



UNIVERSITA' DEGLI STUDI DI PADOVA

**DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI
"M. FANNO"**

CORSO DI LAUREA IN ECONOMIA

PROVA FINALE

**"Factor Redundancy in Tail Events:
Empirical Evidence and Convex Payoff Strategies"**

RELATORE:

CH.MA PROF.SSA Russo Alessia

LAUREANDO: Buscema Matteo

MATRICOLA N. 2103155

ANNO ACCADEMICO 2025 – 2026

Dichiaro in conformità con le linee guida di Ateneo “Linee guida per l’impiego degli strumenti di IA generativa nella didattica e nella redazione delle tesi di laurea e di dottorato” (https://www.unipd.it/sites/unipd.it/files/2025/LineeGuidaImpiegoAI_Unipd_ITA_rev20251128.pdf) di:

- di NON aver usufruito di tecnologie di intelligenza artificiale generativa (ad esempio ChatGPT, Claude, Perplexity) per supportare vari aspetti della ricerca e della scrittura della mia prova finale;
 - ✗ di aver usufruito di tecnologie di intelligenza artificiale generativa (ad esempio ChatGPT, Claude, Perplexity, Copilot) per:
 - Revisione della letteratura: utilizzo per identificare articoli scientifici pertinenti, generare stringhe di ricerca e organizzare la bibliografia. Tutti i riferimenti sono stati successivamente verificati attraverso database accademici tradizionali (WoS, Scopus, PubMed, Google Scholar).
 - ✗ Analisi linguistica e revisione testuale: correzione grammaticale, ortografica e stilistica del testo. Il contenuto concettuale, i ragionamenti e le argomentazioni rimangono interamente frutto del mio lavoro.
 - Strutturazione del lavoro: supporto nella definizione della struttura iniziale del lavoro e nell'organizzazione dello stesso.
 - Traduzione: assistenza nella traduzione di testi per consultazione di fonti in lingua straniera.
 - Analisi dei dati: supporto nella generazione o verifica di codice per l'elaborazione statistica/analisi dati. Tutti i risultati sono stati verificati e validati autonomamente.
 - Formattazione: assistenza nella formattazione della bibliografia, tabelle, o altri elementi grafici secondo le norme editoriali richieste.
 - Altro:
-

Il/La sottoscritto/a dichiara inoltre che:

L'utilizzo degli strumenti di intelligenza artificiale è stato coadiuvante e non sostitutivo delle proprie competenze;

Tutto il ragionamento critico, l'interpretazione dei risultati, le conclusioni e le argomentazioni presenti nella tesi sono frutto del proprio lavoro intellettuale indipendente;

Tutti i contenuti generati dall' intelligenza artificiale sono stati attentamente verificati, rivisti e rielaborati; Si assume la piena responsabilità per la qualità, l'accuratezza e l'integrità scientifica del lavoro presentato.

Firma


I hereby declare, in accordance with the University Guidelines “Guidelines for the Use of Generative AI Tools in Teaching and in the Drafting of Bachelor’s and Doctoral Theses” (https://www.unipd.it/sites/unipd.it/files/2025/LineeGuidaImpiegoAI_Unipd_ITA_rev20251128.pdf), that:

- I have NOT made use of generative artificial intelligence technologies (e.g., ChatGPT, Claude, Perplexity, Copilot) to support any aspects of the research and writing of my final thesis;
- ✗ I have made use of generative artificial intelligence technologies (e.g., ChatGPT, Claude, Perplexity, Copilot) for the following purposes:
 - Literature review: use to identify relevant scientific articles, generate search strings, and organize the bibliography. All references were subsequently verified through traditional academic databases (WoS, Scopus, PubMed, Google Scholar).
 - ✗ Linguistic analysis and textual revision: grammatical, spelling, and stylistic correction of the text. The conceptual content, reasoning, and arguments remain entirely the result of my own work.
 - Structuring of the work: support in defining the initial structure of the thesis and in organizing its contents.
 - Translation: assistance in translating texts for consultation of sources in foreign languages.
 - Data analysis: support in generating or verifying code for statistical processing/data analysis. All results were independently verified and validated.
 - Formatting: assistance in formatting the bibliography, tables, or other graphical elements according to the required editorial standards.
 - Other:

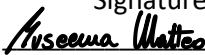
The undersigned further declares that:

The use of artificial intelligence tools was supportive and not a substitute for their own skills and competencies;

All critical reasoning, interpretation of results, conclusions, and arguments presented in the thesis are the result of their own independent intellectual work;

All content generated by artificial intelligence was carefully verified, reviewed, and reworked;

Full responsibility is assumed for the quality, accuracy, and scientific integrity of the work presented.

Signature


A Elena, per esserci stata in ogni fase di questo percorso.

A mio padre, per avermi dato fiducia, supporto e un esempio da seguire.

Alla mia famiglia, per avermi dato, in modi diversi, la spinta a cercare la mia strada.

Table of Contents

<i>Abstract</i>	<i>5</i>
<i>Introduction</i>	<i>5</i>
<i>Description of the Organization</i>	<i>6</i>
<i>Analysis of the Competitive Environment</i>	<i>7</i>
<i>Description of the Internship</i>	<i>8</i>
<i>Factor Investing: Theoretical Foundations</i>	<i>9</i>
<i>Market-Neutral Factor Premia: Construction</i>	<i>10</i>
<i>Implementation via ETF</i>	<i>11</i>
<i>Portfolio Implications of Factor Investing</i>	<i>13</i>
<i>Trend Following: Empirical Evidence and Convex Payoff Properties.....</i>	<i>15</i>
<i>Data and Methodology</i>	<i>18</i>
<i>Factor Redundancy in Tail Events</i>	<i>19</i>
<i>Conclusions.....</i>	<i>22</i>
<i>References.....</i>	<i>24</i>

Abstract

I fattori di rischio, ampiamente documentati dalla letteratura accademica, rappresentano esposizioni sistematiche potenzialmente utili per diversificare le fonti di rendimento dei portafogli.

Tuttavia, esiste un divario sostanziale tra la formulazione teorica dei fattori e la loro implementazione concreta tramite ETF.

A causa di vincoli di rischio, liquidità, turnover e investibilità, l'implementazione tramite ETF modifica la struttura originaria dei fattori, alterandone il comportamento effettivo rispetto alla formulazione teorica.

L'effetto principale è l'introduzione di una marcata esposizione comune al mercato, che riduce il beneficio di diversificazione fattoriale rispetto a quanto suggerito dalla classificazione formale degli ETF.

Il presente lavoro analizza questa ridondanza, particolarmente rilevante durante fasi di mercato avverse, e valuta il Trend Following come strategia investibile a payoff convesso per mitigarne gli effetti.

L'analisi empirica, basata su rendimenti mensili storici, valuta prima la ridondanza degli ETF fattoriali attraverso la loro esposizione comune al mercato e, successivamente, l'effetto dell'integrazione del Trend Following durante scenari di mercato avversi.

Introduction

This report is structured in two parts. The first presents the organization, its competitive environment, and the activities carried out during my internship at FinecoBank. The second develops the empirical research conducted on factor investing, focusing on the gap between theoretical factor premia and their implementation through ETFs, and on the role of Trend Following as a convex payoff strategy.

Description of the Organization

FinecoBank, founded in 1999, is one of Europe's leading fintech banks.

Listed on the FTSE MIB, it combines an advanced platform with an extensive network of personal financial advisors.

Since 1999, Fineco has experienced significant growth: in 2002 it combined banking, trading and investment services within a single platform; in 2008 Fineco merged with Xelion, strengthening its personal financial advisors network; in 2014, it was listed on the Italian Stock Exchange, entering the FTSE MIB in less than two years; in 2018 Fineco Asset Management was founded in Dublin, to develop global investment strategies; finally, in 2019, UniCredit sold its controlling stake on the market, making FinecoBank an independent and autonomous company.

Fineco operates in Europe and previously served clients in the United Kingdom, before gradually discontinuing its UK operations following Brexit-related regulatory changes.

As of 31 March 2026, Fineco had 1.85 million clients, with aggregate wealth of €162.1 billion; of this amount, €81.2 billion was attributable to clients with more than €500,000 in assets held with the bank. This highlights Fineco's positioning not only as a digital bank for retail and affluent clients, but also as a relevant player in the private banking segment.

According to FinecoBank's corporate disclosures, FinecoBank's Common Equity Tier 1 ratio – a measure of a bank's financial strength and solvency – stood at 23.34%, confirming its strong capital position within the Italian banking sector.

Fineco's scale is also reflected in its workforce and distribution network, which included more than 1,500 employees, 3,100 personal financial advisors and 440 Fineco Centres.

Analysis of the Competitive Environment

FinecoBank's competitive environment can be analysed by distinguishing between macro-environmental factors and industry-level competitive forces.

From a PESTEL perspective, the most relevant external factors are economic and technological.

Economically, the bank's ability to contain churn and grow its client base strongly depends on the economic cycle. In fact, dovish central bank policy, accompanied by contained and stable inflation and positive GDP growth, represents the most favourable scenario for investor confidence, implying higher assets under management for private bankers and higher fees for the bank. Conversely, an uncertain environment characterized by restrictive monetary policy, rising inflation, and slower or negative GDP growth poses a threat to the bank's managed wealth.

Technologically, the use of social media by finance professionals both strengthens and disrupts the bank's business. In fact, private bankers can extend their reach to potential clients through social media, increasing perceived authority and trust; however, independent financial advisors with a similar perceived reputation could highlight the conflict of interest between acting in the client's best interest and serving the interests of the private banker or the bank. To this end, transparent and comprehensive communication could further strengthen perceived trust, including when advising clients on ETFs rather than actively managed funds. Additionally, social media and artificial intelligence further widen the gap among financial advisors who will remain competitive and those who will struggle: this is because knowledge is becoming increasingly accessible, meaning that only financial advisors with deep expertise and a commitment to continuous learning are likely to thrive.

From a Porter's Five Forces perspective, FinecoBank operates in a highly competitive industry. Rivalry is strong, as the bank competes with traditional banks, private banking networks, online brokers, independent financial advisors and financial advisory firms.

The threat of new entrants is moderate, since fintech players and advisory boutiques can enter specific niches, while regulation, scale, trust and advisory networks remain relevant barriers. Clients have medium-high bargaining power, as they can compare fees, platforms and investment solutions more easily, although trust in the financial advisor may reduce switching.

Supplier power is moderate, mainly linked to product providers, technology and advisors. Finally, substitutes are increasingly relevant, including low-cost ETFs, robo-advisory, fee-only advisory services and independent financial education channels.

Description of the Internship

At FinecoBank, I was a Private Banking Intern for a team of two Private Bankers managing approximately €100 million in client assets. I assessed client portfolios and developed construction or restructuring proposals, later reviewed to ensure consistency with each client's needs, risk profile, and investment horizon. My work focused on analytically grounded portfolio proposals, framed by several market and portfolio-construction challenges:

- On the equity side, cyclically adjusted valuations were far above the historical average, with the Shiller CAPE Ratio standing at 42.66 according to Robert Shiller's official dataset and approaching levels last observed during the late-1990s technology bubble. This pointed to lower-than-average forward-looking return expectations, increasing the risk of falling short of objectives for clients with shorter investment horizons. My focus was on risk-factor diversification while reducing the weighted-average valuation multiple of the equity allocation;
- On the bond side, persistent inflation increased the risk of rates remaining elevated for longer, putting pressure on duration-heavy allocations; a higher-for-longer stance from central banks, combined with the policy uncertainty surrounding Kevin Warsh's appointment as Federal Reserve Chair, made duration management a central consideration. My focus was on breakeven inflation and duration exposure, comparing nominal bonds and inflation-linked securities under different inflation and interest-rate scenarios.
- Within the real assets allocation, gold's extended multi-year rally, combined with uncertainty around real yields, made its portfolio role more difficult to assess. Additionally, the closure of the Strait of Hormuz triggered a spike in inflation expectations and fuelled an extended rally across broad commodities. Although gold and commodities do not generate cash flows and therefore cannot be valued through conventional discounted cash flow or income-based methods, my focus was on assessing their portfolio role and suitability for each investor;
- Alternative Risk Premia Strategies such as Volatility Risk Premium, Commodity Carry or Trend Following were not eligible within the advisory perimeter given their derivative-based implementation. This created a portfolio-construction challenge, as these strategies could offer diversification benefits that were difficult to replicate through eligible instruments.

A central competence developed during the internship was understanding Lombard credit within Private Banking. I analysed how securities-backed lending can provide liquidity without liquidating invested assets, while supporting client-specific financial needs. The experience also

highlighted key risks, including collateral quality, loan-to-value limits, interest-rate exposure, margin calls and client suitability.

Factor Investing: Theoretical Foundations

Returns can be decomposed into a systematic and a residual component. The former reflects exposure to common risk factors, which empirical evidence shows to explain a substantial portion of average returns.

Back in 1964, William Sharpe developed the Capital Asset Pricing Model (CAPM), a one-factor model to estimate the expected return of a financial instrument based on the risk-free rate plus the exposure to the systematic risk (β) multiplied by the Equity Risk Premium.

This model was extended in 1992 by Eugene Fama and Kenneth French who, based on documented anomalies (Banz, Basu), developed the three-factor model, including the already-known market factor (β), and other factors related to firm size (SMB – Small Minus Big) and firm value (HML – High Minus Low).

Fama and French discovered that used alone or in combination with other variables, β had limited explanatory power in the cross-section of average returns, while SMB and HML performed better in explaining the cross-section of average returns on NYSE, Amex and NASDAQ stocks for the 1963-1990 period.

Later, in 2015, the three-factor model was extended again by Fama and French, by adding variables grounded in valuation theory: profitability (RMW – Robust Minus Weak) and investment (CMA Conservative Minus Aggressive).

They discovered that the five-factor model outperformed the three-factor model in explaining average returns, significantly reducing pricing errors (lower intercepts).

However, its role as a benchmark remains debated.

First, it maintains the CAPM relation between market beta and return, despite mounting evidence that the empirical relation is flat [Black, Jensen, Scholes (1972), Fama, MacBeth (1973)], or even negative [Haugen, Heins (1975)]: the Low Volatility Premium (Betting Against Beta) has been widely documented [Frazzini, Asness, Pedersen (2014)], and it challenges the positive relation between β and expected return implied by CAPM.

Moreover, the model ignores the empirically robust momentum-effect [Jegadeesh, Titman (1993)], and several robustness concerns affect the two new factors (as highlighted also by Fama

and French).

Overall, when regressing realized returns on factors (e.g. the five-factor model), significant alpha may remain, suggesting that existing factor models do not fully capture the cross-section of expected returns.

Academic research has continued to identify new factors over time.

To date, a large number of factors has been documented (the “Factor Zoo”, John Cochrane), but many of them appear to be redundant, and can be reduced to around fifteen [Swade et al. (2023)].

Among these, style factors (such as Momentum, Quality, Value, Size, and Low Volatility) remain persistent over time.

Market-Neutral Factor Premia: Construction

Pure risk factors – as shown by the academic literature – are constructed by sorting assets cross-sectionally according to observable characteristics, such as market capitalization (Size) and book-to-market equity (Value).

According to Fama and French, stocks from NYSE, AMEX, and NASDAQ are included.

For Value, stocks are sorted by book-to-market equity using NYSE breakpoints, sorting stocks into Low (L, the bottom 30%), Neutral (M, the middle 40%), and High (H, the top 30%).

Size is determined based on market capitalization: the NYSE median market capitalization is used as the breakpoint; stocks are classified into Small (S) and Big (B).

The Value factor (HML) is constructed as:

$HML = (S/H + B/H)/2 - (S/L + B/L)/2$, where the first component represents the long leg and the second the short leg.

As shown, HML is constructed within size-sorted portfolios, isolating the value effect from size-related influences, mitigating size-related biases.

Using the same portfolios, the Size factor (SMB) is constructed as:

$SMB = (S/H + S/M + S/L)/3 - (B/H + B/M + B/L)/3$.

Similarly, SMB is constructed across value-sorted portfolios, isolating the size effect from value-related influences, mitigating value-related biases.

Portfolios are formed at the end of June, held from July to the following June; factor returns are given by the spread between the long and the short leg.

The Momentum factor (WML/UMD) is based on market price behaviour rather than firm fundamentals.

A ranking is formed on cumulative past returns over the 12–2 month period; stocks are then sorted into top performers, or winners (W) and bottom performers, or losers (L). Winners are held long, and losers are held short.

$$\text{WML/UMD} = (\text{S/W} + \text{B/W})/2 - (\text{S/L} + \text{B/L})/2.$$

As shown, WML/UMD is constructed within size-sorted portfolios, isolating the momentum effect from size-related influences.

The Quality factor (QMJ) is constructed as a long-short portfolio based on a composite quality score, where stocks are ranked cross-sectionally using standardized measures of profitability, growth and safety, with high-quality stocks (Q) held long and low-quality (junk) stocks (J) held short.

$$\text{QMJ} = (\text{S/Q} + \text{B/Q})/2 - (\text{S/J} + \text{B/J})/2.$$

As shown, QMJ is constructed across size-sorted portfolios, isolating the quality effect from size-related influences.

The Betting Against Beta factor (BAB) is constructed by ranking stocks by estimated beta; low-beta stocks are held long, and high-beta stocks are held short; returns are rescaled by the inverse of portfolio beta to achieve a zero-beta profile.

$$\text{BAB} = (1/\beta^L)R(\text{Low Beta}) - (1/\beta^H)R(\text{High Beta}).$$

Proceeds from the short leg finance the long leg, making the portfolio self-financing, with zero net investment. Moreover, the long and short legs tend to offset common market exposure, resulting in limited market exposure ($\beta \approx 0$) and an approximately market-neutral profile.

Implementation via ETF

Although original risk factors are long-short, their implementation through investment vehicles (such as Exchange Traded Funds) differs. The short leg is removed, therefore erasing their market-neutral characteristic and resulting in a core β exposure with a factor-tilt.

The reasons behind this alteration are structural and economic constraints [Stambaugh et al. (2012); Chu, Hirshleifer, Ma (2020)].

Risk factors overall imply high turnover, that is, the frequency with which a portfolio's holdings are bought and sold to maintain a specific investment style or exposure to a certain factor.

The costs tied to high turnover are amplified in the short leg, as short positions involve additional costs, particularly borrowing fees.

On average, shorting fees are more than three times higher than normal for the short leg of Value, Momentum, Volatility-related and profitability portfolios [Blitz, Baltussen, Vliet (2020)].

It is well established that short positions are significantly less liquid than long positions [Diether, Lee, Werner (2009)], with a typical volume of about 24% for NYSE and 31% for Nasdaq stocks, affecting costs.

Investors may face implementation hurdles, because many stocks can be sold short only to a limited extent; other stocks cannot be shorted at all, and existing short positions may unexpectedly be recalled [D'Avolio (2002), Geczy, Musto, Reed (2002)].

Stocks that are designated for shorting are typically the stocks that are harder and more expensive to short; moreover, short selling entails additional risks, such as the potential for unlimited losses, short squeeze scenarios, counterparty risk and reputational risk.

Legal impediments to short selling may exist.

These constraints led asset managers to design factor funds without the short leg; this is particularly relevant for investors, because the nature of investable factor exposure changes, leading to different portfolio-level implications.

The removal of the short leg raises the question of whether factor premia retain their explanatory power for expected returns.

Empirical evidence suggests that the importance of the long and short legs differs; although factor premia originate in both long and short legs of factor portfolios, most added value comes from the long legs, as they provide diversification and exhibit near-zero correlation [Blitz, Baltussen and Vliet (2020)]. Conversely, short legs concentrate downside risk, common exposures, and positive correlation with other factors.

For example, extreme negative returns of the Momentum factor are mainly driven by the short side [Barroso, Santa-Clara (2015); Daniel, Moskowitz (2016)]. Moreover, the idiosyncratic volatility anomaly is mostly a short-side phenomenon [Ang, Hodrick, Xing, Zhang (2006)].

Abnormal returns are stronger for the short-leg portfolios for 11 anomalies selected [Stambaugh et al. (2012)].

This evidence indicates that the short leg is the primary source of extreme losses and common downside co-movement across factors.

As a result, Sharpe ratios have been highest for the long legs of factors and lowest for the short legs.

Portfolio Implications of Factor Investing

Long-short factor investment strategies provide valuable diversification relative to traditional market exposures and exhibit lower sensitivity to macroeconomic environments. A consistent and disciplined allocation to a well-diversified multi-factor portfolio is difficult to outperform, as cross-factor diversification mitigates idiosyncratic noise and improves risk-adjusted returns [Aghassi et al. (2023)]. For investors seeking to move beyond pure β exposure, factor investing provides a systematic way to access additional sources of return.

However, long-only factor investment strategies only partially retain this property as they embed factor tilts on top of a core β exposure, due to the short leg being absent.

Therefore, multi-factor diversification in a long-only setting is possible but less efficient than a long-short diversification, leading to partial redundancy across factors.

Investors seeking to isolate the risk premium could hedge market β through a derivative contract [Blitz, Baltussen and Vliet (2020)], reducing implementation costs.

Although β dominates return variation in long-only implementations, redundancy in long-only multi-factor portfolios is structurally present due to overlapping beta exposure, reducing diversification benefits and portfolio resilience particularly during tail events.

Given the benchmark $R(\text{excess}) = \alpha + \beta(\text{MKT} - r_f) + \epsilon$, where $R(\text{excess}) = R_i$ for long-short factors and $R(\text{excess}) = R(\text{ETF}) - r_f$ for ETF, the market beta β_i is estimated to assess the differences between pure risk factors and their ETF implementations.

Beta Exposure of Pure Risk Factors

Factor	Sample	β	R ²
HML	2014-11 to 2025-12	0.000	0.000
WML	2014-11 to 2025-12	-0.329***	0.141
QMJ	2014-11 to 2025-12	-0.250***	0.280
SMB	2018-04 to 2025-12	0.223***	0.129
BAB	2014-11 to 2025-12	-0.044	0.006

Pure Risk Factors' β exposure through monthly regressions.
Data elaborated by the author from Fama-French and AQR datasets.

The table shows that pure risk factors have limited exposure to market beta. HML and BAB display approximately zero beta and negligible R², while WML and QMJ have negative and statistically significant betas. SMB is the only factor with a positive significant beta, although both its magnitude and R² remain low. Overall, these results suggest that academic long-short factors are not primarily driven by common equity-market exposure, providing a benchmark for comparison with ETF implementations.

Beta Exposure of Factor ETF Implementations

ETF Proxy	Sample	β	R ²
Value ETF	2014-11 to 2025-12	0.839***	0.699
Momentum ETF	2014-11 to 2025-12	0.877***	0.839
Quality ETF	2014-11 to 2025-12	0.890***	0.932
Size ETF	2018-04 to 2025-12	1.058***	0.870
Min Vol ETF	2014-11 to 2025-12	0.589***	0.674

Factor ETFs' β exposure through monthly regressions.
Data elaborated by the author from iShares and Xtrackers ETF datasets.

The table shows that factor ETF implementations display consistently positive and statistically significant market betas; Value, Momentum, Quality and Size ETFs all exhibit high beta exposure, while even the Min Vol ETF retains a substantial beta of 0.589. R² values are also high across all ETFs, indicating that a large share of ETF return variation is explained by MKT-RF.

Overall, these results suggest that factor ETFs behave largely as long-only equity products with factor tilts, rather than as market-neutral factor premia.

Beta Exposure Comparison: Pure Risk Factors vs Factor ETFs

Factor	Academic β	ETF β
Momentum	-0.329	0.877
Quality	-0.250	0.890
Size	0.223	1.058
Min Vol	-0.044	0.589
Value	0.000	0.839

Comparison on β exposure.

Data elaborated by the author from Fama-French, AQR, iShares and Xtrackers datasets.

The comparison highlights that ETF implementations do not provide direct access to market-neutral factor premia. Instead, they behave as long-only equity products with factor tilts, introducing a common market component across strategies. This shared β exposure reduces the diversification benefit expected from factor allocation and creates the conditions for factor redundancy, particularly when market risk dominates portfolio returns.

A natural implication is that mitigating factor redundancy requires an exposure whose payoff is not primarily linear in market beta.

Trend Following: Empirical Evidence and Convex Payoff Properties

Diversifying alternatives are crucial when seeking to maximize risk-adjusted returns.

However, there is a misperception of diversification due to performance extrapolation: investors tend to overweight assets that have done well in the past, while ignoring assets that performed poorly.

A well-documented strand of the literature shows that investors form expectations by extrapolating past returns, overweighting recently well-performing assets while underweighting those with poor past performance [He, Shen (2010)]. In this context, sustained strong performance of ETFs may lead investors to over-allocate to these factor strategies, potentially overlooking their underlying common exposures and limiting the perceived benefits of diversification.

To this end, Trend Following is appealing to investors who seek to participate in large market moves during strong bull markets while mitigating losses during prolonged bear markets.

Trend Following is a time-series momentum strategy, TSMOM, and a source of alternative risk premia.

This strategy is related to, but different from, the phenomenon known as momentum, which is primarily cross-sectional: the momentum literature focuses on the relative performance of securities in the cross-section, while time series momentum focuses purely on a security's own past return.

Despite this, time series momentum captures the returns associated with individual stock (cross-sectional) momentum, most notably Fama and French's UMD factor [Moskowitz et al. (2012)].

The academic literature shows that since the beginning of the sample in 1880, time-series momentum has been profitable, on average, for nearly all equity index futures, fixed-income futures, commodity futures, and currency forwards [Hurst et al. (2014)].

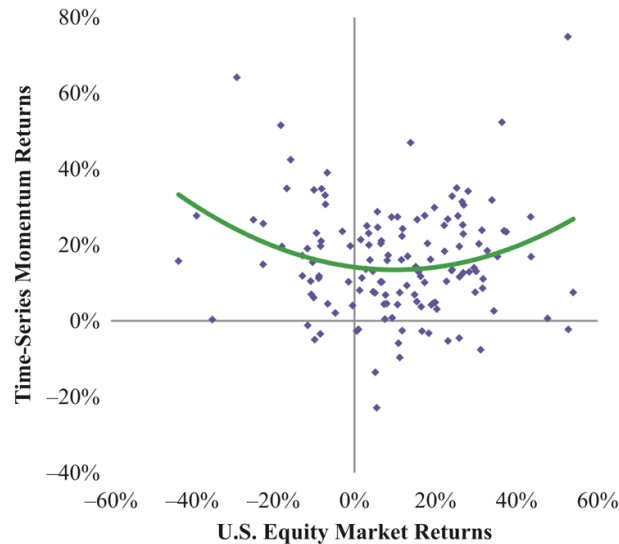
The simplest form of Trend Following consists in assessing the past excess return in a specific market over a relevant look-back horizon, typically 12 months; a positive past excess return is considered an "up" trend and leads to a long position, while a negative past excess return is considered a "down" trend and leads to a short position. Therefore, each strategy always holds either a long or short position in every market. Each position is sized to target the same amount of volatility, both to provide diversification and to limit the portfolio risk from any one market [Hurst et al. (2014)].

Trend Following exhibits little exposure to standard asset pricing factors as it entails a dynamic exposure that abruptly changes over time: this is key to mitigating factor redundancy.

According to Moskowitz et al. (2012), TSMOM exhibits a significant positive exposure to squared market returns, while the linear exposure to the market is generally insignificant; in other words, TSMOM returns are positively correlated to magnitude and movement persistence, regardless of direction.

Its structure is similar to an option straddle that goes long both call and put options, benefiting from large market movements; although Trend Following does not buy options, it dynamically replicates a similar payoff.

Time-Series Momentum “Smile,” 1880–2016



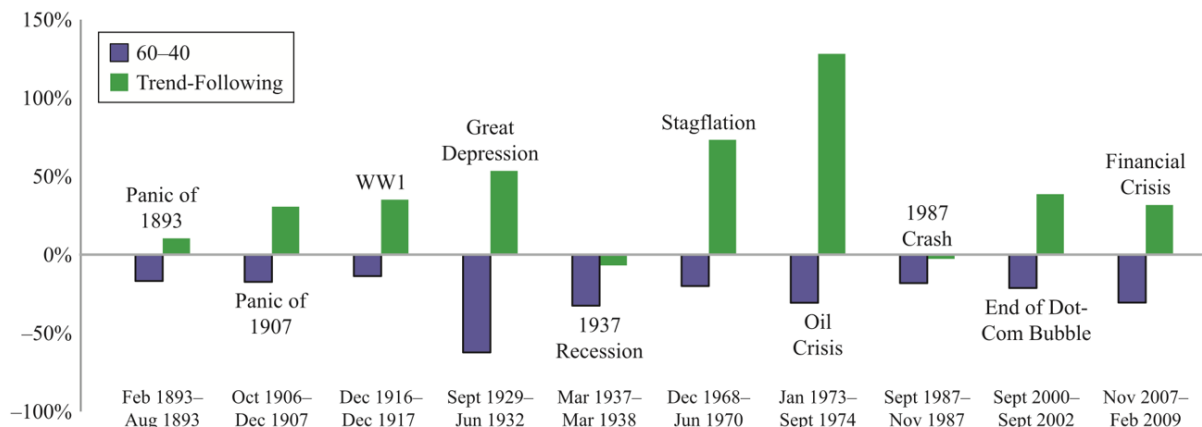
Convex Payoff, graph from “A Century of Evidence on Trend-Following Investing” (Hurst, Ooi, Pedersen), 2017

Its performance is negative or flat during sideways markets, as the strategy has performed best in large equity bull and bear markets, showing a convex payoff: frequent small losses, infrequent large gains.

In fact, over the past 137 years, the time-series momentum strategy experienced positive returns in 8 out of 10 of the largest drawdowns: this is because most bear markets have historically occurred gradually over several months, rather than over a few days, giving trend followers an opportunity to position themselves short after the initial market decline and profit from a continued market decline.

In contrast, the strategy could perform poorly in fast, sharp market crashes, because it may not be able to position short quickly enough to benefit from sharp market movements.

Time-Series Momentum during the 10 Worst Drawdowns for 60/40



Graph from “A Century of Evidence on Trend-Following Investing” (Hurst, Ooi, Pedersen), 2017

The returns to the strategy have exhibited low correlations to stocks and bonds from 1880 onwards, substantially improving portfolio diversification given the positive correlation between stocks and bonds observed in recent years [Asness, Villalon, Ilmanen (2026)].

Data and Methodology

The results reported in the following sections are based on the author's own analysis using publicly available official datasets.

In particular:

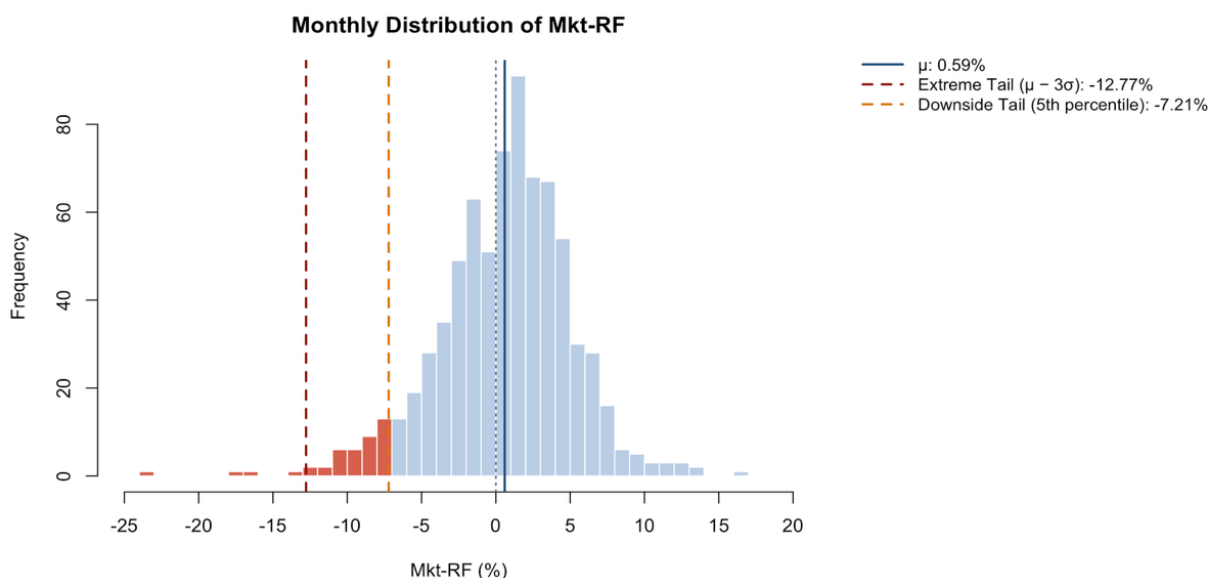
- The monthly distribution of MKT-RF is constructed from the Fama-French Data Library over the 1963–2025 period.
- The aggregate evidence on MKT-RF is obtained by partitioning the distribution into increasingly adverse market regimes.
- The analysis of the 20% TSMOM allocation across adverse market regimes is based on data from AQR for TSMOM, iShares for the Quality, Value and Size ETFs, Xtrackers for the Momentum and Minimum Volatility ETFs, and the Fama-French Data Library for MKT-RF.

The factor-only portfolio is constructed as an equal-weighted portfolio of Momentum, Quality, Minimum Volatility and Value ETFs. The Size ETF is excluded because of its later inception date in 2018 and because the size premium becomes weak when it is not controlled for quality or value [Asness et al. (2018)].

The live ETF sample runs from 2014 to 2026, reflecting the availability of the factor ETF return series. The analysis is based on monthly observations and focuses on negative months and the worst 20%, 10%, and 5% of MKT-RF observations. MKT-RF is used as the market benchmark. The Factor + TSMOM portfolio is constructed by allocating 80% to the equal-weighted factor ETF portfolio and 20% to TSMOM.

Factor Redundancy in Tail Events

Tail risk, or fat-tail risk, refers to the risk that an asset or portfolio experiences an extreme movement, typically beyond three standard deviations, with a probability greater than that implied by a normal distribution. These events can occur at both ends of the return distribution; however, the analysis focuses on the negative tail, as it captures severe downside risk and represents the most adverse phase of the investment cycle.



Monthly Distribution of ERP, from 1963 to 2025.
Data elaborated by the author from Fama-French dataset.

Given that factor ETFs are exposed to $\beta \cdot \text{MKT}$, they have a linear payoff, implying co-participation in market crashes. Conversely, Trend Following is exposed to $\gamma \cdot \text{MKT}^2$, showing a non-linear payoff.

As a result, not only are average returns diversified, but the distribution of returns is also reshaped, particularly in the tails.

Aggregate Evidence

Regime	N	Mean MKT-RF	Mean TSMOM	Corr
Tail ($\mu - 3\sigma$)	4	-17.45%	3.44%	0.927
Worst 5%	25	-10.27%	3.02%***	0.145
Worst 10%	49	-8.20%	2.51%***	0.007

Average performance of MKT-RF below the 10th percentile of its distribution, from 1985 to 2025.
Data elaborated by the author from Fama-French, AQR datasets.

Considering the period ranging from 1985 to 2025 (481 months), as shown in the table above, there have been four tail events ($\mu - 3\sigma$), twenty-five months below the 5th percentile, and forty-nine below the 10th percentile. I isolated increasingly adverse market conditions to compare the results more clearly.

Although MKT-RF deteriorated monotonically across regimes – ranging from -9.20% to -17.45% – TSMOM consistently delivered positive average returns across all regimes, ranging between 2.5% and 3.4%. Despite the increasing severity of market drawdowns, its returns remain relatively stable, suggesting no linear dependence on market losses.

TSMOM returns are statistically significant in the Worst 5% and Worst 10% regimes (t-stats 2.90 and 3.63), but not in the extreme tail (t-stat 0.73). The loss of significance is primarily attributable to limited sample size ($N = 4$) rather than reflecting a weaker economic performance. Conditional correlation between TSMOM and MKT-RF remains low or near zero in the broader adverse regime, indicating diversification benefits. Additionally, it exhibits a consistent positive bias, with positive returns in approximately 69% of adverse months, increasing to 75% in the tail. This indicates that TSMOM is more likely than not to perform positively when the market is negative.

Overall, the analysis shows that TSMOM behaves asymmetrically in adverse market regimes, delivering positive average returns with limited correlation to equity drawdowns.

To assess whether TSMOM mitigates the downside consequences of factor ETF redundancy, the analysis compares two portfolios over the live ETF sample from November 2014 to February 2026. Factor ETF returns are obtained from historical ETF performance data, while MKT-RF is taken from the Fama-French Data Library. TSMOM returns are constructed following the AQR time-series momentum methodology, using monthly excess returns and trend-following signals across asset classes. All portfolio returns are computed at monthly frequency. The factor-only ETF portfolio is equal-weighted across Momentum, Quality, Value and Minimum Volatility ETFs. The Factor + TSMOM portfolio reallocates 20% of capital to TSMOM, resulting in an 80% equal-weighted factor ETF allocation and a 20% TSMOM allocation. All tables below are the author's own calculations performed in R. The comparison is conducted across increasingly adverse market regimes defined by MKT-RF.

Effect of a 20% TSMOM Allocation across Adverse Market

Regime	Months	Market avg return	Factor-only portfolio	Factor + TSMOM portfolio	TSMOM improvement
Full Sample	136	0.98%	0.73%	0.65%	-0.08%
Negative Market Months	46	-3.70%	-3.06%	-2.17%	0.89%
Worst 20%	28	-5.48%	-4.51%	-3.17%	1.34%
Worst 10%	14	-7.76%	-6.43%	-4.68%	1.75%
Worst 5%	7	-9.41%	-8.40%	-6.18%	2.22%

Comparison between an equal-weighted Factor Portfolio and an 80% Factor Portfolio + 20% TSMOM.
Data elaborated by the author from iShares, Xtrackers, and AQR datasets.

The results show that the benefit of TSMOM is concentrated in adverse market regimes. Over the full sample, the 20% TSMOM allocation slightly reduces average monthly performance by 0.08 percentage points, suggesting that it does not act as an unconditional return enhancer. However, its contribution becomes positive when market conditions deteriorate. In negative market months, the factor-only ETF portfolio loses on average 3.06%, while the portfolio including TSMOM loses 2.17%, implying an improvement of 0.89 percentage points. The effect strengthens in more severe regimes: the improvement rises to 1.34 percentage points in the worst 20% of market months, 1.75 percentage points in the worst 10%, and 2.22 percentage points in the worst 5%.

This pattern suggests that TSMOM mitigates downside participation. Its contribution is not constant across regimes, but becomes more relevant as market stress intensifies. This is consistent with the role of trend following as a complementary payoff strategy whose value is concentrated during adverse equity market environments.

Market Exposure Reduction from a 20% TSMOM Allocation

Portfolio	Market beta	R-squared	Downside beta
Factor-only ETF portfolio	0.796	0.886	0.865
80% Factor ETF + 20% TSMOM	0.585	0.799	0.634
Relative change	-26.5%	-9.8%	-26.7%

β mitigation.

Data elaborated by the author from iShares, Xtrackers, and AQR datasets.

Adding a 20% allocation to TSMOM reduces the market beta of the factor ETF portfolio by 26.5%, from 0.796 to 0.585. This reduction is similar for downside beta, which falls by 26.7%, from 0.865 to 0.634. This suggests that TSMOM mitigates beta-driven downside participation, even though R-squared remains high, signaling that the portfolio remains materially exposed to market risk. However, its decline from 0.886 to 0.799 indicates that the addition of TSMOM reduces the degree to which portfolio returns are explained by the common market component, thereby mitigating beta-driven redundancy.

Conclusions

This study examined the gap between theoretical risk factors and their practical implementation through ETFs. The results show that factor ETFs only partially retain the diversification properties documented in the academic literature, as they remain largely dominated by market beta and provide only a residual tilt toward the selected factor.

The empirical analysis confirms that this common beta exposure creates redundancy across factor ETFs, especially during adverse market regimes. Adding a 20% allocation to Trend Following reduces market beta from 0.796 to 0.585 and downside beta from 0.865 to 0.634. Its benefit is concentrated in negative market environments: the improvement ranges from 0.89 percentage points in negative months to 2.22 percentage points in the worst 5% of market months.

Overall, the findings suggest that long-term investors should not rely exclusively on traditional equity-bond allocations, conventional multi-asset diversification, or long-only factor ETFs when seeking portfolio robustness. Convex payoff strategies may provide an additional source of

diversification, particularly during prolonged market downturns.

As longer ETF return series become available, future analysis may further assess whether these results remain stable across different market cycles.

References

- Aghassi, M., Asness, C., Fattouche, C., & Moskowitz, T. J. (2023). *Fact, fiction, and factor investing*. *The Journal of Portfolio Management*, 49(2), 57–94.
- Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259–299.
- Asness, C. S., Frazzini, A., Israel, R., Moskowitz, T. J., & Pedersen, L. H. (2018). Size matters, if you control your junk. *Journal of Financial Economics*, 129(3), 479–509.
- Asness, C., Villalon, D., & Ilmanen, A. (2026). *A positive stock-bond correlation is a terrible reason to add more equity risk to your portfolio*. AQR Capital Management.
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18.
- Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116(1), 111–120.
- Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, 32(3), 663–682.
- Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, 12(1), 129–156.
- Black, F., Jensen, M. C., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests. In M. C. Jensen (Ed.), *Studies in the theory of capital markets* (pp. 79–121). Praeger.
- Blitz, D., Baltussen, G., & van Vliet, P. (2020). When equity factors drop their shorts. *Financial Analysts Journal*, 76(4), 73–99.
- Chu, Y., Hirshleifer, D., & Ma, L. (2020). The causal effect of limits to arbitrage on asset pricing anomalies. *The Journal of Finance*, 75(5), 2631–2672.
- Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance*, 66(4), 1047–1108.

- D'Avolio, G. (2002). The market for borrowing stock. *Journal of Financial Economics*, 66(2–3), 271–306.
- Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2), 221–247.
- Diether, K. B., Lee, K.-H., & Werner, I. M. (2009). Short-sale strategies and return predictability. *The Review of Financial Studies*, 22(2), 575–607.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427–465.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636.
- Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1), 1–25.
- Geczy, C. C., Musto, D. K., & Reed, A. V. (2002). Stocks are special too: An analysis of the equity lending market. *Journal of Financial Economics*, 66(2–3), 241–269.
- Haugen, R. A., & Heins, A. J. (1975). Risk and the rate of return on financial assets: Some old wine in new bottles. *Journal of Financial and Quantitative Analysis*, 10(5), 775–784.
- He, W., & Shen, J. (2010). Investor extrapolation and expected returns. *Review of Behavioral Finance*.
- Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2017). A century of evidence on trend-following investing. *The Journal of Portfolio Management*, 44(1), 15–29.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65–91.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228–250.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425–442.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2), 288–302.

Swade, A., Hanauer, M. X., Lohre, H., & Blitz, D. (2023). Factor zoo (.zip). *The Journal of Portfolio Management*, 50(3).

Data sources

AQR Capital Management. (2025). *Time series momentum: Factors, monthly*. AQR Data Library.

BlackRock. (n.d.). *iShares ETF historical performance data*. iShares.

DWS. (n.d.). *Xtrackers ETF historical performance data*. Xtrackers by DWS.

French, K. R. (n.d.). *Fama/French factors*. Kenneth R. French Data Library.

Shiller, R. J. (n.d.). *Online data: U.S. stock markets 1871–present and CAPE ratio*. Yale University.

Institutional sources

FinecoBank. (2026). *Financial results and corporate information*. FinecoBank.