LUISS

DEPARTMENT OF BUSINESS AND MANAGEMENT

Chair of Equity Markets and Alternative Investments

Portfolio performance optimization by shorting ETFs: A practical application on the major European markets

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ACADEMIC YEAR 2022/2023

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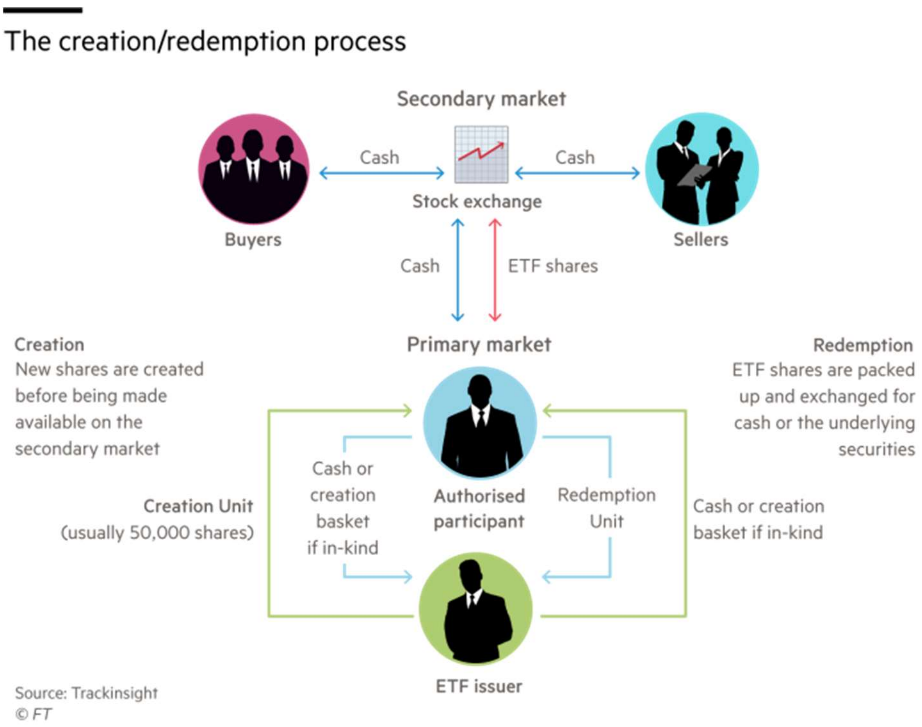
Introduction

1.1 ETF functioning

ETFs, or Exchange Traded Funds, are an investment vehicle that has gained much popularity in recent years. ETFs are collections of securities that are traded on an exchange, just like individual stocks. They are typically designed to track the performance of a particular market index, such as the S&P 500, or a specific sector or asset class. Inside the ETF ecosystem, value creation is managed by an intricate system that is developed in more phases. ETFs are created and managed by specialized entities known as ETF sponsors or issuers. These sponsors work closely with authorized participants (APs), typically large institutional investors. Those entities coordinate the creation and redemption process which is crucial for maintaining the ETF's market price in line with its net asset value (NAV). When an ETF is created, APs deliver a specified basket of underlying securities or assets to the ETF sponsor. In return, the sponsor issues a block of ETF shares to the AP, a creation unit. Creation units are typically large blocks of shares, ranging from 25,000 to 100,000. This process ensures that the ETF has enough underlying assets to represent its target index or investment strategy accurately. Conversely, when an AP wants to redeem ETF shares, they return creation units to the ETF sponsor in exchange for the underlying assets. The sponsor can then sell these assets in the market or use them to fulfill future creation requests. ETF shares are traded on stock exchanges, just like individual stocks. This is known as the secondary market. Authorized participants play a crucial role in maintaining the liquidity and efficiency of ETFs. They are responsible for creating and redeeming ETF shares, as mentioned earlier. APs also act as market makers, providing liquidity by continuously offering to buy or sell ETF shares on the secondary market. Market makers help to guarantee that the ETF's market price remains closely aligned with its NAV. If the ETF's market price starts to deviate significantly from its

NAV, they will step in to create or redeem shares, helping to bring the price back in line. ETFs charge management fees to cover the costs associated with fund operations. These fees are typically expressed as an annual percentage of the fund's total assets under management (AUM). The ETF sponsor deducts the costs from the fund's assets, reducing the net asset value of those items. ETFs that hold dividend-paying securities or income-generating assets may distribute dividends to their shareholders. These dividends are typically paid out on a periodic basis, such as quarterly or annually, and are proportionate to an investor's holdings in the ETF. The ETF sponsor is responsible for collecting the dividends from the underlying assets and distributing them to the ETF shareholders.



(1.1) (*source: Financial Times*)

1.2 ETF properties

The properties of these items generate some inherent benefits for investors since for example, they offer diversification. By investing in an ETF, you are essentially investing in a basket of securities, which can help to spread out your risk. This can be particularly helpful for investors looking to gain exposure to a desired market or sector that they are interested in or comfortable with the functioning but want to take on a manageable amount of risk. Another benefit of ETFs is that they are typically low-cost because they are passively managed. For instance, this passive characteristic gives the advantage of low active involvement requirements as mutual funds do. That is the main reason why they are less expensive. Additionally, because they trade on an exchange, investors can buy and sell ETFs throughout the day, just like they would with a stock. This can help to provide liquidity and flexibility options for investors. ETFs also offer tax efficiency; because they are structured as passively managed index funds, they typically have lower turnover than actively managed funds. This can help to reduce capital gains taxes and other tax liabilities for investors. The final argument that supports passively managed asset comes from SPIVA (S&P Indices Versus Active) reports, which consistently show that most traditional, actively managed mutual funds fail to beat their benchmarks over the long term. Basically, investors with money in these funds may pay higher fees for the "privilege" of underperforming the market. This problem was highlighted in the past by Sharpe (1991), which explores the concept of active management in financial markets. It demonstrates that, on average, the returns of active managers tend to converge to the market return over the long term, suggesting that the trading market tends to rise over time. The passive versus active argument has a huge impact on investor behavior. Indeed, the market has seen a significant shift in recent years, with more and more investors choosing to give more credit to ETFs rather than traditional mutual funds. According to data from Morningstar, ETFs have experienced significant inflows in recent years, while conventional mutual funds have seen outflows. Investors increasingly keep giving more and more credit to the benefits of ETFs. As a result, we may see continued growth in the ETF industry in the years to come as more investors seek out these products to gain exposure to the market while minimizing costs and maximizing returns. The popularity of these items helps to bring curiosity to the matter and keeps advancing the ingenuity on how ETFs could be exploited with the aim of enhancing gains.

1.3 Equity premium puzzle and research question

People have tried from the beginning of the stock trading market activity to gain extra profit by betting on assets that carry more risk within it, hoping to benefit from their intuition, and ending in higher expected returns rate. However, these specific investors will lead and stimulate also less sophisticated beginners and specialists, posing a challenge to entering the "equity game" and hoping for the best possible development on the asset chosen. In the literature, this interest in the perpetual growth of the capital "put on the table" is justified by the so so-called from authors such as Mehra, Rajnish, and Edward C. Prescott(1985), and Ravi Bansal and Amir Yaron (2004) "the equity premium puzzle," which refers to the empirical observation that the average return on equities (stocks) tends to be significantly higher than the average return on safer assets such as government bonds. This "imperfection" arises because, from a standard economic perspective, investors should not be willing to hold risky equities unless they offer higher expected returns to compensate for the additional risk. This statement relates to Markovitz's theory (see Methodology chapter) since a conscious investor wants to benefit from potential higher expected returns of stocks, helping themselves find the most logical, optimally allocated, and safer position available considering the risk-return trade-off of such a lucrative activity. Regarding the puzzle, Mehra, Rajnish, and Edward C. Prescott (1985) highlight the historical evidence of higher long-term returns in the stock market compared to other investments, justifying the investor's "gold rush" behavior in that sense. Instead, the Ravi Bansal and Amir Yaron (2004) paper examine the empirical evidence of the equity premium puzzle and long-run risk in financial markets. It suggests that stock returns are positively related to the long-run growth rate of consumption and concludes that equity markets tend to rise over the long term.

Trying to find a suitable tactic that can exploit ETFs properties, also helping investors in carrying more risk while betting on positive outcomes of selected traditionally picked stocks, this paper presents a trading strategy created from shorting ETFs as a means to lower the expected losses deriving from specific markets high insecurity period, focusing on regional allocation. Indeed, the peculiarity of diversification and the broad range of stocks that compose every one of the funds that replicate such index trends, make these products suitable to represent a geographically diversified market (such as the Italian stock exchange reproduced by FLIY or Franklin FTSE Italy ETF).

The aim is to verify if ETFs help performance optimization of a long portfolio applied to the European market. The process will consist of using such Items to shield long positions in undervalued European stocks, with ETFs representing regional stock exchanges, trying to obtain a better performance by creating hedged pairs consisting of companies and funds instead of leaving those stocks alone and "naked," with the ultimate goal of reducing market risk exposure.

The main questions that these papers try to answer through a quantitative analysis are:

1) First, verify how much worth employ the covered strategy of short-term hedging over a long position already held in the portfolio, instead of leaving the asset "naked".

2) How much influence on the compounded returns has the choice of weighting the assets following the literature formulas.

3) If it will show better performance than the single stock strategy, is the hedge portfolio created by shorting ETFs able to beat the market. Will also be analyzed the cost-effectiveness of resorting to the use of ETF as a short position and consideration regarding quantitative analysis will follow.

2. Literature review

Bloomberg reported that "*hedge funds mainly use ETFs to take short positions. …As a group, hedge funds have $105 billion in short ETF positions—-more than double their $43 billion in long positions. …The funds' shorts don't necessarily indicate bearish sentiment, but rather are used to hedge out part of the market in order to isolate a long positio*n" (Balchunas 2017). This paragraph states the relevance of ETFs as hedging instruments used by institutional investors. The existence and consistency of such a wide usage of short positions, bring curiosity to the subject, contributes to the growing interest in this matter, and subsequentially leads to the increased possibility of "re-arranging" these items in investment strategy building.

The most relevant literature source for this research, that explore shorting ETF to improve performance efficiency, is expressed in Shiyang Huang, Maureen O'Hara, Zhuo Zhong (2021)(HOZ), after expanded by Atilgan, Yigit and Demirtas, K. Ozgur and Gunaydin, A. Doruk and Oztekin, Mustafa(2023) (AYDOGDOM), where exploiting financial innovation, both developed a strategy based on shorting industry ETFs (IETFs) with the final purpose of offsetting long position opened on stocks that compose the same ETFs. The approach in this analysis differs since ETFs used to cover long positions are chosen for geographical reasons, so the whole sample represents various European developed countries' economies instead of an entire economic sector/industry. Moreover, as HOZ and AYDOGDOM have chosen to do, are excluded from the analysis both inverse and leveraged ETFs. Inverse ETFs are exchange-traded funds that aim to provide the opposite return of a particular benchmark or index. These ETFs use financial derivatives, such as futures contracts, options, or swaps, to achieve their base item's inverse performance. Leveraged ETFs are composed of similar derivatives and seek to provide a multiple of the daily returns of their underlying index, often two or three times the daily returns, using leverage. This "exclusion" approach is sustained by the findings of Pessina, Colby J.; Whaley, Robert E.(2021) and Crouse, M.(2022), which explain that LETFs are riskier for more extended holding periods, and suffer from losses due to the compounding effect described as: "*This is based(compounding effect, i.e.) on the principle that the geometric mean (average return) of a series of numbers will be lower for a series that has greater variance.*";

$$CLR = \prod_{t=1}^{T} (1 + LR_t) - 1 \neq L\left[\prod_{t=1}^{T} (1 + R_t) - 1\right] = LCR$$

where L is the leverage ratio, Rt is the daily benchmark index return on day t, and T is the holding period expressed in number of days. It becomes more intuitive if numbers are applied to it. Assume for instance that an investor buys a –2x fund and plans to hold it for two days. The benchmark return ends up being 5% on day one and –5% on day two. Thus, the two-day benchmark return is –0.25%; the investor, however, expects that the return of his –2x fund to be 0.50%. The reality, of course, is that the two-day fund return is –1.00% resulting in a loss. Moreover, there is rebalancing effect also described in Pessina, Colby J.; Whaley, Robert E.(2021), which is the outcome of the process of buying and selling derivatives on a daily basis to maintain the desired level of leverage. It is expressed as a generalized formula (see the appendix):

$$\begin{aligned}\Delta_{t_{n+1}} &= L_{t_{n+1}} - E_{t_{n+1}} \\ &= A_{t_n}(x^2 - x)r_{t_n,t_{n+1}}\end{aligned}$$

where $L_{t_{n+1}}$ is the value of the notional amount of the total return swaps exposure that is required before the market opens on the next day to replicate the intended leveraged return of the index A_{t_n} represent a leveraged or inverse ETF's NAV, $E_{t_{n+1}}$ the exposure of the total return swaps, and $(x^2 - x)$ the scalar of times the index's performance is multiplied according to leverage ratio x. Since each time an ETF is rebalanced, there are transaction costs involved, these payments can be significant and erode the returns over time. Said so, The ETF issuer requires an enhancement of effort in adjusting securities to reproduce a multiple of the performance kept by the leveraged $1x$ Index, which brings more expenses and increases instability. Also, Carrier and Grant (2018) show that actual returns in shorter periods also deviate significantly from Expected returns due to higher volatility caused by the compounding effect carrying uncertainty. As stated in Pessina, Colby J.; Whaley, Robert E.(2021), LETFs are suitable mainly for placing directional bets, neither for hedging nor for buy and hold strategy, since the estimated long-term value of those funds is 0. A mathematical demonstration of the long term value erosion of leveraged and inverse items can be found in the appendix section, formulated by Cheng*,* Minder*, and* Madhavan(2009).

In their paper, Michalik and Shubert (2009) discuss the use of ETFs as a hedging instrument in markets without transaction costs. They opted to pursue the analysis under those conditions because rebalancing daily is necessary otherwise for perfect hedging, but high transaction costs make the hedge imperfect for more extended periods. The payoff of the hedge came out as a sickle-shaped chart, with high positive and negative returns causing a positive return for the hedge. Following their findings, short ETFs can be used as portfolio insurance for up to a year, with maximum losses not exceeding -6% and the chance of achieving a return of 5% to 15%. The return distribution of the short ETF has positive skewness. They did not discuss the use of short ETFs with higher leverage factors, but already, at the time, financial institutions recommended very short periods when higher leverage factors were applied. As it is said in the same paper, "*The process of hedging can be defined in a very general way as the temporary compensation of losses of one or more assets by the profit of one or some other investments.*". This statement is important because it distinguishes between possible misunderstandings with the diversification effect, which aims to obtain lower risk-adjusted performance by "smoothing" it through a multitude of different assets. Hedging, instead, relates to the optimization of one asset's performance, offsetting it with another specific one. As Michalik and Shubert explain, traditionally, hedging is performed using financial instruments such as options and futures. For instance, an investor who is holding a long position in a stock may purchase a put option to protect against the possibility of a decline in the stock's value. Similarly, a futures contract can be used to hedge against changes in the price of a particular commodity or financial instrument.

Cui, Z., & Simaan, M. (2021) discuss with empirical results the problem of optimal hedge ratio using inverse ETFs and ETNs. ETNs or exchange-traded notes, in a similar fashion to the funds, are debt securities issued by financial institutions that offer investors exposure to the performance of an underlying index or benchmark. Unlike ETFs, ETNs do not actually hold any underlying assets but instead promise to pay investors the return of the index or benchmark, minus fees and expenses. ETNs are structured as unsecured debt, and the creditworthiness of the issuer determines their value. The paper proposes a formula to quantify the opportunity cost of hedging under incomplete information and links portfolio selection under estimation risk with the aim of finding the out-of-sample optimal hedge ratio. The analysis reveals that investors who rely on the unconditional optimal hedge ratio earn hardly any reward in the long run and may be better off depending on an arbitrary value of 20%. The results also suggest that nonlinearity is essential in constructing the optimal hedge ratio. Estimation risk makes it unclear whether retail investors should use the optimal hedge ratio, and they may benefit from imposing "wrong constraints" or relying on more robust statistics. Furtherly, they suggest more guidance on estimation risk and the opportunity cost associated with hedging would help retail investors. Considerations regarding the low usefulness of cost-effective risk reduction of optimal Hedge ratio influence this research undermining the solidity of the statements regarding the contribution in performance of Michalik and Shubert's (2009) cross-hedging correlation-based formula, which is going to be explained in the methodology section.

The effect on market volatility of Federal Reserve (FED) announcement and so rate policy aimed to fight inflation is shown by Prasad, A.; Bakhshi, P.; Seetharaman, A. (2022) and Vähämaa, S. and Äijö, J. (2011), where it is stated that FED's meetings contribute in a statistically significant way to increase VIX index. The VIX, or CBOE Volatility Index, is a measure of expected volatility in the stock market over the next 30 days. More specifically, the VIX is based on the prices of options contracts on the S&P 500 index, which traders use to hedge against market volatility. The VIX is often called the "fear index" because it tends to rise when investors are fearful or uncertain about the stock market's future direction. The VIX is influential in the stock market because it can be used as a gauge of investor sentiment and risk appetite. When the VIX is high, it can indicate that investors are concerned about the potential for market volatility and may be selling stocks or taking other defensive measures to protect their portfolios. Following Cocozza R., Curcio D., and Pacifico A.(2020), findings result that VIX and its European counterpart VSTOXX (Euro Stoxx 50 Volatility Index) are highly correlated. Thanks to this research, it is possible to give credibility and academic authority to the statement that: The trends observed in developed markets are mutually influenced by one another, creating a reciprocal relationship. The primary outcome from these papers that affect this analysis regards the reference point taken into consideration for the hedging periods that coincide with the quarterly FED meetings when "projection materials" are discussed by the board.

Now it is essential to point out which are most appropriate methods of choice for stocks and ETFs picking. In HOZ and AYDOGDO, for example, the stock picking criteria were decided with the help of post-earnings announcement drift (PEAD) (Livnat, J., and R. Mendenhall. 2006.), described as "*Post–earnings announcement drift is the tendency for a stock's cumulative abnormal returns to drift in the direction of a recent earnings surprise for several weeks following an earnings announcement.*"; can also be called standardized unexpected earnings (SUE), defined as actual earnings minus expected earnings divided by stock price. For ETFs picking, HOZ (2021) is used as an indicator for potential convenient IETF to choose, short interest ratio (SIR), which is practically the measure of the level of short interest in the ETF. Short interest refers to the number of shares of the ETF that have been sold short by investors who are betting that the price of the ETF will decline. It is calculated by dividing the total number of shares sold short by the average daily trading volume of the ETF. This ratio indicates how many days short sellers would take to cover their positions if the average trading volume remains constant. A high short-interest ratio suggests that there may be many short sellers in the ETF, which could put downward pressure on the price of the ETF if these short sellers decide to cover their positions with the funds. HOZ took from literature pieces of evidence showing that short interest results negatively predict stock returns, further justifying the usage of shorting ETFs as a tool for covering long positions. To differentiate the approach of this paper regarding asset selection, the literature suggests a more generalized and less industry-specific pool of stocks to create a more straightforward option to drive and address investor choice, the P/E ratio. Basu.S. (1983) is through the first to notice the stock price behavior of overperforming peers by stocks with lower P/E ratios. In the paper, they compute E/P, the inverse ratio, but the considerations remain the same. Regarding more recent findings about price-earnings ratio (P/E) used as a benchmark to evaluate which stocks are worth investing in, Bulkowski T.N. (2012) analyzed the performance of a relevant sample of stocks, resulting in a 3% overall better performance of stocks which P/E ratio was below the median of the sample, over those which relative value was over that threshold.

3. Data

All assets' data came from the Refinitive platform. Regarding stocks the sample was chosen between traded items in 5 different stock markets, selected by geographical reasons and relevance of their markets: Italian stocks market (FTSE-MIB), German stocks market Big-Cap(DAX) and Mid-Cap(MDAX), The Netherlands market(AEX), UK stocks market (FTSE 100) and UK Small-Mid-cap (FTSE 250), and whole European market, that represent and comprehend all of the latter.

In order to find appropriate ETFs, I followed the suggestion that I got from Atilgan, Yigit and Demirtas, K. Ozgur and Gunaydin, A. Doruk and Oztekin, Mustafa (2023), searching on etfdb.com screener, that was particularly useful since from the factsheets on the pages regarding every single ETF, it is possible to get the percentage of geographical exposition that such indexes have in the same market. However, the condition upon its consented to utilize one ETF came from Shiyang Huang, Maureen O'Hara, and Zhuo Zhong (2021), and it is the required minimum of 30% exposition of the components to one of the over-mentioned "regional" markets. Therefore, for the group of ETFs selected by the literature instead, the criteria have the same percentage of exposure, but the components needed to be part of a determined industry, that the IETF would have represented.

In those papers, the analysis was done on the integrity of NYSE stocks. Instead, this research focuses on the European market, and every ETFs are used to hedge a single stock related to the reproduced market by geographical criteria, as will be explained further in the methodology section.

All price data are calculated to account for any corporate actions that may have taken place during the trading day, such as stock splits, dividends distributions, or mergers and acquisitions. The adjusted closing price is computed by first dividing the original closing price by the adjustment factor, which is calculated as the total number of corporate actions that have taken place. This factor ensures that the adjusted closing price reflects the stock's actual value. Data are expressed on a daily basis to better understand all price shifts in a shorter time due to market announcements. Interestingly, all prices are expressed in a single currency, EURO, traded at a "dynamical evolving in time" exchange rate: that was possible thanks to a particular Refinitive tool that helps align and format prices expressed in different currencies, avoid miscalculation on exchange rate. As a result, currency risk is not considered in this analysis.

The outcome was 31 pairs distributed through all five categories that split through the whole 5 years period, generating 651 observation outputs. The only concern may regard the Netherlands stocks exchange represented only by one pair since there is only one ETF that meets the criteria settled by HOZ (Shiyang Huang, Maureen O'Hara, Zhuo Zhong) (2021), iShares MSCI Netherlands (EWN).

The sample stocks try to give the broader and most complete representation of all industries across the old continent, including some significant sectors detected through the Fama-French 12 main industries, in particular: consumer non-durables, consumer services, manufacturing, energy, chemicals, business equipment, telecom, utilities, health.

4. Methodology

4.1 Indicators, risk-free rate, and Fama French 3 factor model

After the data collection then started the indicators compounding procedure. To help understand the data better is necessary to use widely recognized to be best-tailored indicators to interpret results through investing community. On the topic of investment, the landmark point of view in portfolio building is expressed by Markovitz in 1952. The Theory is a framework for constructing an optimal investment portfolio that seeks to maximize returns for a given level of risk. The basic idea behind Markowitz's portfolio Theory is that investors should consider not only the expected returns of various investment options but also the risk associated with each option. This risk is typically measured using the standard deviation of returns, which reflects the degree of variability in an investment's returns over time. Furthermore, the theory assumes that investors are risk-averse, meaning that they prefer less risk to more risk, all else being equal. As such, the optimal portfolio maximizes expected returns while minimizing the portfolio's overall risk. This theorem explains why investors are willing to hedge their open positions in market uncertainty, trying to obtain standard deviation minimization, which measures the volatility of stocks and consequentially risk.

It is possible to define Expected Returns of a portfolio as the estimate of the average return an investment is expected to generate over a given period. In this paper, they are computed using the formula:

$$\mathbb{E} \sum_{n=1}^{N} x_n R_{n,t} \text{ such that } \sum_{n=1}^{N} x_n = 1$$

where is the $R_{n,t}$ is the return of the asset at time t, and x_n the weight associated with a specific asset. Instead, the standard deviation σ in statistics is the measure of the variability or dispersion of a set of data points. It is calculated by finding the square root of the variance, which is the average of the squared differences from the mean. It is easy to compute with the Excel St.dev.c function, which calculates the standard deviation of a sample of data, not their entire population. The latter is represented and calculated by st.dev.p. The difference is explained by the absence of Bessel's correction, -1, which gives the sample a statistical significance dimension lower and more accurate. Expected returns are expressed in percentage points due to standardization and easiness of visualizing numbers.

It is essential to give an accurate "label" to help read the information on a return series better, including all the basic information for an overall idea of "stand-alone" stock versus paired performance. This became possible when combining Expected returns and Standard deviation with the addition of a risk-free rate; the Sharpe ratio is obtained. The formula of This relation between the two leading indicators is computed:

$$S = \frac{E(r_{as}) - r_f}{\sigma_{as}}$$

Where the nominator $E(r_{ds}) - r_f$ express the excess returns of an investment, and the numerator is the standard deviation of that specific asset. This ratio helps quickly visualize, and is able to enlighten, the performance of a specific asset on an absolute basis over the market represented by a risk-free rate. It is a common way to analyze any fund's manager performance even if it has some flaws, like the possibility of smoothing returns to give the impression that the fund’s pattern achieved higher standards of profits, thanks to the action of the fund’s executive, and consequentially appearing more successful than competitors to the public. Besides its imperfections is still considered the best and most applied ratio to evaluating investors’ achievements.

Regarding the risk-free rate, it is typically considered to be the yield on a hypothetical investment with no default risk, such as a U.S. Treasury bond. This rate is used as a benchmark for evaluating the performance of other investments, as it represents the minimum return that an investor should expect from an investment that carries no risk. The one-month treasury bill was chosen for this analysis from Fama French Library. This bond is considered a safe investment because T-bills are backed by the full faith and credit of the U.S. government, which has never defaulted. The risk-free rate is a crucial variable because it contributes to explain over the market returns on the Capital Asset Pricing Model. Remember that the intention behind the hedging strategy pursued in this paper is to shield the investments from part of the market risk carried by geographical reasons, so it is important to define carefully how it is possible to measure such trends and the relevance of each component to the outcome in term of returns. The most recognized way of calculating stock performance based on factors such as over mentioned market is running a regression following the Fama-French three-factor model.

$$E(R_i) - r_f = \alpha_i + \beta_M\left(E(R_M) - r_f\right) + \beta_{HML}E(R_{HML}) + \beta_{SMB}E(R_{SMB}) + \varepsilon_i$$

This model, which was published in 1993, is one of the crucial theorems of the whole investing academic world. It is an "expansion" of CAPM since it adds more factors to the initial formula and is widely used to calculate the composition and the effect of different components that drive the portfolio's performance; plus, it helps better understand the significance(p-value) of the results. The main outputs of the entire operation can be summarized as the beta coefficients for all factors, which will be analyzed in depth later, and the alpha value. The intercept (Jensen's alpha) represents the quality of the manager in beating the market. It is calculated by regressing the excess returns of a portfolio (the difference between the portfolio's return and the risk-free rate) on the excess returns of a market index (the difference between the market return and the risk-free rate). The three factors that this analysis is going to scrutinize are divided into market risk premium, Small minus Big (SMB), and High minus Low (HML). The "Small minus Big" factor, more precisely, represents the difference in returns between small-cap stocks (small capitalization) and large-cap stocks (large capitalization). Small-cap stocks are generally defined as those with a market capitalization of less than $2 billion, while large-cap stocks have a market capitalization of $10 billion or more. The Small minus Big factor captures the premium that investors receive for holding small-cap stocks, which tend to be riskier and more volatile than large-cap stocks. High minus Low instead represents the difference in returns between high book-to-market ratio stocks and low book-to-market ratio stocks. The book-to-market ratio measures the value of a company relative to its stock price, and stocks with high book-to-market ratios are often considered undervalued. The High minus Low factor captures the premium that investors receive for holding stocks with high book-to-market ratios, which tend to outperform those with low book-to-market ratios over the long term. The model was also implemented by 2 "new" factors: market Momentum and Quality, that are not going to be analyzed in this analysis.

From the Fama French Library official site, it is possible to acknowledge how all factors are used in computations and how academics developed such data series. The beta coefficients, for instance, which represent the sensitivity of a security's returns to changes in all these three factors, are obtained, as was previously mentioned, by regressing excess returns of an asset, with a series of returns crafted specifically for this purpose, via some passages described in the online library and findings can be explained as follows:

1) Market beta (beta_m) is the measure of the sensitivity of a security's returns to the overall market returns. A beta of 1 means that a security's returns correlate perfectly with the market. In contrast, a beta of less than 1 indicates lower risk and lower expected returns, and a beta greater than 1 indicates higher risk and higher expected returns. "*Labeled as Rm-Rf, the excess return on the market Market, is the return on a region's*

value-weight market portfolio minus the U.S. one month T-bill rate. (from Ibbotson Associates)

2) Size beta measures an asset's exposure to size risk; a positive size beta indicates that the performance is driven by smaller companies, which as mentioned before, tend to have higher returns than larger companies. Size returns are computed as follows*: SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios, SMB =1/3 (Small Value + Small Neutral + Small Growth)- 1/3 (Big Value + Big Neutral + Big Growth).*

3) Value beta measures an asset's exposure to value risk; a positive value beta indicates that the main drivers of asset performance are value stocks. Value returns are computed as follows: *HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, HML =1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).*

Tab 1.

This tab reports the starting date of every observation in this paper, which is computed starting from the first of the two-day meeting. The "projection materials" period on the Federal Reserve's FOMC calendar refers to the release of the Summary of Economic Projections (SEP) by the Federal Open Market Committee (FOMC). The SEP is typically released four times per year, after every other FOMC meeting, and provides the FOMC's updated projections for key economic variables such as GDP growth, inflation, unemployment, and interest rates. During the "projection materials" period, the FOMC members submit their individual projections for these variables, and the median projections are published in the SEP. The SEP provides essential insights into the FOMC's outlook for the economy and its possible future policy actions.

Year	**Month**	**Day**	**Activity**
2023	March	21-22	*Press Conference, Projection Materials*
2022	December	13-14	*Press Conference, Projection Materials*
	September	20-21	*Press Conference, Projection Materials*
	June	14-15	*Press Conference, Projection Materials*
	March	15-16	*Press Conference, Projection Materials*
2021	December	14-15	*Press Conference, Projection Materials*
	September	21-22	*Press Conference, Projection Materials*
	June	15-16	*Press Conference, Projection Materials*
	March	16-17	*Press Conference, Projection Materials*
2020	December	15-16	*Press Conference, Projection Materials*
	September	15-16	*Press Conference, Projection Materials*

	June	9-10	*Press Conference, Projection Materials*
	March	17-18 (canceled)	*Press Conference, Projection Materials*
2019	December	10-11	*Press Conference, Projection Materials*
	September	17-18	*Press Conference, Projection Materials*
	June	18-19	*Press Conference, Projection Materials*
	March	19-20	*Press Conference, Projection Materials*
2018	December	18-19	*Press Conference, Projection Materials*
	September	25-26	*Press Conference, Projection Materials*
	June	12-13	*Press Conference, Projection Materials*
	March	20-21	*Press Conference, Projection Materials*

4.2 Hedging Strategy and pairing procedure

The concept behind this analysis is to verify by a back test if it pays off to open a short position in an ETF with a specific geographical market relevance, in order to cover possible losses of a stock listed in the same market that the paired ETF represents. Downward movements in stocks occur when a firm-specific event brings the stock price down or when a macroeconomic trend influences a particular industry or market. Hedging operation mainly covers the external risk, so that specific risk deriving from motivations outside the cases of management issues or poor financial performance. Similarly to what was done in AYDOGDOM (2023), two separated strategies were created: a “naked one” formed by just a long stocks position and a hedged one, where for all identified stocks in the relative market, a short position in geographical ETF is taken with a numerical relation of just one ETF for one stock. Starting from day zero, represented by the dates when FED announced the action taken in place regarding interest rates (Tab 1), so quarterly every year, four different holding periods of respectively: 10 days, 20 days, 30 days, and 50 days, were computed. The time window for both strategies was open at T-Days (10,20,30,50) of the observation radius and closed at T+Days. Then all periods’ mean results are summed up, leaving us with an expected sum of 21 observations for each pair, which multiplied by the number of days, gives the equally weighted average of compounded market portfolio returns. The FED calendar is the primary reference for this research in order to give some legit starting points for observation to be built since it was demonstrated by the literature that stock markets are more volatile around interest rate announcements. The stock selection process was quite straightforward: from various reports and the Refinitive data stream archives, averages of P/E ratios were computed relative to the year 2018 through the five specific regional markets. Then starting from a detected group of stocks that met the P/E criteria of being undervalued, the sample of 31 stocks was chosen to pair, which could have covered the majority of 12 Fama French industries. Then through the screener etfdb.com, thanks to the geographical screening function, ETFs with weighted geographical exposition higher than 30% to the relative market were taken, with the exception of European equity ETFs, which were selected by an asset under management relevance criteria.

Tab 2.

This table shows all of the assets chosen to construct the pairs for this analysis: they are divided by region and market, plus, the weighted exposure of the components is indicated in percentage, specified to confirm the fairness of the exclusion criteria following HOZ's paper. Regarding the Europe market, a different methodology was used, which is why no weighting percentage is shown. The logical explanation is that Europe ETFs were selected from the "Europe Equity" label explicitly expressed by ETFdb. So it is reasonable to assume that all the components or a percentage near 100% are from European markets.

Market	ETF	Weighted exposure	Stock	Ticker
Italy	Franklin FTSE Italy ETF	88,5%	ENEL SpA	FLIY-ENEL
	iShares MSC Italy ETF	86,43%	Leonardo SpA	EWI-LDO

Germany	Franklin FTSE Germany ETF	97,70%	Deutsche Post	FLGR-DPW
	iShares MSCI Germany ETF	96,93%	HeidelbergCement	EWG-HEI
	First Trust Germany AlphaDEX Fund	96,52%	Sudzucker	FGM-SZU
	Xtrackers MSCI Germany Hedged Equity	95,01%	BMW	DBGR-BMW
	ETF	94,91%	Continental	HEWG-CON
	iShares Currency Hedged MSCI Germany	94,79%	RWE	DXGE-RWE
	ETF	89,22%	BASF	DAX-BAS
	WisdomTree Germany ETF	80,84%	Hochtief	EWGS-HOT
	Global X DAX Germany ETF	30,83%	ArcelorMittal	FEUZ-MT
	iShares MSCI Germany Small-Cap ETF	29,83%	Covestro	HEDJ-COV
	First Trust Europe Hedged Equity Fund			
	WisdomTree Europe Hedged Equity Fund			
UK	iShares MSCI United Kingdom Small-cap	95,65%	Centrica	EWUS-CNA
	ETF	91,45%	Kingfisher	FKU-KGF
	First Trust United Kingdom AlphaDEX	90,54%	National Grid	EWU-NGG
	Fund	88,21%	Aviva	FLGB-AV
	iShares MSCI United Kingdom ETF	86,80%	W.R Berkley	HEWU-WRB
	Franklin FTSE United Kingdom ETF	34,15%	Rio Tinto	FTRI-RIO
	iShares Currency Hedged MSCI United	33,82%	Ashtead Group	EUDV-AHT
	Kingdom ETF	29,63%	DS Smith	IEUS-SMDS
	First Trust Indxx Global Natural Resources			
	Income ETF			
	ProShares MSCI Europe Dividend Growers			
	Income ETF			
	iShares MSCI Europe Small-Cap ETF			
Netherlands	iShares MSCI Netherlands ETF	90,03%	ING Groep	EWN-ING
Europe	Vanguard FTSE Europe ETF		HSBC Holdings	VGK-HSBC
	JPMorgan BetaBuilders Europe ETF		Imperial Brands	BBEU-IMB
	iShares MSCI Eurozone ETF		Vinci	EZU-DG
	iShares core MSCI Europe ETF		Bayer	IEUR-BAYN
	Xtrackers MSCI EAFE Hedged Equity ETF		Royal Dutch Shell	DBEF-SHEL
	iShares MSCI United Kingdom ETF		Vodafone	EWU-VOD
	SPDR EURO STOXX 50		Volkswagen	FEZ-VOW
	iShares Europe ETF		Credit Agricole	IEV-ACA
	iShares MSCI Germany ETF		Allianz	EWG-ALV
	WisdomTree Europe Hedged Equity Fund		Sanofi	HEDJ-SNY

The pairing procedure instead was not so straightforward due to formatting and computing issues. First of all, the data series downloaded from Refinitive had misaligned lengths due to non-identical time series for stock markets. Different regions mean different opening days, so the mismatched columns in Excel needed to be made congruent to conduct the regression via the analysis tool pack, otherwise the algorithm would not have worked. To solve this problem, a mixed operation between the usage of the function

V.LOOKUP and manual arrangements helped execute the otherwise repetitive and not optimizable operation. Starting from the resulting data columns, a basic hedging operation of the sum for all daily returns was computed. In particular, returns of the long position were summed with the inverse returns of ETF, then both assets were weighted following Michalik and Shubert's (2009) perfect hedging formula:

$$x_L = \frac{\sigma_S^2 - \text{cov}(r_L, r_S)}{\sigma_L^2 + \sigma_S^2 - 2\,\text{co}\ \ (r_S, r_L)} \text{ and } x_S = 1 - x_L$$

$$x_L = \frac{\lambda}{\lambda+1} \text{ and } x_S = \frac{1}{\lambda+1}$$

The first one is the equation to calculate the weights of the hedging. Instead, the other two represent the leverage effect that helps to compute the amount of money someone should invest in relation to the budget of the long asset that, for this paper, is just 1x due to the "exclusion" approach taken by the literature. σ^2 is the variance of the asset and λ represents the leverage ratio, the $x_{L,S}$ are the weights of the long and short positions, and cov is the covariance between the two assets. This particular formula is used to create a Cross-Hedging: Commonly, hedging is performed between a derivative instrument and its underlying future with stocks, and those items are bonded since regards the same underlying. Differently cross-hedging is a tactical allocation where the investor uses a financial instrument or commodity that is not directly related to its primary business activities. For example, suppose a company is exposed to price risks related to the price of oil but does not produce or consume oil directly. In that case, it may use futures contracts on natural gas as a cross hedge to reduce its exposure to oil price fluctuations. To compute the actual weights is necessary to find the correlation between to data series, which will be used to compute the covariance by multiplying it with the standard deviations of the respective stock and ETF. It is important to note that the sign of the correlation must be inverted because the series is taken from a short perspective, Otherwise, the equation does not make sense. Following the literature findings, the weighting equation should be the most rewarding option in terms of the numerical position to open. To furtherly verify that, Excel provides a scenario analysis tool, making it possible to change some data cells and show the results changed in the whole sheet. It will be shown later in this paper that there is indeed a difference between 50-50 weighting and weights computed using the perfect hedging formula. Finally, for the computation of returns after transaction fees, were taken transaction fees data from the ETFs prospectus recurring again to ETFdb.com screener, then a simple mean was computed, and the costs were subtracted from the final sum output as many times as the time window was opened.

Tab 3.

Pairs by Market	**Volatility ETF**	**Volatility Stock**	**Correlation**	**Covariance**
Italy				
FLIY-ENEL	0.014961574	0.016293232	0.644496884	-1.57110555
EWI-LDO	0.015258444	0.024671791	0.500809827	-1.885314268
Germany				
FLGR-DPW	0.013626499	0.018104312	0.667702979	-1.647212521
EWG-HEI	0.014042979	0.01978077	0.649652253	-1.80461012
FGM-SZU	0.016401156	0.01965053	0.256206392	-0.825731174
DBGR-BMW	0.014017055	0.018991845	0.596932335	-1.589091959
HEWG-CON	0.014269607	0.02463883	0.566052701	-1.990164398
DXGE-RWE	0.014916251	0.018723951	0.352919441	-0.98567278
DAX-BAS	0.014095471	0.018912518	0.694297874	-1.850865213
EWGS-HOT	0.013516163	0.022209251	0.514778386	-1.545281603
FEUZ-MT	0.013925455	0.029439049	0.573544557	-2.351258337
HEDJ-COV	0.013542636	0.022341451	0.532903086	-1.612363047
UK				
EWUS-CNA	0.014422874	0.025686309	0.433365592	-1.605491242
FKU-KGF	0.016878798	0.022999728	0.438660374	-1.702913703
EWU-NGG	0.013008374	0.0150258	0.458946513	-0.89706246
FLGB-AV	0.012760104	0.019841411	0.645551212	-1.634396601
HEWU-WRB	0.012489324	0.017919476	0.627545693	-1.404460717
FTRI-RIO	0.01551962	0.020485587	0.632652195	-2.011381709
EUDV-AHT	0.011409049	0.02463217	0.639322835	-1.796686659
IEUS-SMDS	0.012882735	0.02182771	0.561800228	-1.579785687
Netherlands				
EWN-ING	0.01372076	0.023955135	0.510029954	-1.676380004
Europe				
VGK-HSBC	0.012443053	0.017930562	0.5265	-1.174679026
BBEU-IMB	0.012491794	0.017426599	0.333087461	-0.725096359
EZU-DG	0.013669656	0.021722758	0.772119697	-2.292752457
IEUR-BAYN	0.012319878	0.019878412	0.473037214	-1.158466306
DBEF-SHEL	0.012387711	0.021794305	0.475700629	-1.284303954

EWU-VOD	0.012997958	0.018031196	0.554374752	-1.299281051
FEZ-VOW	0.013787586	0.023328406	0.631924122	-2.03253587
IEV-ACA	0.012342037	0.02100995	0.608601078	-1.578136551
EWG-ALV	0.014042979	0.016482408	0.675880588	-1.56440747
HEDJ-SNY	0.013502416	0.013384245	0.349142283	-0.630968694

This tab represents the Covariance computation results, the outcome of the formula,

$$COV = corr \cdot \sigma_L \cdot \sigma_S$$

following Michalick and Shubert's(2009) paper. Results are expressed in Daily terms and covariance has negative sign because the computations are made on an inverse of the return series.

In order to make consideration on findings and help better interpreting the regression analysis output, it is worth explaining a paper by Andrea Frazzini and Lasse Heje Pedersen "Betting against beta"(2014), which is considered one of the most prominent regarding factor-based investment strategy. Their analysis discusses the impact of funding constraints on investors' required returns and the deviations from the standard Capital Asset Pricing Model (CAPM). It highlights that portfolios of high-beta assets tend to have lower alphas and Sharpe ratios than portfolios of low-beta assets. This deviation from CAPM is observed not only in the US equity market but also in international equity markets, Treasury markets, corporate bonds, and futures markets. They found that "betting against beta" (BAB) factors is a way to capture this anomaly in standard theories such as the Fama-French 3 and 5-factor model and suggests its usefulness as a control variable in future research. The BAB factor is shown to have significant economic magnitude, statistical significance, and robustness across various time periods, stock subsets, and global asset classes. Not directly related to this analysis, the paper also discusses the implications of funding constraints on the BAB factor's performance in the time series and the compression of betas in the cross-section of securities. Additionally, it mentions the portfolio selection of constrained and unconstrained investors, with mutual funds and individual investors holding riskier portfolios with betas above one on average. In contrast, leveraged buyout funds and institutions with access to leverage indeed tend to buy stocks with betas below one on average. These findings align with the model's predictions and suggest that leveraging safe assets can take advantage of the BAB effect, benefiting investors facing borrowing constraints.

Tab 4.

This table shows the numerical rationale behind choosing stocks following P/E selection criteria. Data came from the Refinitive Data stream, plus some integrations from other public sources, such as reports and yahoo finance, where data went missing.

Market	Mean P/E (2018)	Stock	Stock's P/E (2018)
Italy			
FTSE-MIB	14,5	ENEL	13,33
		Leonardo	11,3
Germany			
DAX	14,87	Deutsche Post	12,95
MDAX	17,5	HeidelbergCement	8,86
		Sudzucker	13,4
		BMW	7,5
		Continental	11,24
		RWE	11,68
		BASF	12,29
		Hochtief	14,52
		ArcelorMittal	7,71
		Covestro	8,37
UK			
FTSE 100	16,7	Centrica	10,05
FTSE 250	20,6	Kingfisher	12,3
		National Grid	14,3
		Aviva	11,27
		W.R Berkley	17,32
		Rio Tinto	8,1
		Ashtead Group	15,95
		DS Smith	17,8
Netherlands			
AEX	19,8	ING Groep	10,8
Europe			
MSCI Europe	18,5	HSBC Holdings	14,00
Developed		Imperial Brands	11,59
Markets index		Vinci	14,7
		Bayer	14,9
		Royal Dutch Shell	11,4
		Vodafone	16,1
		Volkswagen	6,79
		Credit Agricole	10,1
		Allianz	10,2
		Sanofi	13,95

5. Findings

The outcome of the analysis conducted will be exposed by the same geographical repartition that characterizes the whole paper. First will be beheld a brief introduction to the stock market index of every region, focusing on the main components and most relevant industries. Afterward, the indicator's output of the overall strategy and the naked position will be displayed. Furtherly will be added the confrontation between, both with or without computation of transaction cost, and will be shown the difference between weighting with perfect hedging formula and simple 50-50 weighting. Finally, regression analysis output and ratio values will be discussed.

One general finding regards the application of Markovitz's portfolio theory, which, as expected, shows that hedging generates a variance minimization process that has held for all pairs, resulting in a more predictable pattern for the investments and a substantial decrease in risk. Statistically speaking, these results were obtained mainly because the assets, due to mathematical properties, benefitted from inverse correlation, so they gained market protection from the intrinsic nature of short selling, which gives, as it was said before, gains to the investors when the asset itself live a bearish period. This concept can be applied to this specific analysis, where the portfolio benefitted from a whole market insecurity. Differently from the literature, the strategy did not work for all the time windows of choice. More in-depth, significant results were obtained by applying the radius of 10 and 20 days, where for all samples shorting ETFs helped obtain revenues higher than the alone stock. Instead, for the more extended holding periods, the risk-reward trade-off of keeping only a single stock in the portfolio paid, since pairs not only proportionally lowered the generated returns, but also were substantially beaten by the riskier uncovered position alone. From what was funded in AYDOGDO, it is still better to hedge for all-time windows before transaction costs since the metrics, alphas and Sharpe ratios, result in all positive and encouraging values, instead, following these paper results, even before subtracting transaction costs, it is far more valuable not to pursue the pairing strategies for longer time spans of 30 and 50 days radius built around interest rates announcement. One explanation of this effect, sustained by another part of the literature examined in this paper, can come from Pessina, Colby J.; Whaley, Robert E.(2021), where regarding the inverse performance of ETFs they funded that the long-term value of such items tends to 0 due to higher costs associated with short positions, and so suggest the application of short ETFs for a shorter time-span. Another possible cause of these findings can be the continuous growth tendency of equity market premiums, evidence widely recognized through the economic academic community. The observation that markets tend to rise in the long run is supported by historical data, which show an overall upward trend in equity markets over extended periods. This long-term upward movement can be attributed to factors such as economic growth, technological advancements, productivity gains, and the overall progress of societies. Through all the available eminent sources, Philippe Jorion (2007) in his paper analyzes the long-run equity risk premium using historical data from multiple countries. It provides empirical evidence supporting the notion that equity markets exhibit an upward trend over extended periods. Since ETFs represent and reproduce comprehensive market index returns, as was said in the introductive part of this analysis, it is safe to assume that their long-term investment orientation makes them more prone to increase in value, due to the continuous expansion of assets under management and awareness through the less sophisticated part of investors community. This literature branch confirms the legitimacy of the numerical findings of this analysis regarding the longer windows performance of hedged positions and instead the properties of exploiting ETFs in reaction to short-term volatility increase.

5.1. Italian market

5.1.1 Market introduction

The benchmark stock market index for the Italian equity market is FTSE MIB. It represents the performance of the 40 largest and most actively traded companies listed on the "Borsa Italiana", which is the Italian stock exchange. The composition of the Italian main index is diverse, encompassing companies from various sectors. However, certain industries tend to significantly impact the market, and their performance is closely tied to the overall Italian economy. In particular, there are:

1) Financial Services: Italy has a robust financial sector, and several major Italian banks and financial institutions are listed on the FTSE MIB. These companies play a crucial role in the Italian economy, providing essential services like banking, insurance, and asset management. As a result, their performance can significantly influence the whole country's economy.

2) Energy and Utilities: The energy sector, including oil and gas companies, as well as utilities, is another vital component of the FTSE MIB. Italy has a diverse energy mix, with both conventional and renewable energy sources. Therefore, those companies involved in exploration, production, distribution, and renewable energy generation contribute to the index's composition.

3) Industrial and Manufacturing: Italy is known for its manufacturing prowess, particularly in sectors such as automotive, machinery, and engineering. Manufacturing and industrial production companies include automobile manufacturers, machinery producers, and engineering firms.

4) Consumer Goods and Retail: these include renowned brands in sectors like luxury goods, fashion, food and beverages, and retail. Domestic consumption trends and global demand for Italian products influence the performance of these companies.

5.1.2 Numerical results and Comments

The diverse composition of the Italian listed companies in terms of capital weight though, is heavily driven by the banking and energetic fields, which performance can undermine the direction towards FTSE MIB shifts due to downward movements of those industries instead. One of the companies taken for building a strategy in the Italian market is ENEL, which provides energy distribution services and green energy production; it could have been paired with an energy ETF following the AYDOGDOM system, instead here was paired with a less industry-specific ETF. Since the logical trend correlation explained before, the pair created was expected to have a positive outcome. The other component of such a small sample is Leonardo, a company specializing in aerospace, defense, and security. It operates in the industrial and manufacturing sectors and is involved in designing, developing, manufacturing, and maintaining a wide range of products and systems. The industry choice, where the second stock belongs, was made to avoid the meaningful influence that the other crucial sector, financial and banking, could have had on the contribution to Italian market performance and explore other strategic companies' impact on the FTSE MIB returns pattern. It is essential to enlighten also an anomaly in this sample since the Italian government is a shareholder of both companies called "Partecipate," which can also explain why the connection between the inverse performance of the ETFs representing FTSE-MIB and the performance of those companies is so well negatively correlated for short terms. Now Speaking of numerical results, as it is shown in Tab.5, Italian pairs performed well for the 10 days and 20 days radius portfolios, resulting in Sharpe ratios of respectively 0,1291 and 0,1955 that suggest the possibility of taking in consideration such an investment since it successfully surpasses the benchmark. Italian pairs managed to beat the market for the whole period of 5 years, yielding positive alpha of 0.000321 for the 10 days radius and 0.000341 for the 20 days. The Italian market portfolio is able to generate compounded revenues far better than the naked positions. The most successful and influential pair is EWI-LDO, which contributes to the mean value of the Italian portfolio returns generated, and gives a positive output, also taking in consideration transaction costs, which were calculated by the mean value of the cost reported in the relative ETFs prospectus. The interpretation of those results "in the money" means that entering a hedged position in the Italian market sample, not only avoids suffering losses in long stocks value, but gives the investor a positive surplus over a dollar-neutral strategy. Betas' results follow the path of findings computed by Frazzini and Pedersen (2014) since, even if positive, factor betas are low, indicating that the performance is not entirely related to the market trends but generated indeed by diverse causes, in this case, the hedging strategy. In particular, for the time windows of 20 days, betas are low, never negative, but significant from a statistical perspective due to the low P-value. For this sample, the hypothesis that investing in stocks with a lower P/E ratio generates more value than the relatively "less undervalued," at least considering Hedged positions, holds since LDO generates higher returns than ENEL.

Tab 5.

Italy	Cumulative returns	Sharpe	Alpha	P-value Alpha
Hedged				
(-10, +10)	14,6906%	0,1291	0.000321	0.3504
t-Statistics			(0.831077)	
(-20, +20)	28,4401%	0,1955	0.000341	0.207962
t-Statistics			(1.293924)	
Naked				
(-10, +10)	-5,28%	NG*	0.000235	0.797386
t-statistics			(0.256892)	
(-20, +20)	4,4599%	NR*	0.000342	0.54097
t-Statistics			(0.611599)	

Beta	Market	Size	Value
Hedged			
(-10, +10)	0.160692936	0.051809883	0.222820962
P-value	(2.60511E-09)	(0.527247256)	(1.49386E-05)

(-20, +20)	0.075587621	0.097336745	0.06009266
P-value	(1.10869E-05)	(0.006710225)	(0.008515207)
Naked			
(-10, +10)	0.221230519	0.632394095	-0.018352582
P-value	(0.001176624)	(0.002751182)	(0.88818091)
	0.215819315		
(-20, +20)	(5.11118E-06)	0.557129889	0.003517462
P-value		(6.14399E-05)	(0.966542115)

Here are reported general data for the Italian market portfolio for hedged positions and naked positions with t-Statistics and P-value where necessary. NG stays for negative, so the ratio where not computed for such positions since, due to the nature of the Sharpe ratio itself, a negative result shows non-suitability for investment, due to computed out-of-the-money excess returns. NR* stays for not relevant, and it means that the ratio presents a low value that, after calculations, shows poor performance from the indicator, and/or after considering costs, the results are negative, so it is not worth pursuing an effort of investment. Moreover, there are only reports just for the smaller time windows since those are the data that plainly express the strategy's validity. Finally, compounded returns results are done by making a sum of the mean of daily returns multiplied by the whole number of observations.*

5.2 Germany market

5.2.1 Market introduction

To represent the German regional sample, it is helpful to introduce not one but two stock indexes where it is possible to pick undervalued assets to match with the ETFs sample. Together with the Europen strategy, Germany presents the more extensive group of ETFs employable in the analysis, counting ten units.

The first and most relevant in terms of capitalization is the DAX, the flagship stock market index in Germany, representing the 30 largest and most actively traded companies listed on the Frankfurt Stock Exchange. It is mainly composed of firms operating in the following areas:

1) the Automotive industry, which Germany is renowned for. Several major automobile manufacturers, such as Volkswagen, BMW, and Daimler are included in the DAX. These companies contribute significantly to the index's performance and are influential in the global automotive market.

2) Germany has a strong presence in the Chemicals and Pharmaceuticals industry. Companies like BASF, Bayer, and Merck are part of the DAX, driving innovation and research in these industries.

3)Industrial Engineering: The DAX includes companies like Siemens, one of the world's largest engineering companies, which is a prominent constituent of the index.

Introducing the other index used as a "pot" for the stock selection, it is possible to witness a shift in influential industries: The MDAX represents the 60 largest companies listed on the Frankfurt Stock Exchange after the DAX constituents. It includes a broader range of mid-cap companies, often with a focus on the German market. Industries that have a higher representation in this index include:

1)Technology, with companies operating in various sectors, such as software development, information technology services, and telecommunications. Companies like Infineon Technologies and Siemens Healthineers are part of it.

2)Retail, since Germany has strong companies engaged in food retail, consumer goods, and online retail. Examples include Metro AG and Zalando;

3)Financial Services, which includes providers such as Deutsche Wohnen (real estate), Aareal Bank (banking), and LEG Immobilien (real estate investment).

5.2.2 Numerical results and Comments

Like the Italian market, there is an improvement before transaction costs of performance for the shorter time windows of 10 days and 20 days, helping the long positions recover from momentary losses generated by market uncertainty. Germany's results are lower than Italian counterparts but can be considered more accurate thanks to the bigger sample. Also, in this case, alphas are over 0 and higher for the shorter period of 10 days radius, with a Sharpe ratio of 0.16, prominent and in line with the literature than the same indicator for the 20-day rolling window. Interestingly beta market and beta value results are significant and negative, which means an inverse relation of the 10-days German portfolio with market risk premium and value premium, sustaining Betting Against Beta findings. Cumulative returns pre-transaction costs are solid for both portfolios. However, only the 10 days radius manages to be cost-effective with a result of 0,9267704% on the overall period of 5 years in the money. This specific portfolio is lowly correlated with market premium since betas are for both periods negative and significant. FEUZ-MT, FGM-SZU, and DBGR-BMW were the best performance provider match, in part sustaining the low P/E hypothesis, with the exception of SZU, which gave the best overall performance throughout the German market, probably derived by a contribution of factors, such as small size and lowest correlation with the matched ETF, the smaller value throughout the whole sample of 31 pairs. HEWG-CON instead results in a heavily out-of-the-money investment, respectively of -16,81 % compounded returns for 10 days of Hedging and -25,24% for 20 days, contributing to lower the overall mean returns of otherwise dollar zero portfolio of 20 days. (that was also computed using scenario analysis)

Tab 6.

Here are reported general data for the German market portfolio for hedged positions and naked positions with t-Statistics and P-value where necessary. NG* stays for negative, so the ratio where not computed for such positions since, due to the nature of the Sharpe ratio itself, a negative result shows non-suitability for investment, due to computed out-of-the-money excess returns. NR* stays for not relevant, and it means that the ratio presents a low value that, after calculations, shows poor performance by the indicator, and/or after considering costs, the results are negative, so it is not worth pursuing an effort of investment. Moreover, there are only reports just for the smaller time windows since those are the data that plainly express the strategy's validity. Finally, compounded returns results are done by making a sum of the mean of daily returns multiplied by the whole number of observations.

Germany	**Cumulative returns**	**Sharpe**	**Alpha**	**P-value Alpha**
Hedged				
(-10, +10)	12,10%	0.160397	0.00026	0.775112
t-Statistics			(0.455979)	
(-20, +20)	10,14%	0.045376	4.92E-05	0.340138
t-Statistics			(0.285788)	
Naked				
(-10, +10)	-22,162%	NG*	-0.00087	0.463231
t-statistics			(-0.7342)	
(-20, +20)	-23,888%	NG*	-4.48E-05	0.951479
t-Statistics			(0.060868)	

Beta	Market	Size	Value
Hedged			
(-10, +10)	-0.161661262	0.026616957	-0.042136508
P-value	(9.86999E-26)	(0.417228143)	(0.044970196)
(-20, +20)	-15.57255076	2.248448258	0.226825017
P-value	(3.35476E-48)	(0.024807373)	(0.820615261)
Naked			
(-10, +10)	0.043174264	0.267393405	0.080052481
P-value	(0.623258438)	(0.326631125)	(0.63628162)
(-20, +20)	0.052324349	0.410797939	-0.034015357
P-value	(0.397514237)	(0.024135694)	(0.757669187)

5.3 UK market

5.3.1 Market introduction

the London Stock Exchange is one of the oldest stock markets on the planet, so considering its status and history, the UK capital has become one of the most relevant and developed stocks exchange. As for Germany, the British stocks market is divided into two relevant indexes that encompass the majority of pound-denominated stocks and present, according to ETFdb screeners, the highest number of ETFs traded in their market along with those which are traded in the USA market. Starting from the introduction of both indexes, we got: FTSE 100, the primary stock market index, representing the 100 largest companies listed on the London Stock Exchange. It includes a wide range of firms, with the following sectors having significant representation:

1) Financial Services, which plays a vital role in the UK economy and includes companies such as HSBC, Lloyds Banking Group, and Barclays.

2) Energy and Resources, which companies are involved in oil and gas exploration, production, and distribution. Examples include BP and British Gas. In addition, mining companies like Rio Tinto and BHP Group are included and also represent the resources sector.

3)Consumer Goods, This includes companies like Unilever, British American Tobacco, and Tesco, among others.

FTSE 250 index, like MDAX for Germany, represents the 250 largest companies listed after the FTSE 100 constituents. It includes a broader range of mid-cap companies, with a focus on the UK market. The majority of stocks belong to these Industries:

1) Industrials, with companies involved in engineering, construction, transportation, and manufacturing, there are names like Rolls-Royce Holdings, Serco Group, and Stagecoach Group taking part in that index.

2)Technology: with companies operating in software development, information technology services, and telecommunications.

3) Consumer Services, with firms engaged in hospitality, leisure, media, and retail services.

5.3.2 Numerical results and Comments

UK pairs present the highest Sharpe Ratios throughout all the portfolios created; in particular, the 10-Days radius portfolio reached a satisfying 0.317611 output, successfully beating the market with an alpha of 0.00028, even if the significance of the intercept value is high. The same portfolio compounded returns for the whole period resulted in 18,46%, resulting in a position in the money of about 7,62%, which is the third highest income, according to this research, that an investor could gain in investing in such a geographical market-risk-shielded portfolio, positioning behind Italy's 10 days and 20 days portfolios, which respectively gained 8,49% and an astonishing 22.24% after transaction costs. It is possible to say that UK pairs deliver a bargain with more consistency since the sample is composed of a far higher number of pairs, eight, and it can overperform the market with higher mean costs associated, as it is possible to see in tab.10. Also the 20-Days portfolio pays the investment strategy choice by a less lucrative margin of 4,29% after transaction costs. One of the reasons why those results have such a positive output can be found by considering the results for naked positions, which are lesser negative than other European countries' stock performance during the same period. Regarding regression results, there is a continuous trend already observed in the Literature of negative Market Beta that held for all the samples with a high number of observations, like it was for Germany, and how it will be shown for the Europe portfolio, that specifically for UK portfolio amount to -0.153744396 for 10-Days radius portfolio, and -0.124890009 for 20-Days radius pairs, both with a high significance, stating that the portfolio tends to perform poorly when the market risk premium increases. For London stocks exchange traded pairs also results true that the gains are negatively driven by the Value factor, which is significant just for the 10-days radius, and even if both size factors are negative, none of them results accountable due to their low P-value. Regarding individual performance, FTRI-RIO showed the highest individual numbers for both times spans of 31,36% and 27,97% beating all the other portfolio components. Looking at the second-placed EWUS-CAN, with an overall of 24,18% and 20,24%, it is safe to assume that the lower P/E ratios companies contribute the most to the value created by the UK portfolio, showing the same tendency as Italy and Germany portfolios.

Tab 7.

Here are reported general data for the UK market portfolio for hedged positions and naked positions with t-Statistics and P-value where necessary. NG stays for negative, so the ratio where not computed for such positions since, due to the nature of the Sharpe ratio itself, a negative result shows non-suitability for investment, due to computed out-of-the-money excess returns. NR* stays for not relevant, and it means that the ratio presents a low value that, after calculations, shows poor performance by the indicator, and/or after considering costs, the results are negative, so it is not worth pursuing an effort of investment. Moreover, there are only reports just for the smaller time windows since those are the data that plainly express the strategy's validity. Finally, compounded returns results are done by making a sum of the mean of daily returns multiplied by the whole number of observations.*

UK	Cumulative returns	Sharpe	Alpha	P-value Alpha
Hedged				
(-10, +10)	0.184633	0.317611	0.00028	1.164792
t-Statistics			(0.244754)	
(-20, +20)	0.151272	0.104717	7E-05	0.462015
t-Statistics			(0.644191)	

Naked				
(-10, +10)	-0.02774	NG*	-0.00026	0.67704
t-statistics			(-0.41679)	
(-20, +20)	0.01248	NR*	-1.86E-05	0.964634
t-Statistics			(0.044353)	

Beta	**Market**	**Size**	**Value**
Hedged			
(-10, +10)	-0.153744396	-0.05055847	-0.098431867
P-value	(1.37005E-16)	(0.361347278)	(0.004395126)
(-20, +20)	-0.124890009	-0.059934494	-0.031034168
P-value	(1.38831E-21)	(0.109846338)	(0.171840084)
Naked			
(-10, +10)	0.2872877	-0.087219247	0.323064039
P-value	(1.28722E-08)	(0.175142489)	(0.63628162)
(-20, +20)	0.052324349	0.410797939	-0.034015357
P-value	(1.56223E-09)	(0.545852881)	(2.10791E-05)

5.4 Netherlands market

5.4.1 Market introduction

As was done for the previous markets, the explanation will start with an introduction of its financial landscape, which is crucial to have a better interpretation of the context. Euronext Amsterdam, commonly known as the Amsterdam Stock Exchange, is the oldest stock exchange in the world, tracing its roots back to the early 17th century. It is currently part of the Euronext group, which operates multiple exchanges across Europe, giving integration benefits to the companies listed on the Dutch stocks exchange since they become part of the more comprehensive Euronext network, which has connections in other major European cities. This "convergence" allows for potential cross-listing opportunities and access to a more extensive investor base across multiple European markets. The Dutch Authority regulates Netherlands stock exchange for the Financial Markets (AFM), which considering the historical tradition of the institution, has a reputation for strong corporate governance and robust regulatory frameworks. This trait gives confidence to investors in the overall safety of the exchange trade market and enhances the transparency and credibility of listed companies. The main components of the AEX index are firms that operate in the following:

1) Financial Services, since several major banks and insurance companies are listed on Euronext Amsterdam. This includes institutions like ING Group, ABN AMRO, and Aegon.

2)Technology, because, for instance, ASML, the biggest semiconductor supplier company, is listed on the exchange, and also other software developments, IT services, and e-commerce are gaining prominence on the exchange in recent years.

3)Consumer Goods: these include companies like Heineken, a renowned global brewing company, and Koninklijke Ahold Delhaize, a multinational retail company.

5.4.2 Numerical results and Comments

The Netherlands sample is unconventional and differs from the others since it comprises just one pair. Constructing the case presented some trouble because the specimen for Dutch ETFs suitable for the strategy, following literature criteria settled by HOZ, left only one Regional ETF, as was previously mentioned in the Data section, even if The Netherlands stocks are listed in a relatively high number of ETFs, as it is shown by ETFdb screener. The causes of that lack of material can be explained, for instance, by the presence of multinational companies that have settled their juridical seat over their origin countries like the Stellantis case, which are not technically Dutch mainly oriented companies but are considered parts of AEX anyway. Another reason could be the network where AEX is finding itself, which considered the stock exchange part of a broader system focused not only on Dutch territory but also expanded it to France, Portugal, Ireland and Belgium, making it perhaps less profitable and attractive in Financial terms to create a “branched” ETF of such interdependent system like this broad stocks exchange network. Even if a single pair cannot truly express what could be the effect of exploiting the paper strategy in the Netherlands market, data are not looking good since it is true that EWN-ING, in the shorter periods, performed better than the naked positions, but both strategies are out-of-the-money if we take in consideration transaction costs. This result does not change if, for example, the perfect hedging formula is not applied and instead, a fifty-fifty percentage weighting is computed. The stocks alone saw a gain throughout the period of 5 years, but the strategy application failed, giving a slightly positive performance for the 20-Days radius pair as an outcome. Further observations are needed, maybe including the other countries' network stocks and ETFs, in order to state if it is worth pursuing hedging in the Netherlands market. Regarding beta values, it is interesting to see that the negativity of Market sensibility results in line with previous portfolios and is significant from a statistical computation.

Tab.8

Netherlands	Cumulative returns	Sharpe	Alpha	P-value Alpha
Hedged				
(-10, +10)	-0.070954	-0.12352	-0.01174	0.684537
t-Statistics			(-0.40642)	
(-20, +20)	0.008727	-0.10926	-0.00011	0.587472
t-Statistics			(-0.54291)	
Naked				
(-10, +10)	-0.21187	NG*	-0.00025	0.676663
t-statistics			(-0.41731)	
(-20, +20)	-0.32276	NG*	-0.00025	0.41565
t-Statistics			(-0.8144)	

Beta	Market	Size	Value
Hedged			
(-10, +10)	-2.114780155	0.020916573	21.20231003
P-value	(0.213046618)	(0.99682744)	(2.36294E-10)
(-20, +20)	-0.060970077	0.110047629	0.574067001
P-value	(0.007487959)	(0.100385302)	(6.05904E-41)
Naked			
(-10, +10)	0.021468804	0.307571792	0.555057398
P-value	(0.837386216)	(0.343161969)	(0.006090163)
(-20, +20)	0.161049233	0.508598572	0.364216507
P-value	(0.029556124)	(0.019523837)	(0.005821499)

Here are reported general data for the Netherlands market portfolio for hedged positions and naked positions with t-Statistics and P-value where necessary. NG stays for negative, so the ratio where not computed for such positions since, due to the nature of the Sharpe ratio itself, a negative result shows non-suitability for investment, due to computed out-of-the-money excess returns. NR* stays for not relevant, and it means that the ratio presents a low value that, after calculations, shows poor performance by the indicator, and/or after considering costs, the results are negative, so it is not worth pursuing an effort of investment. Moreover, there are only reports just for the smaller time windows since those are the data that plainly express the strategy's validity. Finally, compounded returns results are done by making a sum of the mean of daily returns multiplied by the whole number of observations.*

5.5 European market

5.5.1 Market introduction

The final sample of the analysis regards the whole European market, also comprehending the previously analyzed regions. The main index representing European stock markets is the Euro Stoxx 50. It includes 50 of the largest and most liquid blue-chip companies from 19 European countries, encompassing a wide range of industries, and serves as a benchmark for European equity performance. The index consists of major European companies from various sectors. Some prominent components include companies like Nestle, SAP, TotalEnergies, Siemens, Unilever, L'Oréal, Volkswagen, and many others. Recently European stock markets have experienced both positive and challenging trends, first and foremost the economic recovery, showing signs of recovery following periods of economic uncertainty, particularly the global financial crisis and the COVID-19 pandemic, helped by centralized monetary policies. Another critical aim the community pursues is digital transformation embracing significant growth in technology-related sectors and witnessing substantial advancements. Last but not least, there is sustainable investing considering ESG (Environmental, Social, and Governance) target requirements; in fact, companies focusing on renewable energy, clean technologies, and responsible business practices have gained growing attention. European stocks display significant representation from various industries; however, some sectors have a powerful influence and drive the community scenario:

1)Financial Services is a constant key industry in terms of capital across all the analyzed countries' stock markets.

2) Automotive, especially strong in Germany.

3) Energy, where Europe has been actively transitioning toward cleaner energy sources.

4) with a special mention for luxury goods led by LVMH, Consumer Goods reached worldwide peaks by breaking revenue records.

5.5.2 numerical results and Comments

Numerical results of this vast market give encouraging indicators, such as positive alpha of 0.000127 for the 10 days portfolio and a Sharpe ratio of 0.084606, approximately providing half of the performance of Italy and Germany portfolios, and speaking strictly about 10 days radius observations, a quarter of UK market results. Cumulative returns for 20 Days portfolio are favorable; however, they do not manage to beat the market since their Sharpe ratio is negative, which means that a risk-free investment, for example in a bond, can furnish higher gains than the strategy. An excellent trait of the European ETFs sample though is that they are relatively cheap when confronted with the other groups; in fact, the average transaction cost for opening a position in one of the 10 most traded funds is 0.36%. This characteristic does not help the pairs deliver a positive compounded performance after costs since the result is slightly negative for the 10 Days portfolio at -0.56% and for the 20 Days radius one at -4.99%. The positive compounded returns after costs are carried by BBEU-IMB, EWG-ALV, and HEDJ-SNY, which carried a pretty solid returns pattern of respectively 21,01% for 10 days and 19,23% for 20 Days, 16,38% and 18,74%; 21,52% and 20,59% that also after their relatives ETFs cost subtraction gives in-the-money-output, but other pairs carry them down. The leading cause of that reduction in profitability could be explained by the downside trend that all the naked positions show on the whole observation period, the lowest among all the long assets. Those modest results can derive from a wrong stock pick and from the less specificity that Europe ETFs have compared to the market ones. The more extensive environment of the European market, where a multitude of economic cultures and relevant interests collide, may impact the correlation between stock trends and less specific community indexes, which are influenced by a significative lower number of variables, resulting in a much more significant challenge to interpreting and understanding shifts than those smaller and more concentrated market like the Italian one can have. Since some of the pair's singular results are encouraging, a broader sample is needed to confirm or dismiss the initial hypothesis of the strategy application. Regarding betas instead, both hedged portfolios confirm the Betting against Beta literature, as much as the other findings in this paper with a negative value of -0.160394765 for the 10-Days portfolio and -0.136210129 for the 20 Days portfolio, both with high significance, confirming the counter market premium feature of the strategy

Tab.9

Here are reported general data for the European market portfolio for hedged positions and naked positions with t-Statistics and P-value where necessary. NG stays for negative, so the ratio where not computed for such positions since, due to the nature of the Sharpe ratio itself, a negative result shows non-suitability for investment, due to computed out-of-the-money excess returns. NR* stays for not relevant, and it means that the ratio presents a low value that, after calculations, shows poor performance by the indicator, and/or after considering costs, the results are negative, so it is not worth pursuing an effort of investment. Moreover, there are only reports just for the smaller time windows since those are the data that plainly express the strategy's validity. Finally, compounded returns results are done by making a sum of the mean of daily returns multiplied by the whole number of observations.*

Europe	**Cumulative returns**	**Sharpe**	**Alpha**	**P-value Alpha**
Hedged				
(-10, +10)	7,017%	0.084606	0.000127	0.637935
t-Statistics			(0.470925)	
(-20, +20)	2,5927%	-0.01816	-2.4E-05	0.883931
t-Statistics			(-0.14603)	
Naked				
(-10, +10)	-61,019%	NG*	-0.00138	0.328396
t-statistics			(-0.97847)	
(-20, +20)	-62,761%	NG*	-0.00055	0.53277
t-Statistics			(-0.62404)	

Beta	**Market**	**Size**	**Value**
Hedged			
(-10, +10)	-0.160394765	0.15419075	0.044765293
P-value	(1.07788E-14)	(0.013348825)	(0.246238015)
(-20, +20)	-0.136210129	0.077893672	0.105046706
P-value	(9.91237E-22)	(0.055875189)	(2.27201E-05)
Naked			
(-10, +10)	0.092045061	0.495345174	0.050050579
P-value	(0.041361352)	(0.000425464)	(0.563812268)
(-20, +20)	0.211728654	0.200065224	0.110669648
P-value	(1.45058E-15)	(0.009112382)	(0.017265343)

Conclusions

Starting with Some general topics, it came out that Michalik and Shubert's perfect hedging equation holds, since, through the whole pot of observations, positive earnings deriving from the covered position strategy for the 10-Days and 20-Days radius were enhanced by the application of the formula, with relevant differences from 50-50 more straightforward computation of the balance between the two components. The weights of all exchange-traded funds (ETFs) in the sample are greater than those of their corresponding individual stocks, which has a notable impact on the regression results pertaining to beta coefficients. This observation is consistent with existing literature and can be attributed to the significant presence of short ETFs within the hedged pairs. The negative and low correlations observed between the market premium factor and the overall sample are a direct consequence of this composition. Furthermore, the positive cumulative returns of the hedged positions can be explained by the short assets benefiting from market downturns. The literature about the intensification of market uncertainty, within the general increase in the VIX index and VSTOXX index around the FED announcement on the interest rate, is confirmed by the findings on volatility and expected distributed losses shown by naked position performance in the immediate periods, before and after, the announcements of 10- and 20-Days radius portfolios. These results give credibility to the logic behind the selection of starting periods when the pairs begin to be computed. Moreover, there are no solid and generalized confirmations regarding the better outcomes of the lower P/E ratio stocks, which should have shown higher results than the other relatively underpriced asset that composed pairs presented in the analysis. As was said before in the findings section, only the shorter time windows portfolios of 10-Days and 20-Days were able to provide a noteworthy in-the-money performance, demonstrating that the strategy should have an application in the Italian, German, and UK markets, being able to generate generalized and significant incomes. The European continental portfolio may have been more optimal with a wiser choice of long stocks, or with applying the tactic on a higher number of pairs, trying to skew the variance effect and gain benefit from a more diversified asset collection. Instead, the abnormal Dutch market sample must be scrutinized under a network vision, including more pairs in the observation pot. It may be worth investigating other regional stocks and ETFs, considering the role of the AEX in the larger institution where it is inserted. A peculiar result comes from the regressions' outcome, which presented overall high P-values, stating the non-significance of the model applied in order to justify Jensen's Alphas values. These findings can have more interpretations: first of all, the sample used for the analysis considered a relatively low number of observations, leading to an enhancement of data noise. In fact, in literature, the time windows where the strategy was applied were computed for a more extended period of time, that for AYDOGDOM for instance, was of 11 years and with 18,824 observations upon the integrity of USA traded common stocks, that were skimmed through HOZ criteria. However, the numerical conclusions in this study remain valid because the alphas' output of the strategy closely aligns with the low value reported in the literature. This consistency is also sustained by the significance of betas, similar again to what was discussed in the AYDOGDOM paper. The lower specificity of ETFs used as short positions also can explain the conclusive values, due to possible higher linkage given by the utilization of industry-specific ETFs in literature papers instead of regional market ETFs. Another reason could be the low suitability of only three factors, excluding momentum and quality, to explain the extra profits of such a strategy. The high "noisy" value could also be a symptom of unexplained variables and casualty in the generation of positive earnings by hedging, stating again that further diverse tests should help Fama-French to give a statistical explanation of those gains.

Tab.10

The Data represented in this Table regard the unit costs for opening an ETF position according to the public reports plus the missing time-windows results. In particular, those are the compounded returns for the 30 and 50 days radius for Hedged and Naked pairs, compute by ed multiplying the average daily returns of the 5-year period for the rolling windows of 60 and 100 days.

Pairs	ETF Cost	Hedged 30 Compounded	Hedged 50 Compounded	Naked 30 Compounded	Naked 50 Compounded
Italy Portfolio	0,30%	12.3660%	5.7040%	62.6475%	83.9576%
FLIY-ENEL	0,09%	-1.8900%	-8.0344%	50.1112%	44.0396%
EWI-LDO	0,50%	26.6220%	19.4424%	75.1838%	123.8756%
Germany Portfolio	0,53%	-19.6230%	-25.8950%	20.8408%	38.9552%
FLGR-DPW	0,09%	0.6076%	3.2344%	25.8374%	84.4051%
EWG-HEI	0,80%	-20.4664%	-18.9109%	18.1127%	54.1877%
FGM-SZU	0,45%	11.6961%	-3.9683%	31.6573%	47.3639%
DBGR-BMW	0,53%	-18.0533%	-22.8815%	46.8131%	68.6351%
HEWG-CON	0,48%	-56.4352%	-46.1062%	-58.4120%	-30.0981%
DXGE-RWE	0,53%	15.6852%	11.7289%	129.4824%	218.6623%
DAX-BAS	0,48%	-37.6142%	-49.5559%	-20.8180%	-60.6257%
EWGS-HOT	0,58%	-19.3069%	-39.8256%	15.9711%	-7.5480%
FEUZ-MT	0,80%	-6.5494%	-24.2614%	68.2726%	97.9757%
HEDJ-COV	0,58%	-65.7937%	-68.4038%	-48.5089%	-83.4063%
UK portfolio	0,52%	-4.9907%	-11.0347%	50.5481%	103.8884%
EWUS-CNA	0,59%	8.4418%	-14.4101%	49.0799%	57.6663%
FKU-KGF	0,80%	-31.6871%	-29.5129%	-3.3017%	54.6079%
EWU-NGG	0,50%	2.8034%	0.3171%	49.3120%	99.9739%
FLGB-AV	0,09%	-6.5899%	-15.0472%	10.0760%	37.8205%
HEWU-WRB	0,50%	11.6250%	14.7935%	115.7708%	214.3625%
FTRI-RIO	0,70%	-3.9171%	-16.4564%	89.3001%	129.6338%
EUDV-AHT	0,55%	-0.9875%	5.1773%	112.2081%	250.8057%
IEUS-SMDS	0,40%	-19.6139%	-33.1387%	-18.0603%	-13.7632%
Netherlands Portfolio					
EWN-ING	0,50%	-23,072%	-48,012%	20,98%	69,59%
Europe Portfolio	0,36%	-19.9941%	-23.1669%	15.4069%	45.4876%
VGK-HSBC	0,11%	-17.0025%	-18.5976%	-4.8745%	27.7112%
BBEU-IMB	0,09%	-22.0041%	-25.7721%	-10.9847%	1.0129%
EZU-DG	0,52%	-5.5520%	-5.1101%	71.4063%	158.5037%
IEUR-BAYN	0,09%	-16.6206%	-24.5038%	15.2534%	26.4150%
DBEF-SHEL	0,35%	-18.3936%	-24.7339%	42.2272%	69.5568%
EWU-VOD	0,50%	-38.2992%	-37.0111%	-44.3444%	-34.3396%
FEZ-VOW	0,29%	-27.5326%	-30.5260%	13.1534%	38.6821%
IEV-ACA	0,58%	-40.0951%	-27.2945%	-19.8549%	66.3873%
EWG-ALV	0,50%	-5.6877%	-10.4876%	32.8439%	53.1845%
HEDJ-SNY	0,58%	-8.7536%	-27.6322%	59.2435%	47.7618%

Tab.11

Those are the compounded results computed before costs, like for the previous Tab.5-9 but with a weights distribution of exactly 50%-50% for both components. As it is possible to see, mean regional portfolio results are lower than the performance achieved by computing using Michalik and Shubert's formula.

Pairs	Hedged 10 compounded 50-50	Hedged 20 Compounded 50-50
Italy Portfolio	13.521%	27.690%
FLIY-ENEL	20.331%	26.617%
EWI-LDO	6.711%	28.763%
Germany Portfolio	6.841%	5.133%
FLGR-DPW	7.596%	17.720%
EWG-HEI	0.309%	-9.446%
FGM-SZU	40.865%	21.564%
DBGR-BMW	17.360%	20.131%
HEWG-CON	-29.591%	-39.714%
DXGE-RWE	5.118%	28.139%
DAX-BAS	-1.665%	-8.477%
EWGS-HOT	13.108%	17.431%
FEUZ-MT	17.318%	26.719%
HEDJ-COV	-2.012%	-22.738%
UK portfolio	14.118%	12.323%
EWUS-CNA	15.571%	13.709%
FKU-KGF	14.223%	9.135%
EWU-NGG	19.792%	5.950%
FLGB-AV	16.419%	2.084%
HEWU-WRB	-0.187%	22.884%
FTRI-RIO	29.759%	31.469%
EUDV-AHT	-4.923%	19.831%
IEUS-SMDS	22.287%	-6.477%
Netherlands Porfolio		
EWN-ING	-23.489%	-27.689%
Europe Portfolio	2.309%	-3.182%
VGK-HSBC	-1.481%	-15.122%
BBEU-IMB	22.695%	22.191%
EZU-DG	-6.422%	-7.954%
IEUR-BAYN	9.563%	-6.323%
DBEF-SHEL	13.572%	5.706%
EWU-VOD	-22.360%	-41.127%
FEZ-VOW	-16.196%	6.507%
IEV-ACA	-14.020%	-35.449%
EWG-ALV	13.920%	16.977%
HEDJ-SNY	23.820%	22.774%

Appendix

a. Rebalancing effect

This demonstration conducted by Cheng, Minder, and Madhavan (2009) and then recalled by Pessina, Colby, Whaley, Robert (2021), explains the rebalancing effect on inverse ETFs, discussing the swap contracts' hedging demands associated with these funds at the end of the day, which is necessary to keep aligned the NAV of the asset under management with the actual index leveraged returns.

Let A_{t_n} *represent a leveraged or inverse ETF's NAV at the close of day* n *or at time* t_n. L_{t_n} *represent the notional amount of the total return swaps exposure required every day to reproduce the* x *leverage ratio from time* t_n *to time* t_{n+1}.

$$L_{t_n} = xA_{t_n} \quad \textit{(1.a)}$$

Moving on, at $n+1$*, the underlying index generates* r_{t_n}, t_{n+1} *of returns, making the exposure to the swap became like equation (2.a):*

$$\begin{aligned} E_{t_{n+1}} &= L_{t_n}\left(1 + r_{t_n}, t_{n+1}\right) \\ &= xA_{t_n}\left(1 + r_{t_n}, t_{n+1}\right) \end{aligned} \quad \textit{(2.a)}$$

With $E_{t_{n+1}}$ *representing the exposure. In the meanwhile, the fund's NAV reflects the x time index performance, becoming at the end of the day like equation (3.a)*

$$A_{t_{n+1}} = A_{t_n}\left(1 + xr_{t_n, t_n + 1}\right) \quad \textit{(3.a)}$$

suggesting that the notional amount of the total returns swap required before the market opens maintains constant exposure of:

$$\begin{aligned} L_{t_{n+1}} &= xA_{t_{n+1}} \\ &= xA_{t_n}\left(1 + xr_{t_n, t_{n+1}}\right) \end{aligned} \quad \textit{(4.a)}$$

so, the amount by which the exposure of the total return swaps need to be adjusted or re-hedged at time, t_{n+1} *is given by the difference between equation (2.a) and (4.a) leaving with:*

$$\begin{aligned} \Delta_{t_{n+1}} &= L_{t_{n+1}} - E_{t_{n+1}} \\ &= A_{t_n}(x^2 - x) r_{t_n,t_{n+1}} \end{aligned} \qquad (5.a)$$

b. Value of Leverage ETFs and Inverse ETFs tends to 0

Here is shown de compound returns dynamic and the computation process that ends in a generalized formula that gives a conceptual framework for interpreting the properties in different scenarios of such risky assets. The objective is to understand return dynamics and the role of the embedded option within the leveraged and inverse product to address questions concerning the suitability of these products for individual investors, particularly those with longer holding periods.

$$A_{t_N} = A_0 \left(\frac{S_{t_N}}{S_0}\right)^x \exp\left(\frac{(x-x^2)\sigma^2 t_N}{2}\right) \qquad (10.c)$$

Equation (10) is the key to reading the framework conclusions and will be demonstrated in section c. after the following theoretical explanation. x *represents the Leverage ratio,* σ^2 *the squared of variance,* S_{t_N} *index value at time t,* S_0 *index value at 0 and finally* A_0 *the NAV of the LETF at 0.*

While leveraged and inverse ETFs do offer limited liability, this comes at a cost. From Eq. (10.c) it is possible to acknowledge that the N -period realized gross return of a leveraged or inverse ETF is just the gross return of its underlying index over that period, *raised to the xth power, then multiplied by the scalar* $\left(\frac{(x-x^2)\sigma^2 t_N}{2}\right)$*, which rise to the value of the embedded option in the first place, but is also the source of long-run erosion in value. To demonstrate this, note that the scalar decreases with tN and asymptotically approaches zero as* t_N *approaches infinity. As a result, the gross return of the LETF (relative to the underlying index return) will decline with the duration of holding and the volatility of the underlying index. Note that the first term in Eq. (last) reflects the realized sample path of index returns. If the mean return is large and positive and x > 0, then this term can imply substantial payoffs to the leveraged ETF holder over many sample realizations. Consequently, examining the expected value of a longer-term investment is interesting. The expression can be explicitly derived using the moment generating function of the lognormal distribution. Specifically, if Z is a random variable that is distributed normally with mean m and standard deviation s, it can be shown that the expected value of exp(kZ) is:*

$$E\,[\exp(kZ)] = exp\left(km + \frac{k^2 s^2}{2}\right) \quad (1.b)$$

Consder that the N -period index gross return $ln(S_{TN}) - ln(S_0)$ *has a mean* $\left[\mu - \frac{\sigma^2}{2}\right] t_N$ *while the corresponding x-times leveraged or inverse ETF has a mean of* $\left(x\mu - \frac{x^2\sigma^2}{2}\right)$*. Applying those data to Eq. (10.c) with m equal to the corresponding mean, the expected gross return of the index at time tN is*

$$exp(\mu t_n) = exp\left(\left[\mu - \frac{\sigma^2}{2}\right] t_N + \frac{\sigma_{t_n}^2}{2}\right) \quad (2.b)$$

while the expected value of leveraged or inverse ETF is $exp(x\mu t_n)$*. This result is a reflection of Jensen's inequality and the convexity of the exponential function. According to this theory, if an investment has a nonlinear payoff function, the expected return of the investment will not be equal to the average return of the portfolio. In other* *words, the order in which the investment returns and the portfolio returns are combined can affect the overall return. That theory published in 1968 states that If an investment's payoff function is convex, meaning it is curved upwards, then the expected return of the investment will be greater than or equal to the average return of the portfolio. Conversely, if the payoff function is concave, meaning it is curved downwards, the expected return of the investment will be less than or equal to the average return of the portfolio. Conclusions deriving from the random theory demonstration follows immediately: if $x\mu < 0$ (i.e., an inverse ETF with positive index drift or a leveraged ETF with negative index drift) that the expected value of a leveraged or inverse ETF will tend to zero, i.e., a scenario of long-term value destruction. It is important to understand that the expected value derived above is a mean value; it is affected by the small probabilistic weight placed on extreme sample paths. Because the lognormal distribution is positively skewed, the simple expectation is not likely the typical experience of the average investor. Since the skewness of the lognormal distribution increases with variance, the mean value is especially unrepresentative for volatile assets. Consequently, it makes sense to focus on the typical or median investor's value change over an interval of time. Again, from the properties of the lognormal distribution, if Z is distributed normally with mean m and standard deviation s, the median value of exp(Z) is exp(m), which does not depend on the variance. Formally, substituting $m = \left(x\mu - \frac{x^2\sigma^2}{2}\right)t_N$ for the mean return in a given interval of time tN , we can now explicitly characterize situations in which leveraged or inverse ETFs have a negative median return which is the case of all LETF. Following equation (10.c) we goth those output based on diverse values of dependent variables and the scalar output:*

1. $x < 0$ (e.g., inverse and leveraged inverse ETFs) and $\mu > 0$, i.e., the index drift is positive;

2. x > 0 (e.g., leveraged long ETFs) and 0 <μ< $x\frac{\sigma^2}{2}$*;*

3. x > 0 and μ < 0, i.e., negative drift of index returns.

In case 1, the returns to inverse ETF holders (i.e., x < 0) over long periods of time should be negative because we expect μ > 0 in equilibrium, so the first term in Eq. (10.c) will also tend to zero as tN increase. It is crucial for this analysis, since, due to mathematical properties of the exponent x, the numerator and the nominator will swap for inverse and so negative value. This creates a continuous path of erosion due to the upward trend of the underlying index that at S0, in the long run will be higher than St. In case 2, the variance term dominates μ so the leveraged ETF has a negative drift. Case 3, the polar opposite to case 1, seems unlikely in a long-run equilibrium, so it is not included. For a more detailed study, check the Cheng, Minder, and Madhavan (2009) paper, where the demonstration comes from.

c. Demonstration of formula (10.c), for computing the returns dynamic.

In order to compute returns over longer periods of time, it is needed to model explicitly the evolution of security prices in continuous time.

The index level St is assumed to follow a geometric Brownian motion, that is often used as a mathematical model to describe the random behavior of various phenomena:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \qquad (1.c)$$

The equation is composed by a drift rate of μ and a volatility of σ. Here, Wt in Eq. (1) is a Wiener process, that is a specific mathematical formula that characterizes the continuous-time version of Brownian motion, with a mean of zero and a variance of t. It is possible define ln(St) a generalized Wiener process, as given by:

$$d\ln(S_t) = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma dW_t \qquad (2.c)$$

So, to relate the dynamics of the NAV of a leveraged or inverse ETF to the dynamics of the ETF's underlying index level is recalled equation (3.a) that re-arranged obtain relation (3.c):

$$\frac{A_{t_{n+1}}-A_{t_n}}{A_{t_n}} = x\left(\frac{S_{t_{n+1}}-S_{t_n}}{S_{t_n}}\right) \qquad (3.c)$$

when the time interval between tn and tn+1 is sufficiently small, this expression can be derived, becoming:

$$\frac{dA_t}{A_t} = x\frac{dS_t}{S_t} \qquad (4.c)$$

At and St represent the NAV of a leveraged or inverse ETF and the ETF's underlying index level, respectively, at time t. As described earlier in(4.c), a leveraged ETF hedges at discrete time intervals but always maintains economic exposure at x× the underlying index return. Merging (4.c) and (1.c) it can be shown (5.c):

$$dA_t = x\mu A_t dt + x\sigma A_t dW_t \qquad (5.c)$$

and then ln(At) follows a generalized Wiener process, as given by:

$$dln(A_t) = \left(x\mu - \frac{x^2\sigma^2}{2}\right)dt + x\sigma dW_t \qquad (6.c)$$

suggesting that At follows a geometric Brownian motion with a drift rate of xμ and a volatility of xσ. In other words, the volatility of a leveraged or inverse ETF is just x times the volatility of its underlying index. This is handy for pricing options on leveraged and inverse ETFs. The various relationships derived in a continuous time setting, i.e., Eqs. (4.c) to (6.c), now can be applied to the earlier analysis at the daily level. Applying the Wiener process, or Eq. (2.c) to Stn and S0 gives us the following relationship of the index level on day N and day 0, or between time tN and time 0:

$$S_{t_N} = S_0 exp\left(\left[\mu - \frac{\sigma_2}{2}\right]t_N + \sigma\sqrt{t_N}z\right) \qquad (7.c)$$

where $exp(z) = e^z$ *is the exponential function and z is a standard normal distribution with a mean of 0 and a standard deviation of 1. So, the return to the index over the period,* $ln(S_{TN}) - ln(S_0)$, *is normally distributed with mean* $\left[\mu - \frac{\sigma^2}{2}\right] t_N$ *and standard deviation* $\sigma\sqrt{t_N}$ *. Likewise, applying Eq. (6.c) to* A_{t_N} *and* A_0 *will give us the following relationship of the leveraged or inverse ETF's NAV on day N and day 0:*

$$A_{t_N} = A_0\, exp\left(\left[x\mu - \frac{x^2\sigma_2}{2}\right] t_N + x\sigma\sqrt{t_N}z\right) \quad (8.c)$$

In other words, the return to the leveraged ETF $ln(A_{tn}) - ln(A_0)$ *is normally distributed with mean* $\left[x\mu - \frac{x^2\sigma_2}{2}\right] t_N$ *and standard deviation* $x\sigma\sqrt{t_N}$ *. These draws are not independent, however, because the same realization of the sample path, captured by z, is in both returns. It can be furtherly simplified as follows:*

$$A_{t_N} = A_0 exp\left(\left[x\mu - \frac{x\sigma^2}{2}\right] t_N + x\sigma\sqrt{t_N}z + \frac{(x-x^2)\sigma^2 t_N}{2}\right) \quad (9.c)$$

$$= A_0\left(\frac{S_{t_N}}{S_0}\right)^x exp\left(\frac{(x-x^2)\sigma^2 t_N}{2}\right) \quad (10.c)$$

So, the total return of a leveraged or inverse ETF over a N-day period (i.e. $\left(\frac{A_{tn}}{A_0}\right)$*) is the xth power of the gross return of the ETF's underlying index over the same time period* $\left(\frac{S_{t_N}}{S_0}\right)$, *multiplied by a scalar* $exp\left(\frac{(x-x^2)\sigma^2 t_N}{2}\right)$. *As* $(x - x^2) < 0$, *the scalar is minor than 1.*

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introduction

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