the portfolios based on low-volatility and ESG factors is found, results show abnormal returns amounting to 3.1% per year for the "overlapping" portfolio. "Doing good, while doing well and safely" seems an achievable investment goal.

To my parents, thank you.

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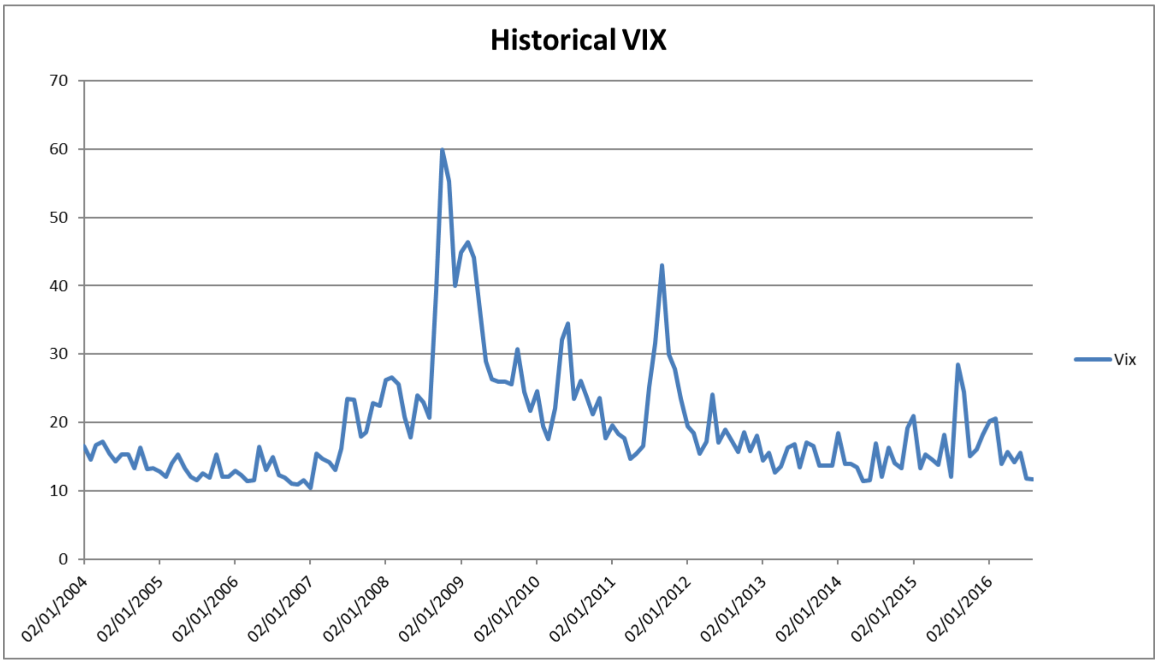
Introduction

This thesis project aims to establish if there exists an investment portfolio which is safe, sustainable, profitable, and easily investable for both institutional and private investors. The objective seems demanding. Lower risk with higher returns seemingly contradicts the really basis of the financial industry, for which higher risk is compensated with higher return and not vice versa. Adding also sustainable companies make the task even more complicated, as they might be judged not pragmatic and money-driven.

The 2008 financial crisis represents a mile stone in the economic world and triggered several changes. A word -or better an acronym- that perfectly describes the market in the recent years is VUCA, which stands for volatility, uncertainty, complexity and ambiguity. Looking at the CBOE Volatility Index (also known as VIX, Figure 1), which track the implied volatility of S&P 500 index options, it is clear how unpredictable has been the market after the economic crisis.

Figure 1 - Historical CBOE Volatility Index. The graph shows the historical CBOE Volatility index (VIX) performance from 2004-2016.



This resulted in a shift on investors' behaviour. On the one hand, economic agents are more reluctant to consider risky solutions for their investments and, moreover, desire companies to act more responsible towards environment and employees. On the other hand, expansionary monetary policies adopted by different countries and regions (e.g. quantitative easing, initially implemented by the USA and the UK and later by the EU and Japan) made particularly unattractive the fixed income market due to zero -sometimes even negative- interest rates. Such economic environment led to an increased interest to low-volatility and responsible investment factors, as demonstrated by the launch of both sustainable and low volatility indexes (e.g. Dow Jones Sustainability Index, S&P 500 Low Volatility Index, and many others). As stated by the Global Sustainable Investment Alliance (GSIA) in the (Global Sustainable Investment Alliance (GSIA), 2014), "(…) the global sustainable investment market has continued to grow both in absolute and relative terms, rising from $13.3 trillion at the outset of 2012 to $21.4 trillion at the start of 2014, and from 21.5 percent to 30.2 percent of the professionally managed assets in the regions covered". The low volatility effect, as defined in (D. C. Blitz & van Vliet, 2007), is not a new factor in the investment industry. The intuition of a flatter-than-expected -if not even negative- risk-return relationship, opposite to what is predicted by the CAPM, found place already in the 70's (Black, Jensen, & Scholes, 1972). On later years the evidence of the anomaly has been supported by several studies by both academics and practitioners. With regards to sustainability, instead, such investment approach became a common practice only in the past decade. Well summarized in (Global Sustainable Investment Alliance (GSIA), 2014), "sustainable investment encompasses the following activities and strategies: Negative/exclusionary screening, Positive/best-in-class screening, Norms-based screening, Integration of ESG factors, Sustainability-themed investing, Impact/community investing, Corporate engagement and shareholder action".

In this thesis project decile portfolios based on low-volatility and sustainability factors are constructed. While the former is quite straight forward in its definition (the first decile portfolio will contain the less volatile companies), the latter deserve an introduction. The strategy is based on ESG factors integration with best-in-class screening. Companies are ranked by their ESG score and the resulting first decile portfolio is composed by high-ESG score companies, the most sustainable. The period of analysis starts in 2003 and ends in 2014, while only US stocks are considered. ESG scores are provided by the Thomson Reuters Datastream ASSET4 financial database while prices from Thomson Reuters Datastream. The obtained data sample has an average of 660 companies (66 in each decile portfolio). While both strategies are constructed and tested, the main purpose of the thesis is to combine them and verify whether the resulting portfolio shows superior performance than the two factor alone. This is done in two ways. In the first case through a simple double sort, where the top 50% ESG score companies are ranked by volatility. In the second, the first quintile portfolios of the two strategies are compared. The companies which happen to be in both these portfolios will form a new portfolio. In both cases, the resulting portfolios contain highly sustainable and low-volatile companies.

In all the cases, the first portfolio of each strategy offers superior performance when compared to the benchmark. And both the top portfolios which combine the two factors are superior than those based on these factors alone. However, only in one case the t-test on the coefficient from the regression of the portfolio returns against those of the market portfolio results statistically significant (26 bps a month with a p-value of 8,11%). This is true for the portfolio which is composed by the overlapping companies between the first decile portfolios of the two strategies. During the period 2003-2014 it shows a CAGR of 4,46%, while the benchmark a CAGR of 1,8% (4,3% if an exogenous benchmark is considered). Notably, considering the Sharpe ratio as measure of comparison, the superiority of the constructed portfolio is even more evident. Respectively, the “overlap” portfolio has a Sharpe ratio of 0,1029 while the benchmark has a Sharpe ratio as low as 0,0240. Concluding, the thesis goal is achieved. This entails that investing safely (low portfolio volatility) in companies with high degree of sustainability, yet achieving superior financial performance, is possible.

To my knowledge, the combination of the minimum volatility anomalies and the sustainability factor has not been considered yet by the financial literature. This thesis contributes in this field proposing two ways for creating investment portfolios based on the two strategies.

The following paragraphs are presented as follow: 1 Literature review provides insights on the low-volatility and sustainability factors; 2 Data presents the data employed for the analysis; 3 Methodology describes how the portfolios are constructed and the tests performed; 5 Results shows the results of the different investment strategies, comparing these to the appropriate benchmark; 6 Conclusion summarize the findings of the thesis and concludes.

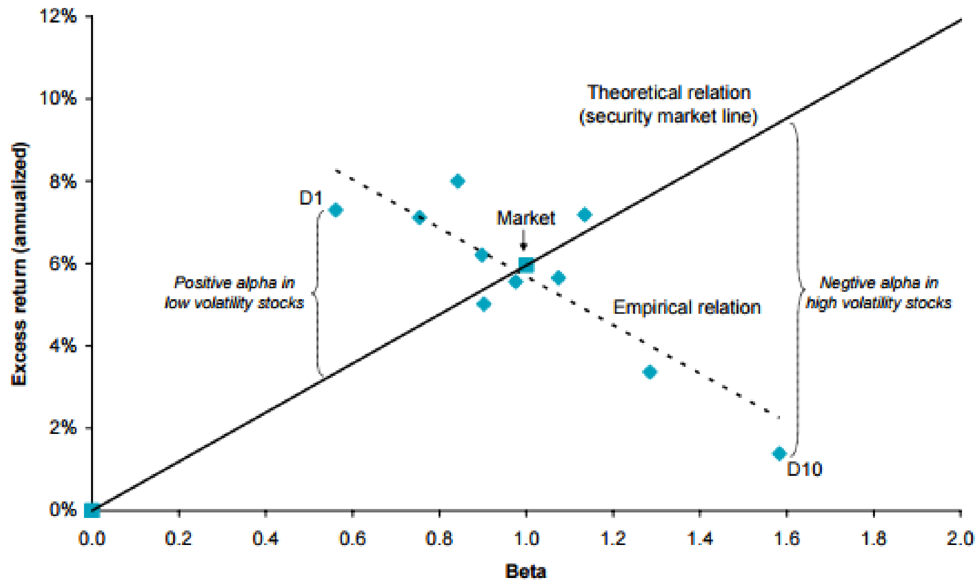
1. Literature Review

1.1 Low-volatility anomaly

The low volatility effect, as defined in (D. C. Blitz & van Vliet, 2007) and also known as the low-volatility or minimum volatility anomaly, is the extra-return originated by a minimum-risk portfolio. In recent years this strategy gained a lot of interest, particularly from the practitioners, and several indexes exploiting this factor appeared in the industry (e.g. S&P500 Low Volatility, Russell 1000 Low Beta, MSCI Minimum Volatility Index family, etc.). However, this anomaly first appeared in literature in the 70's through an empirical test (Black et al., 1972) which results showed a flatter risk-return relationship than predicted by the CAPM. Successively, the work of (Haugen & Heins, 1972) "document the lack of positive relationship between risk and return in the empirical cross-section of stock market returns". On later years the evidence of the anomaly has been supported by several studies by both academics and practitioners which confirmed the presence of the anomaly throughout the forty years since its initial discovery. Examples of such studies are (Baker & Haugen, 2012), (Clarke, de Silva, & Thorley, 2006), (D. C. Blitz & van Vliet, 2007), or (Frazzini & Pedersen, 2014).

Every anomaly by definition contradicts the CAPM theory. Notably, size and value, as defined in (E F Fama & French, 1992) and momentum (Carhart, 1997) are the most renewed in the financial industry. However, the low volatility effect is the anomaly which most severely contradicts the Capital Asset Pricing Model of (Sharpe, 1964) and (Lintner, 1965). Indeed, while the CAPM, the most widely used pricing model in finance, predicts a positive and linear relationship between (systematic)risk and expected returns, minimum volatility portfolios deny such theory providing evidence of the opposite. Figure (2) well describes these findings.

Figure 2- " Empirical versus theoretical relation between beta and return". Source, (D. C. Blitz & van Vliet, 2007)*. The graph shows a set of decile portfolios based on minimum volatility factor and the market portfolio. The empirical trend line is compared to the security market line.*



Being the CAPM defined as the really fundament of financial theory, these empirical findings represents sort of a heart quake for the financial industry. Hence, it is important to understand the reasons of such assets' behaviour and answer two main questions, namely why more risk is not compensated by more returns and why this has been persisting for so long time.

1.1.1 Understanding the low-volatility anomaly

Several papers provide different answers to these questions. In particular, the following paragraph will summarize the work of (D. Blitz, Falkenstein, & van Vliet, 2014). The authors state that "the main objective of our paper is to organize this fragmented literature by providing a broad overview of the various explanations for the volatility effect, and by categorizing each explanation according to the CAPM assumption it relates to."

Following the authors' steps, it is useful for what it follows to list the main CAPM assumption. Indeed, most of the explanations of the minimum variance factor derive from a critique to these assumptions.

(i) “There are no constraints (e.g. on leverage and short-selling)

(ii) Investors are risk-averse, maximize the expected utility of absolute wealth and care only about the mean and variance of return

(iii) There is only one period

(iv) Information is complete and rationally processed

(v) Markets are perfect, i.e. all assets are perfectly divisible and perfectly liquid, there are no transaction costs, there are no taxes and all investors are price takers” (D. Blitz et al., 2014)

1.1.2 No constraints

The three main constraints are leverage, regulation, and short-selling. All of them participate to explain the counter-intuitive evidence of low-risk portfolios returns.

The cost-free leverage described in the CAPM is -theoretically- used to adjust the risk-return profile of the market portfolio according to the investor’s degree of risk aversion. Being in reality difficult -costly- to borrow money (indeed borrowing/leverage constraints), “investors looking to increase their return have no option other than to tilt their portfolio towards high-beta securities in order to garner more of the equity risk premium. This extra demand for high-beta securities and reduced demand for low-beta securities may explain a less steeply upward-sloping security market line than predicted by the CAPM” (D. Blitz et al., 2014). Evidence which supports this idea is provided by (Frazzini & Pedersen, 2014) who showed that less-constrained funds like hedge-funds are more exposed to low-volatility stocks rather than mutual funds which are more constrained.

Another type of constraint comes from the regulatory system. In brief, regulators do not distinguish between low-volatility stocks and other (more volatile) stocks so they cannot represent an option when mutual funds have to balance their exposure to the market (e.g. eventually one might decrease the exposure to bonds buying low-volatility stocks without necessarily decreasing the overall portfolio volatility).

Finally, short-selling constraints may explain why high-risk stocks are overpriced. Due to the *winner's curse* bias, "the demand for a particular security will come from the minority who hold the most optimistic expectations about it (…) [so] as divergence of opinion is likely to increase with risk, high-risk stocks are more likely to be overpriced than low-risk stocks, because their owners will have the greatest bias." (D. Blitz et al., 2014)

1.1.3 Investors utility function

Another factor which might help in explaining the low volatility effect derives from investors' utility function. First, it has been shown[1] that people are more relatively rather than absolutely oriented. According to (Falkenstein, 2009), "the argument is essentially that with utility based on relative wealth, risk taking becomes deviating from the consensus or market portfolio, and in such an environment all risk becomes like idiosyncratic risk in the standard model, avoidable and therefore unpriced." (D. Blitz et al., 2014). Secondly, it seems that agents maximize option value since there is a parallelism between their incentive structure and that of a call option. This leads to a preference (then money flow) for high-risk stocks particularly in the short-term. Third, prospect theory predicts economic agents' preference versus skewness (Kahneman & Tversky,

[1] E.g. (Rayo & Becker, 2007), (Ferrer-i-Carbonell, 2005)

1979). This also explain why agents procrastinate in selecting lottery-style stocks (such as low-priced volatile stocks).

1.1.4 Information is complete and rationally processed

The main typical behavioural biases help to better understand the low volatility anomaly as a consequence of strong economic agents' preference for risky stocks. For instance, "attention-grabbing stocks [documented bias, (Barber & Odean, 2012)] are typically found in the high volatility segment of the market. Boring low-volatility stocks are the flipside of the coin, suffering from investor neglect. The attention-grabbing phenomenon is therefore another argument supporting the existence of the volatility effect" (D. Blitz et al., 2014). Similarly, representative bias (Tversky & Kahneman, 1983), mental accounting (Shefrin & Statman, 2000), and, especially, overconfidence, all lead to a biased preference towards high-risk stocks, partially explaining the persistency of the minimum volatility anomaly.

1.2 Sustainability investing

The United Nations Principles for Responsible Investment (UNPRI) defines Responsible Investment as ''the integration of environmental, social and governance criteria into mainstream investment decision-making and ownership practices''[2]. The PRI works with its international network of signatories to put the six Principles for Responsible Investment into practice. These principles are:

1. "We will incorporate ESG issues into investment analysis and decision-making process.
2. We will be active owners and incorporate ESG issues into our ownership policies and practices.
3. We will seek appropriate disclosure on ESG issues by the entities in which we invest.

[2] https://www.unpri.org/

4. We will promote acceptance and implementation of the Principles within the investment industry.
5. We will work together to enhance our effectiveness in implementing the Principles.
6. We will each report on our activities and progress towards implementing the Principles."(N. S. Eccles, 2010).

These principles collect more than 1,400 signatories from over 50 countries representing US$59 trillion of assets. "Nearly one out of every eight dollars under professional management in the United States today – 12% of the $25.2 trillion assets under management tracked by Thomson Reuters—is involved in sustainable and responsible investing, according to the Social Investment Forum"[3]. Notably, as reported in (Diltz, 1995), in 1991 only $625 billion were considered SRI (social responsible investing), while in 1998 they already almost doubled to $1.185 trillion. These figures are meant to shed light on the clear relevance of this topic within the financial industry.

More debatable are the definition of sustainability investing and its implementation. On this regard, (Sandberg, Juravle, Hedesström, & Hamilton, 2009) commented on the heterogeneity of the SRI, which they disentangle in four levels: terminological, definitional strategic, and practical. The UNPRI definition quoted above helps in defining a common dominator for the terminology, while the investment approach might consider three different aspects, namely screening companies, ESG score implementation, and active ownership. Screening is the simplest investment methodology which account for SRI. Investors simply screen-out (negative screening) companies which do not match certain ethical aspects while consider more sustainability-concerned companies (positive screening). Shareholder activism includes voting at the proposals of companies' General Meetings and, eventually, engage with them on ESG issues. Notably, findings show that "ESG engagements generate a cumulative size-adjusted abnormal return of

[3] http://www.pwc.com/us/en/corporate-sustainability-climate-change/assets/investors-and-sustainability.pdf

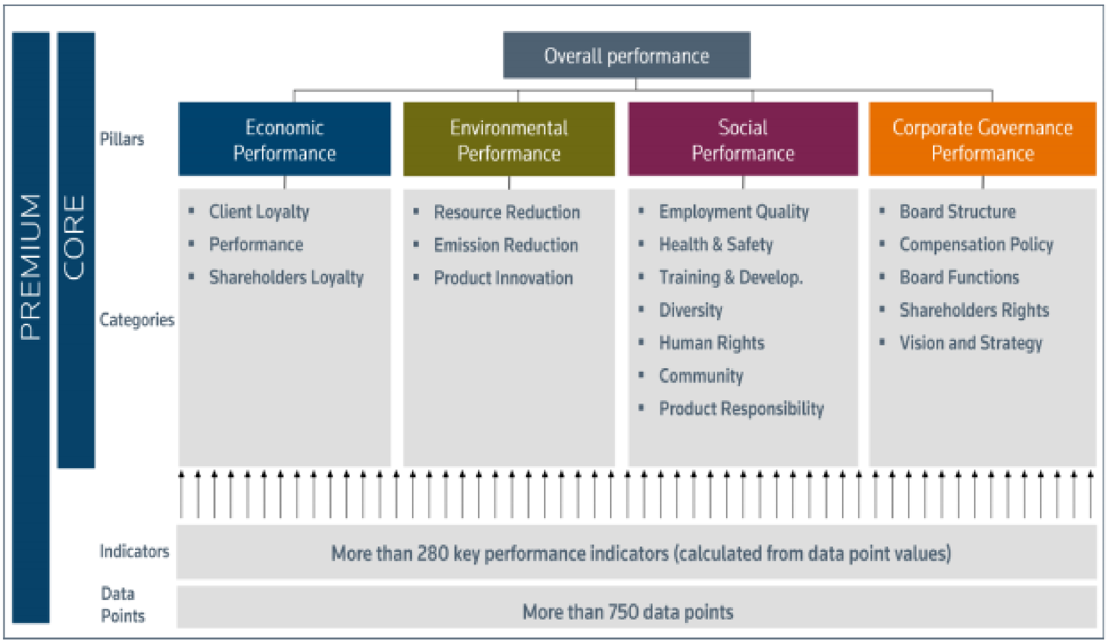
+2.3% over the year following the initial engagement. Cumulative abnormal returns are much higher for successful engagements (+7.1%) and gradually flatten out after a year, when the objective is accomplished for the median firm in our sample." (Dimson, Karakaş, & Li, 2015). Of greatest interest for this thesis is the integration of ESG scores (defined in Data) in the portfolio construction. (Kempf & Osthoff, 2007) find that applying a long-short strategy, namely buying stocks with high socially responsible ratings and sell stocks with low ratings, lead to annual abnormal returns up to 8.7% (significance remain even after accounting for transaction costs). In (Hill, Ainscough, Shank, & Manullang, 2007) the authors study the relationship between corporate social responsibility (CSR) and company's stock valuation across three regions of the world. Their results are somehow less promising financially: only European stocks showed outperformance in the short term, while both European and US stocks outperformed the market in the long term (Asian portfolios were close to significance in the same period). These results are supported by (Shank, Manullang, & Hill, 2005) who also indicate that the market prices social responsibility characteristics in the long run. In addition, findings reveal that high sustainability companies have superior organizational processes, are more long-term oriented, and "significantly outperform their counterparts over the long-term, both in terms of stock market and accounting performance." (R. G. Eccles, Ioannou, & Serafeim, 2014). While the presented studies support the existence of a positive relationship between sustainability investing and financial performance (particularly in the long-term), other studies disagree on that. In (Halbritter & Dorfleitner, 2015) the authors "strongly questions whether there is actually a relationship between ESG ratings and returns which is exploitable with a trading strategy." They also support the idea that results are largely influenced by the particular ESG rating provider.

It is important to consider that SRI represents a shift in the financial industry. While so far there has always been a unique unit of measurement, namely financial performance, the introduction of sustainability concerns acts as a second variable to look at in the investment process. The UNPRI made an incredible number of institutional investors embracing its principles. “The debate must now focus beyond SRI financial performance. The current challenge is to determine whether SRI can encourage companies to take on greater environmental and social responsibility and refocus their strategic decisions to account for stakeholder expectations” (Revelli & Viviani, 2015). Trends suggest this is the case.

2. Data

ESG scores for companies are provided by the Thomson Reuters Datastream ASSET4 financial database. As described in (Reuters, 2011), the ASSET4 ESG rating is an equally weighted rating - which range from 0 to 100- that evaluates the overall performance of a company with regards to economic, environmental, social and corporate governance issues. The assessment relies on approximately 700 individual data points (examples can be found in Figure (6), see Appendix), which are combined into over 250 key performance indicators (KPIs). These KPI scores are aggregated into a framework of 18 categories grouped within 4 pillars that are integrated into a single overall score (Figure 3). A Z-score measure[4] is employed in order to standardize the scores and make them comparable. ESG scores are calculated on an annual base.

Figure 3 - Thomson Reuters Datastream ASSET4 ESG Comprehensive Model. Source, (Reuters, 2011). *The figure schematises what ASSET4 rating considers to construct ESG scores.*



[4] $z - score = \frac{Firm\ (i)\ combined\ category\ score - Average\ combined\ category\ score}{\sigma_{combined\ category\ score}}$

For this thesis, every year, from 2002 to 2014, all the available US companies' ESG scores, together with relative code (ISIN), are provided by Thomson Reuters Datastream ASSET4. This define the size of the sample data from which portfolios are constructed since prices are downloaded from Thomson Reuters Datastream only for companies for which an ESG score was available. Starting with less data points collected (324 in 2002), more data are available from 2009 (981 in 2014), with an average of 697 sample and a total of 1043 companies considered (Table1).

Table 1 - Sample Size by Year. The table shows the sample number of companies in each different year of study. Final investment Universe reduce #Companies sample taking out of the sample those companies for which past-three-year prices were not available.

Year	# Companies	Final Investmet Universe
2002	324	307
2003	325	313
2004	463	439
2005	527	501
2006	536	508
2007	577	542
2008	754	708
2009	857	812
2010	906	854
2011	927	873
2012	933	881
2013	951	907
2014	981	935
Average	697	660
Tot.	1043	

In order to exploit the low volatility effect following the methodology of (D. C. Blitz & van Vliet, 2007) (see Methodology) past-three-years monthly prices are collected every year. Hence, the database will contain companies' prices from January 2000. Notably, the dataset is survivorship bias-free, since none of the companies invested in period t shows lack of data (prices) at the end of the investment period (one year) t+1, providing evidence that these companies "survived" in the study period.

Two different benchmark will be used to test the results. The first is "internal", namely the monthly time series of average returns of all the companies by each different year. The second is the US market portfolio, defined as "Rm-Rf, the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ", obtained from the online library of Professor Kenneth R. French. From the same source are found also the remaining four factors which defined the Five Factor Model (Eugene F. Fama & French, 2015), namely size (SMB), value (HML), profitability (RMW), and investment (CMA). Reporting the description found in Kenneth R. French library, "SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios[…], HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios […], RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios […], CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios [...]."[5] RMW simply refers to the operating profitability (minus interest expense) of a company, respectively high (robust) and low (weak). Probably less straightforward in its definition, the investment factor is calculated as "the growth of total assets for the fiscal year ending in t-1 divided by total assets at the end of t-1"(Eugene F. Fama & French, 2015). This ratio defines the words conservative and aggressive, namely low and high level of investments for a company in a certain year t.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

3. Methodology

3.1 Low-volatility anomaly

Aiming to exploit the volatility effect, the following procedure replicates the methodology of (D. C. Blitz & van Vliet, 2007). Every year, past three years (t-3) and next year (t+1) monthly log-returns are calculated from the time series of companies' prices provided by Thomson Reuters Datastream. Successively, the standard deviation of the past three years is defined. This procedure slightly differs from (D. C. Blitz & van Vliet, 2007) in that monthly instead of weekly returns are considered; no significant difference in terms of results is expected. Companies are now ranked by volatility in ascending order. Companies for which past three years' prices were not available are excluded from the sample, reducing it by ca 5% (see Table 1, "Final Investment Universe"). This step is necessary since companies with less than 36 data points (three years of monthly prices) are more likely to show lower volatility, affecting the factor ranking. The entire sample sorted is divided in portfolio deciles, where the first one is composed of companies with the lowest past three years' volatility. Decile portfolios size[6] vary year by year ranging from 31 (2002) to 94 (2014) companies (see Table 1, divide numbers by ten). In order to define the time-series vector of monthly returns for each decile portfolio, each month the average of returns of all the different companies within each decile portfolio is calculated (see Appendix for summary statistics examples). Portfolio are rebalanced annually.

[6] $Decile\ size\ in\ year\ (i) = \frac{\text{Tot. Companies in year (i)}}{10}$ (rounded)

3.2 Sustainability investing

Considering year t ESG score data, companies' monthly returns are calculated for year t+1. The reason behind this is quite straightforward. As described in the Data section, ESG scores represents a standard metric to assess the sustainability of a company business and are calculated annually, allowing for a final score availability only at the end of the year (or beginning of next year). Every year the whole sample is ranked by ESG scores in descending order in dived in decile portfolios. The time series of average monthly returns for each portfolio is calculated as described in the Low Volatility Effect section (see Appendix for summary statistics examples).

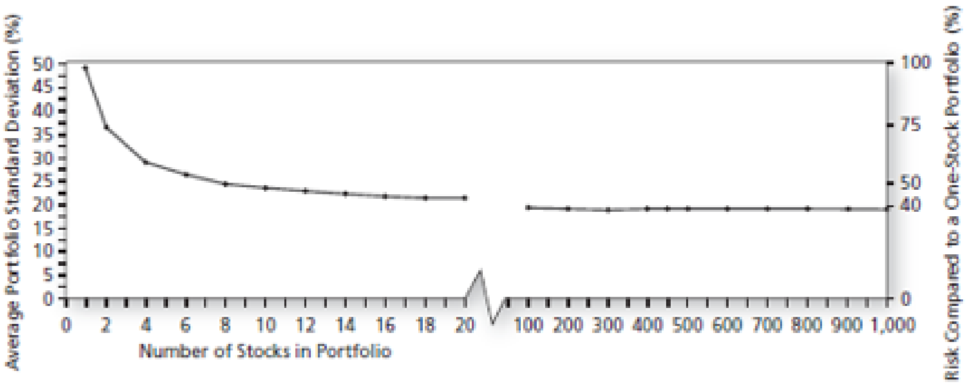
3.2.1 Double Sorting

In order to exploit the potential of the sustainability factor and the one of the minimum volatility anomaly, a double sorting approach is considered. Every year, the whole sample is ranked by ESG scores in descending order. The top 50% and the bottom 50% are separately (double)sorted by volatility -both in ascending order- and divided in quintile. This results in ten sub-quintile portfolios of the size of deciles if the initial whole sample is considered (see Appendix for summary statistics examples).

3.2.2 Factors Overlap

As an alternative to the double sorting, a different methodology -which follows the same purpose- is presented. Every year, the whole sample is ranked by the ESG scores in ascending order and divided in quintile portfolios, of which only the first (highly sustainable companies) and the last (low ESG score) are considered. The same procedure is applied taking volatility as a factor. The companies which happen to be in the first quintile portfolios of both the strategies are considered and will form the "Overlap portfolio". The same procedure is applied to the two least quintile portfolios (see Appendix for summary statistics examples). The size of the two overlap portfolios -high ESG/low volatility and low ESG/high volatility- ranges from ca. 20 companies in 2003 to ca. 60 in 2014 (with an average of ca. 45). This means that this strategy still allows to obtain diversified portfolios, as visible in Figure 4 (Bodie, Kane, & Marcus, 2014) which shows that a sort of diversification break point -say as a good rule of thumbs- happens when at least twenty stocks are in the portfolio.

Figure 4 - Portfolio diversification. Source, (Statman, 1987)*. The graph shows the benefits that diversification (including a larger number of stocks into a portfolio) bring to portfolio's standard deviation.*



With this regards the same methodology described is repeated considering the companies overlaps between decile portfolios instead of quintiles. As expected, the number of companies (see Table 2) resulting in the new overlap portfolios is rather insufficient for a well-diversified portfolio, especially for the first years (2002 to 2007).

Table 2 - Portfolios size from decile portfolios overlap. The table shows 2002-2014 size of the portfolios derived by the overlaps from decile portfolio based on volatility and ESG score.

Year	Overlap Top	Overlap Bottom
2002	6	9
2003	6	7
2004	7	6
2005	4	7
2006	8	9
2007	11	10
2008	24	16
2009	25	18
2010	19	19
2011	19	14
2012	19	17
2013	17	18
2014	22	31

3.3 Tests

In order to find significant alphas, all the different sets of portfolios for each factor -low-volatility and sustainability- and their combination -double sorting and "factors overlap"- are tested against a US benchmark (discussion in Results) and the US based Fama and French Five Factor Model (FF5 Model), as defined in (Eugene F. Fama & French, 2015). If for a given portfolio the alpha is found to be significant in a t-test[7], it can be deduced it delivers abnormal returns which cannot be explained using Kenneth French's US factors. The two regressions, one having as variable the market while the other the FF5Model factors, are respectively shown in Equation (1) and (2).

$$\boldsymbol{r}_{(i)} - \boldsymbol{r}_f = \alpha + \beta_{RMRF}\boldsymbol{r}_m + \boldsymbol{\epsilon} \quad (1)$$

$$\boldsymbol{r}_{(i)} - \boldsymbol{r}_f = \alpha + \beta_{RMRF}\boldsymbol{r}_m + \beta_{SMB}\boldsymbol{r}_{SMB} + \beta_{HML}\boldsymbol{r}_{HML} + \beta_{RMW}\boldsymbol{r}_{RMW} + \beta_{CMA}\boldsymbol{r}_{CMA} + \boldsymbol{\epsilon} \quad (2)$$

[7] $t - statistic = \frac{\alpha}{standard\ error} \sim t_{n-1}$

Where, in equations (1) and (2),

$\boldsymbol{r}_{(i)}$ = returns for portfolio (i)

$\boldsymbol{r}_f$ = risk free rate

α = intercept

$r_{(m)}$ = market excess return

β_{RMRF} = market coefficient estimated trough the regression

$r_{(SMB/HML\ /RMW/CMA)}$ = excess returns for the (i) factor

$\beta_{(SMB/HML\ /RMW/CMA)}$ = Factor (i) coefficient estimated through the regression

Virtually, all financial data shows heteroskedasticity, that is the variance of the residuals is not constant. This contradict one of the assumption under which the Ordinary Least Square model is BLUE. This bias is detected through a White-test, "a diagnostic test for homoscedasticity. The null-hypothesis is that the variance of the residuals can only be explained by a constant […], if we reject that using an auxiliary regression and an F-test, we say the regression suffered from heteroscedasticity" (Versijp, 2015). In this thesis, the null-hypothesis is rejected in all cases. In order to overcome this issue, the regressions of the different portfolios consider Heteroskedaticity-consistent (HC) standard errors. Practically, since they show poor reliability, standard errors are replaced by a weighted average of squared residuals.

4. Results

4.1 Selecting the benchmark

Before showing the results from the regressions explained in the Methodology paragraph, it is important to discuss the selection of the benchmark against which to compare all the different portfolios returns.

It is common practice to compare investors' performance against the adequate passive index, which represents a valid alternative investment opportunity. For instance, a portfolio manager investing in value stocks, might want to consider a value index to oversee his portfolio. Also, other characteristics shall be considered, such the geographic area invested in (e.g. value indexes in emerging markets have different returns than those in developed). Hence, also in this case the benchmark should be a passive portfolio reflecting the sample characteristics (e.g. geographic area, constituents size, etc.). As explained in Data, the time-series of monthly returns for the US market provided by Kenneth R. French website is an optimal solution as choice of benchmark, since also the returns for the FF5 Model are available. Alternatively, renowned indexes managed by Standard&Poor's, such the S&P500, might be a good term of comparison, since the characteristic (companies' size and geographic area) are similar, and represent a valid investment alternative through several ETFs available. However, monthly extra returns time-series from January 2003 to December 2015 of both these benchmarks (Kenneth R. French data library and S&P500) show superior performance when compared to the equally-weighted portfolio created taking into account all the companies of the database from which all decile portfolios for different strategies are created. This difference is substantial (see Table 3). Even though the standard deviation is somehow comparable, the compound annual growth rate (CAGR) for the exogenous portfolios is more than five times higher than that of the endogenous one, with the latter particularly low (1.8%).

Table 3- Different benchmarks performance from 2003-2015. The Table shows the performance for three different US benchmarks. Equally-Weighted endogenous benchmark is the portfolio which include all the stocks employed for constructing the investment strategies in this thesis. FF Mkt-RF is the US market portfolio provided by Professor K. French in his data library. S&P500 in the index portfolio provided by Standard & Poor's accounting for the 500 biggest companies in the US.

Year	Equally-Weighted Endogenous Benchmark	(FF)Mkt-RF	S&P500	S&P 500 (Inc. Dividends)
2003	0,2066	0,3047	0,2638	0,2868
2004	0,1431	0,1063	0,0899	0,1088
2005	0,0893	0,0300	0,0300	0,0491
2006	0,0602	0,1016	0,1362	0,1579
2007	-0,0465	0,0098	0,0353	0,0549
2008	-0,6017	-0,3778	-0,3849	-0,3700
2009	0,4591	0,2825	0,2345	0,2646
2010	0,1456	0,1737	0,1278	0,1506
2011	-0,0530	0,0041	0,0000	0,0211
2012	0,0690	0,1625	0,1341	0,1600
2013	0,2977	0,3518	0,2960	0,3239
2014	0,0406	0,1170	0,1139	0,1369
2015	-0,0879	0,0007	-0,0730	0,0138
CAGR	0,0180	0,0804	0,0614	0,0890
St.Dev	0,2477	0,1845	0,1742	0,1737
Sharpe Ratio	0,0726	0,4356	0,3522	0,5124

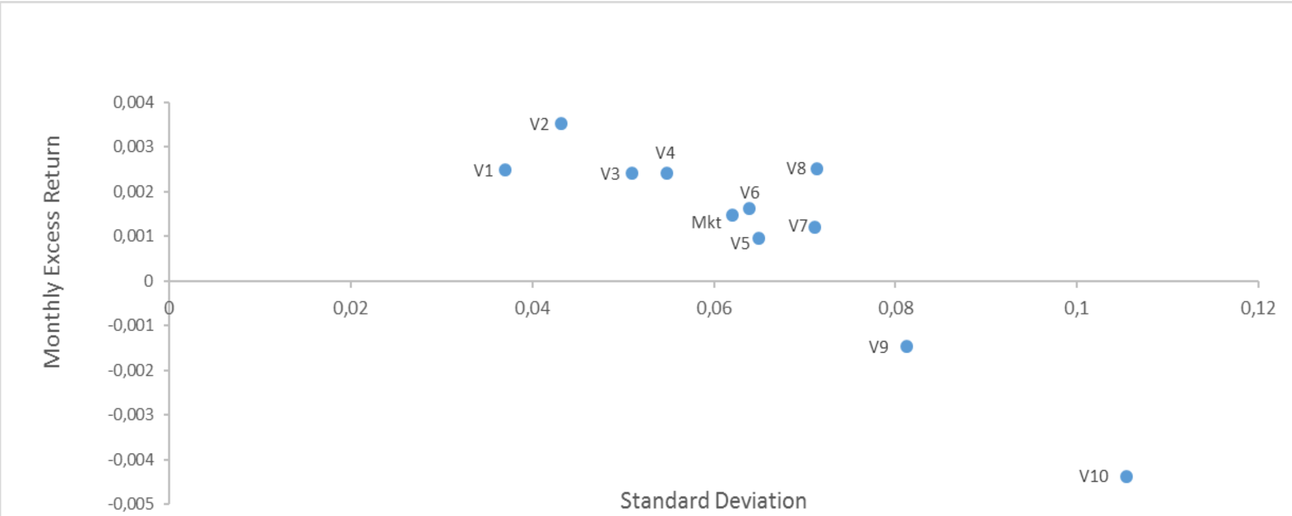
Having the same geographic area and, at least when compared to the S&P 500, also similar stock features (market capitalization), the benchmark characteristic is a rather weak explanation of such under-performance. In this sense, portfolio construction methodology might help. Indeed, the Kenneth R. French portfolio and the S&P 500 are value-weighted[8] (or capitalization-weighted), while the endogenous one is equally-weighted.

For the evident discrepancies on the performance between endogenous and exogenous, regression results are presented considering solely endogenous portfolio, while the regression against the Kenneth R. French market portfolio and Five Factor Model are left in Appendix.

4.2 Low-volatility portfolios

As shown in Figure (5) the disposition of the decile portfolios (V1-V10.) in the Excess Return-Standard Deviation graph is well aligned with previous finding on the low-volatility anomaly ((e.g. (D. C. Blitz & van Vliet, 2007)).

Figure 5- Low Volatility Effect, Portfolio Disposition. The graph shows the disposition of the ten decile volatility-ranked portfolios and the market portfolio.



Contrary to what the finance literature of the CAPM predicts, portfolios with low volatility have also higher return (then also higher Sharpe ratio), cancelling off the reward an investor should benefit from for taking extra risk. Particularly emphasized is the difference between

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

the first two decile portfolios and the last two, leaving rooms for a profitable long-short investment strategy, as found in the previous literature.

Table (4) shows the regression of the monthly extra returns of each of the ten low-volatility portfolios, and the first decile portfolio financed by the last one (V1-V10), against the monthly extra returns of the endogenous market portfolio, as specified in Methodology paragraph.

*Table 4- **Volatility sorted portfolios**. This table shows US equally-weighed decile portfolios performance over the period 2003-2014. Each month, stocks are ranked in ascending order based on their volatility. Portfolios are assigned to one of ten portfolios (V1 to V10), where the first portfolio (V1) has lowest volatility. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in the low volatility portfolio and short-invested in the high volatility portfolio. Portfolio size vary each year (see Table 1), averaging 66 companies for each decile portfolio. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). The explanatory variable is the monthly returns from the market portfolio (MKT). Risk-free rates are deducted from both portfolio and market returns.*

	Mkt	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V1-V10
CAGR	0,0180	0,0303	0,0430	0,0295	0,0295	0,0114	0,0198	0,0145	0,0307	-0,0174	-0,0511	-0,0001
Exp. Ret.	0,0015	0,0025	0,0035	0,0024	0,0024	0,0009	0,0016	0,0012	0,0025	-0,0015	-0,0044	0,0000
St.Dev.	0,0620	0,0370	0,0431	0,0510	0,0548	0,0650	0,0639	0,0711	0,0714	0,0812	0,1055	0,0419
Sharpe Ratio	0,0240	0,0675	0,0815	0,0475	0,0443	0,0146	0,0256	0,0168	0,0354	-0,0180	-0,0414	-
Alpha	-	0,0014	0,0022	0,0010	0,0009	-0,0004	0,0002	-0,0817	0,0012	-0,0024	-0,0042	0,0056
(*p-value*)	-	*0,3650*	***0,0661****	*0,3390*	*0,2740*	*0,7030*	*0,7800*	*0,9370*	*0,3370*	***0,0699****	*0,1470*	*0,1580*

Significant Level: * 10%; **5%; ***1%

The second decile portfolio shows an alpha of 22 bps a month (2,6% annualized), positive and statistically significant at the 10% level. Circa the last portfolios, only the ninth has a negative alpha of -24 bps, statistically significant at the 10% level. Even though from a statistical point of view no conclusion can be drown about the 10th portfolio and the short-long strategy (V1-V10) since both p-values are above 10% (yet around 15%), the coefficients are quite high, respectively 5,15% and 6,9% annualized. Counter-intuitively, both CAGR and expected returns for V1-V10 are not equal to the actual difference (e.g. 0,0025 - (-0,0044) = 0,0069). This is due to the portfolio construction. V1-V10 is the portfolio which returns are the monthly average of V1 and -V10. Due to compounded average, the end result is what reported in Table (4) and not simply the sum of the two portfolios' performance.

When assessing the results for the low volatility anomaly, it is worth to consider other unit of measurement other than coefficient significance. Indeed, while little evidence is found in terms of significant alpha, Table (4) contains several useful information. The first two decile portfolios show higher expected returns (respectively 25 and 35 bps a month) than the others, while the last one has a negative expected returns of 44bps (the highest in absolute value). By construction, it follows naturally that the standard deviation is in a monotonically ascending order, from the first decile to the last, leading to the conclusion that the first two decile portfolios have markedly higher Sharpe ratio also when compared to that of the market. This is clearly visible in Figure (5).

4.3 ESG portfolios

Similarly to what has been presented for the low volatility effect, Table (5) shows the regression results for each of the ten decile portfolio constructed by ranking companies on their ESG score as specified in Methodology paragraph.

*Table 5- **ESG sorted portfolios**. This table shows US equally-weighed decile portfolios performance over the period 2003-2014. Each month, stocks are ranked in descending order based on their ESG score. Portfolios are assigned to one of ten portfolios (ESG1 to ESG10), where the first portfolio (ESG1) has highest ESG scores. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in the high ESG portfolio and short-invested in the low ESG portfolio. Portfolio size vary each year (see Table 1), averaging 66 companies for each decile portfolio. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). The explanatory variable is the monthly returns from the market portfolio (MKT). Risk-free rates are deducted from both portfolio and market returns.*

	Mkt	ESG1	ESG2	ESG3	ESG4	ESG5	ESG6	ESG7	ESG8	ESG9	ESG10	1-10
CAGR	0,0180	0,0262	0,0320	0,0415	0,0147	0,0040	0,0215	0,0171	0,0093	-0,0133	0,0203	-0,0094
Exp. Ret.	0,0015	0,0022	0,0026	0,0034	0,0012	0,0003	0,0018	0,0014	0,0008	-0,0011	0,0017	-0,0008
St.Dev.	0,0620	0,0508	0,0541	0,0628	0,0639	0,0640	0,0597	0,0636	0,0709	0,0696	0,0756	0,0193
Sharpe Ratio	0,0240	0,0424	0,0486	0,0541	0,0191	0,0052	0,0297	0,0223	0,0109	-0,0161	0,0222	-
Alpha	-	0,0007	0,0012	0,0020	-0,0002	-0,0011	0,0003	-0,0059	-0,0005	-0,0023	0,0006	0,0001
(*p-value*)	-	*0,4750*	*0,2290*	***0,0674*** *	*0,8410*	*0,1490*	*0,7550*	*0,9950*	*0,6630*	***0,0631****	*0,7350*	*0,9760*

Significant Level: * 10%; **5%; ***1%

The third decile portfolio shows a positive alpha of 20bps significant at the 10% level. Also significant at the 10%level is the ninth portfolio's negative alpha, -23bps of monthly excess return. None of the remaining portfolios show statistically significant alpha. Other measures seem to better support this sustainable strategy. Indeed, the first three decile portfolios exhibit higher monthly expected return and lower standard deviation (hence higher Sharpe ratio) in comparison to those of other decile portfolios and the market itself.

4.4 Double-sorted portfolios

Table (6) shows the regression results for the ten decile portfolio constructed by ranking by volatility the top 50% ESG scored companies (first five decile portfolio) and bottom 50% (from sixth to tenth decile portfolios) as described in Methodology.

*Table 6- **Double-sorted portfolios**. This table shows US equally-weighed decile portfolios performance over the period 2003-2014. Each month, the whole sample is divided in two halves, top and bottom 50% companies based on their ESG score. Each half is divided in quintiles, and double-sorted on stocks' volatility in ascending order. Portfolios are assigned to one of ten portfolios (Sort1 to Sort10), where the first portfolio (Sort1) has lowest volatility and top 50% ESG scores. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in S1 and short-invested in the S10 (highest volatility and bottom 50% ESG scores). Portfolio size vary each year (see Table 1), averaging 66 companies for each decile portfolio. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). The explanatory variable is the monthly returns from the market portfolio (MKT). Risk-free rates are deducted from both portfolio and market returns.*

	Mkt	Sort1	Sort2	Sort3	Sort4	Sort5	Sort6	Sort7	Sort8	Sort9	Sort10	S1-S10
CAGR	0,0180	0,0390	0,0502	0,0184	0,0299	-0,0075	0,0128	0,0075	0,0110	0,0241	-0,0406	0,0054
Exp. Ret.	0,0015	0,0032	0,0041	0,0015	0,0025	-0,0006	0,0011	0,0006	0,0009	0,0020	-0,0034	0,0005
St.Dev.	0,0620	0,0355	0,0488	0,0617	0,0668	0,0907	0,0468	0,0576	0,0688	0,0715	0,0975	0,0382
SharpeRatio	0,0240	0,0901	0,0837	0,0246	0,0368	-0,0069	0,0227	0,0109	0,0133	0,0277	-0,0353	-
Alpha	-	0,0021	0,0027	0,0892	0,0011	-0,0013	-0,0002	-0,0007	-0,0003	0,0007	-0,0038	0,0059
(*p-value*)	-	*0,1560*	***,00693*****	*0,9210*	*0,3190*	*0,4490*	*0,8840*	*0,5750*	*0,7800*	*0,5900*	*0,1310*	*0,1010*

Significant Level: * 10%; **5%; ***1%

Only the coefficient of the second decile portfolio is statistically significant (1% level) with a magnitude of 27 bps (3.2% on an annual base). Considerably, the magnitude of the coefficient of the long-short portfolio (Sort1-Sort10) is particularly high (7,3% yearly excess return), and almost statistically significant at the 10% level (p-value of 0,101). Looking at different performance, also in this strategy the first two decile portfolios outperform the others. The Sharpe ratio of the first portfolio Sort1 (but also of Sort2), 0,0901, is by far higher than the remaining portfolios, particularly when compared to the last one (Sort10), which has a negative Sharpe ratio of magnitude -0,0353.

4.5 “Overlapping” portfolios

Table (7) shows the regression results for two portfolios and the relative long-short strategy. As described in details in Methodology section, the first, Overlap1, is formed by the companies present on the top quintile portfolio of both an ESG and a low volatility strategy. The latter, follows the same logic considering the bottom, instead of the top, quintile portfolio.

Table 7- "Overlapping" portfolios. Table 4- Volatility sorted portfolios. This table shows US equally-weighed portfolios performance over the period 2003-2014. Each month, on the one hand stocks are ranked in ascending order based on their volatility, on the other hand they are ranked based on their ESG score. In both case the sample is divided in quintile. Companies which happens to be present in both the first quintile (and 10th quintile) will form the considered “Overlap1” (“Overlap5”) portfolio. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in the Overlap1 portfolio (having lowest 20% and highest 20% ESG score) and short-invested in Overlap5 portfolio. Portfolio size vary each year), averaging ca. 45 companies for each portfolio, depending on the overlaps found. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). The explanatory variable is the monthly returns from the market portfolio (MKT). Risk-free rates are deducted from both portfolio and market returns.

	Mkt	Overlap1	Overlap5	Ov.1-Ov.5
CAGR	0,0180	0,0446	-0,0159	-0,0013
Exp. Ret.	0,0015	0,0036	-0,0013	-0,0001
St.Dev.	0,0620	0,0354	0,0936	0,0358
Sharpe Ratio	0,0240	0,1029	-0,0143	-
Alpha	-	0,0026	-0,0018	0,0044
(*p-value*)	-	***0,0811****	*0,4530*	*0,1920*

Significant Level: * 10%; **5%; ***1%

Only Overlap1 shows significant result with a coefficient of 0,0026 (p-value of 8,11%). On an annual base, this portfolio would lead to an excess return of 3,1%. It is worth have a look also at the other measures. Indeed, Overlap1 has a CAGR of 4,46% while the market only 1,8%. Moreover, the constructed portfolio has a standard deviation which is almost half that of the benchmark (0,0354 and 0,0620 respectively) leading to a markedly higher Sharpe ratio (0,1029). We have opposite result for the second portfolio (Overlap10), which shows negative expected return and high standard deviation.

5. Conclusion

The thesis goal of defining a portfolio which combines low-volatility and sustainability factors, yet delivers superior performance than portfolios based on these two factors alone -and the benchmark- is achieved. While both the portfolios resulting from the double sort and the "overlap" methodology show superior adjusted returns, only the latter has a statistically significant coefficient, amounting to 26 bps a month (3,1% extra return annualized). This investment portfolio has a CAGR of 4,46% for the period 2003-2014 and a Sharpe ratio of 0,1029, which happen to be the highest of all the 36 portfolios tested. Such portfolio's features are rather remarkable. It allows to invest in the stock market in a (relatively) safe and sustainable way, yet leaving high expectation for the financial performance, especially if the Sharpe ratio is considered as main metric.

While it is hard to find a clear pattern for the sustainability factor -ideally one would expect to have decreasing performance along with decreasing average portfolio ESG score-, this is not the case for the minimum volatility factor. Findings relative to this anomaly (e.g. (D. C. Blitz & van Vliet, 2007)) are confirmed. As visible through Figure 7, the risk-return relationship is rather negative hence openly contradicting the CAPM.

For further researches, it might be interesting to confirm these findings for different markets other than the US and through robustness test. Sadly, most of the financial database which provide ESG scores started collecting them only in the years 2000', making not possible to back test such portfolio on a longer period of time. In addition, it might be interesting to construct the double sorted and the overlap portfolios using ESG data provided by different databases.

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7. Appendix

Figure 6- ESG metrics covering sustainability reporting[9]. The list below is a sample of the 400+ ESG metrics

ENVIRONMENTAL	SOCIAL	GOVERNANCE
Biodiversity Impact Reduction	Accidents Total	Anti-Takeover Devices
Carbon Offsets/Credits	Average Training Hours	Audit Committee Independence
CO_2 Equivalents Emission Total	Customer Satisfaction	Board Cultural Diversity
Eco-Design Products	Day Care Services	Board Meeting Attendance Average
Energy Use Total	Donations Total	Board Member Affiliations
Environmental Expenditures	Employee/Contractor Fatalities	Board Member Compensation
Environmental Products	Employee Satisfaction	CEO-Chairman Separation
Environmental R&D Expenditures	Flexible Working Schemes	Classified Board Structure
Environmental Supply Chain Management	Health & Safety Policy	Compensation Committee Independence
Estimated CO_2 Equivalents Emission Total	HIV/AIDS Program	CSR Sustainability Committee
e-Waste Reduction	Human Rights Policy	CSR Sustainability External Audit
Green Buildings	Improvement Tools Business Ethics	CSR Sustainability Report Global Activities
Hazardous Waste	Lost Time Injury Rate	Female on Board
Hybrid Vehicles	Lost Working Days	Global Compact
Non Hazardous Waste	Management Training	GRI Report Guidelines
Policy Energy Efficiency	Policy Child Labor	Highest Remuneration Package
Policy Water Efficiency	Policy Diversity and Opportunity	Policy Board Diversity
Renewable Energy Use	Quality Management Systems	Policy Board Experience
Targets Emissions	Supply Chain Health & Safety Training	Policy Board Independence
Waste Recycling Ratio	Total Injury Rate	Policy Board Size
Waste Total	Trade Union Representation	Policy Equal Voting Right
Water Pollutant Emissions	Training Costs Total	Shareholders Vote on Executive Pay
Water Recycled	Turnover of Employees	Voting Cap Percentage
Water Technologies	Women Employees	Staggered Board Structure
Water Withdrawal Total	Women Managers	Veto Power or Golden Share

[9] http://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/esg-research-brochure.pdf

Table 8 – Portfolios 1-10 summary statistics. The table shows examples of summary statistics for the first and last portfolios for each strategy.

	Benchmark	*V1*	*V10*	*ESG1*	*ESG10*	*Sort1*	*Sort10*	*Overlap1*	*Overlap5*
Mean	0,0035	0,0042	0,0025	0,0045	0,0057	0,0049	0,0025	0,0053	0,0043
Standard Error	0,0050	0,0030	0,0084	0,0041	0,0061	0,0028	0,0078	0,0028	0,0075
Median	0,0077	0,0105	0,0107	0,0099	0,0098	0,0090	0,0078	0,0097	0,0078
Standard Deviation	0,0620	0,0369	0,1055	0,0508	0,0756	0,0354	0,0975	0,0353	0,0936
Sample Variance	0,0038	0,0014	0,0111	0,0026	0,0057	0,0013	0,0095	0,0012	0,0088
Kurtosis	4,8223	5,9459	3,0709	4,5705	4,2685	5,2021	2,6878	4,2533	2,6342
Skewness	-1,0975	-1,7798	-0,3087	-1,2089	-0,9837	-1,5757	-0,3120	-1,2877	-0,4309
Range	0,4516	0,2417	0,7803	0,3696	0,5270	0,2262	0,7110	0,2399	0,6624
Minimum	-0,2708	-0,1638	-0,3762	-0,2226	-0,3236	-0,1499	-0,3425	-0,1467	-0,3383
Maximum	0,1809	0,0779	0,4041	0,1471	0,2034	0,0763	0,3684	0,0932	0,3241
Count	156,0000	156,0000	156,0000	156,0000	156,0000	156,0000	156,0000	156,0000	156,0000

Table 9 – Volatility and ESG sorted portfolios. The two tables show US equally-weighed decile portfolios performance over the period 2003-2014. Each month, stocks are ranked in ascending (descending) order based on their volatility (ESG score). Portfolios are assigned to one of ten portfolios, V1 to V10 (ESG1 to ESG10), where the first portfolio V1 (ESG1) has lowest (highest) volatility (ESG score). Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in V1 (ESG1) and short-invested in V10 (ESG10). Portfolio size vary each year (see Table 1), averaging 66 companies for each decile portfolio. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). In FF5 Alpha the explanatory variable is are the one present in the Fama and French Five Factor Model, namely the monthly returns from the market portfolio (MKT), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA). For FF alpha only the market portfolio is considered. Risk-free rates are deducted from both portfolio and market returns.

	Mkt	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V1-V10
CAGR	0,0804	0,0303	0,0430	0,0295	0,0295	0,0114	0,0198	0,0145	0,0307	-0,0174	-0,0511	-0,0001
Exp. Ret.	0,0065	0,0025	0,0035	0,0024	0,0024	0,0009	0,0016	0,0012	0,0025	-0,0015	-0,0044	0,0000
St.Dev.	0,0414	0,0370	0,0431	0,0510	0,0548	0,0650	0,0639	0,0711	0,0714	0,0812	0,1055	0,0419
Sharpe Ratio	0,1562	0,0675	0,0815	0,0475	0,0443	0,0146	0,0256	0,0168	0,0354	-0,0180	-0,0414	-
FF Alpha	-	0,0024	0,0036	0,0023	0,0028	0,0017	0,0023	0,0022	0,0038	0,0003	-0,0001	0,0025
(*p-value*)	-	*0,4270*	*0,3000*	*0,5717*	*0,5260*	*0,7413*	*0,6634*	*0,7029*	*0,5130*	*0,9630*	*0,9900*	*0,7160*
FF5 Alpha	-	0,0026	0,0047	0,0043	0,0043	0,0042	0,0048	0,0056	0,0069	0,0042	0,0031	-0,0005
(*p-value*)	-	*0.409*	*0.194*	*0.3120*	*0.341*	*0.4342*	*0.3623*	*0.3377*	*0.2418*	*0.5269*	*0.726*	*0.9400*

Significant Level: * 10%; **5%; ***1%

	Mkt	ESG1	ESG2	ESG3	ESG4	ESG5	ESG6	ESG7	ESG8	ESG9	ESG10	1-10
CAGR	0,0804	0,0262	0,0320	0,0415	0,0147	0,0040	0,0215	0,0171	0,0093	-0,0133	0,0203	-0,0094
Exp. Ret.	0,0065	0,0022	0,0026	0,0034	0,0012	0,0003	0,0018	0,0014	0,0008	-0,0011	0,0017	-0,0008
St.Dev.	0,0414	0,0508	0,0541	0,0628	0,0639	0,0640	0,0597	0,0636	0,0709	0,0696	0,0756	0,0193
Sharpe Ratio	0,1562	0,0424	0,0486	0,0541	0,0191	0,0052	0,0297	0,0223	0,0109	-0,0161	0,0222	-
FF Alpha	-	0,0022	0,0028	0,0038	0,0020	0,0011	0,0027	0,0022	0,0019	0,0003	0,0030	-0,0009
(*p-value*)	-	*0,5980*	*0,5246*	*0,4514*	*0,7050*	*0,8330*	*0,5830*	*0,6650*	*0,7350*	*0,9600*	*0,6200*	*0,7810*
FF5 Alpha	-	0,0039	0,0044	0,0062	0,0043	0,0036	0,0045	0,0048	0,0047	0,0030	0,0062	-0,0023
(*p-value*)	-	*0,3532*	*0,3270*	*0,2350*	*0,4179*	*0,5031*	*0,3640*	*0,3675*	*0,4290*	*0,6073*	*0,3252*	*0,4872*

Significant Level: * 10%; **5%; ***1%

Table 10- Double-sorted portfolios. This table shows US equally-weighed decile portfolios performance over the period 2003-2014. Each month, the whole sample is divided in two halves, top and bottom 50% companies based on their ESG score. Each half is divided in quintiles, and double-sorted on stocks' volatility in ascending order. Portfolios are assigned to one of ten portfolios (Sort1 to Sort10), where the first portfolio (Sort1) has lowest volatility and top 50% ESG scores. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in S1 and short-invested in the S10 (highest volatility and bottom 50% ESG scores). Portfolio size vary each year (see Table 1), averaging 66 companies for each decile portfolio. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). In FF5 Alpha the explanatory variable is are the one present in the Fama and French Five Factor Model, namely the monthly returns from the market portfolio (MKT), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA). For FF alpha only the market portfolio is considered. Risk-free rates are deducted from both portfolio and market returns.

	Mkt	Sort1	Sort2	Sort3	Sort4	Sort5	Sort6	Sort7	Sort8	Sort9	Sort10	1-10
CAGR	0,0804	0,0390	0,0502	0,0184	0,0299	-0,0075	0,0128	0,0075	0,0110	0,0241	-0,0406	0,0054
Exp. Ret.	0,0065	0,0032	0,0041	0,0015	0,0025	-0,0006	0,0011	0,0006	0,0009	0,0020	-0,0034	0,0005
St.Dev.	0,0414	0,0355	0,0488	0,0617	0,0668	0,0907	0,0468	0,0576	0,0688	0,0715	0,0975	0,0382
Sharpe Ratio	0,1562	0,0901	0,0837	0,0246	0,0368	-0,0069	0,0227	0,0109	0,0133	0,0277	-0,0353	-
FF Alpha	-	0,0031	0,0040	0,0019	0,0033	0,0016	0,0014	0,0012	0,0018	0,0036	-0,0002	0,0033
(*p-value*)	-	*0,2830*	*0,3077*	*0,7030*	*0,5400*	*0,8310*	*0,7160*	*0,8000*	*0,7476*	*0,5330*	*0,9770*	*0,5940*
FF5 Alpha	-	0,0034	0,0058	0,0042	0,0058	0,0050	0,0024	0,0031	0,0050	0,0068	0,0034	-0,0059
(*p-value*)	-	*0,2500*	*0,1526*	*0,4040*	*0,2921*	*0,5044*	*0,5390*	*0,5175*	*0,3784*	*0,2526*	*0,6714*	*0,9993*

Table 11 - "Overlapping" portfolios. This table shows US equally-weighed portfolios performance over the period 2003-2014. Each month, on the one hand stocks are ranked in ascending order based on their volatility, on the other hand they are ranked based on their ESG score. In both case the sample is divided in quintile. Companies which happens to be present in both the first quintile (and 10th quintile) will form the considered "Overlap1" ("Overlap5") portfolio. Portfolios are rebalanced on a yearly basis. The rightmost column reports returns of a self-financing portfolio, that is long-invested in the Overlap1 portfolio (having lowest 20% and highest 20% ESG score) and short-invested in Overlap5 portfolio. Portfolio size vary each year), averaging ca. 45 companies for each portfolio, depending on the overlaps found. While CAGR figures are expressed on an annual basis, Expected Returns, Standard Deviation (hence Sharpe ratio) are monthly figures. Alpha is the intercept in a time-series regression of monthly excess return (below is expressed the relative p-value). In FF5 Alpha the explanatory variable is are the one present in the Fama and French Five Factor Model, namely the monthly returns from the market portfolio (MKT), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA). For FF alpha only the market portfolio is considered. Risk-free rates are deducted from both portfolio and market returns.

	Mkt	Overlap1	Overlap5	Ov.1-Ov.5
CAGR	0,0804	0,0446	-0,0159	-0,0013
Exp. Ret.	0,0065	0,0036	-0,0013	-0,0001
St.Dev.	0,0414	0,0354	0,0936	0,0358
Sharpe Ratio	0,1562	0,1029	-0,0143	-
FF Alpha	-	0,0036	0,0020	0,0016
(*p-value*)	-	*0,2110*	*0,7930*	*0,7840*
FF5 Alpha	-	0,0041	0,0056	-0,0014
(*p-value*)	-	*0,1670*	*0,4761*	*0,8102*