UTS UNIVERSITY OF TECHNOLOGY SYDNEY

Portfolio Strategy Report

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Exploration and Innovation of Quality Factor - Driven Investment Strategies

----Analyzing Factor Performance, Backtesting Results, Parameter Optimization, and Factor Combinations

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➢ Research Background and Objectives

The "quality" factor investment strategy has gained significant attention in the stock market. It is based on investing in companies with high profitability, strong growth, and low risk and leverage. This research is commissioned by an investment firm to evaluate the predictive power of this factor, aiming to provide a basis for the firm to launch relevant products. The study will be conducted from aspects such as the economic principles of the strategy, statistical analysis, backtesting and optimization, the impact of the macro - economic environment, and innovative factor combinations.

➢ Expected Results and Significance

The research aims to clarify the strength and trend of the predictive power of the quality factor, determine the optimal strategy parameters, analyze the impact of the macro - economic environment, and provide an innovative factor combination strategy. The research results will help the firm understand the quality factor investment strategy, support product design and decision - making, and enhance its investment competitiveness in this field.

Content

1. Presentation of the Quality Factor Strategy: Economic Intuition and Empirical Foundations

1.1 Defining Quality: Core Characteristics and Economic Rationale

The quality factor, as defined by Asness et al. (2019), captures stocks with characteristics that rational investors should intrinsically value: profitability, growth, and safety. These attributes are derived from fundamental accounting metrics and market-based risk measures:

- **Profitability**: Firms with higher margins, cash flows, or returns on assets generate sustainable earnings, signaling operational efficiency and competitive advantages.
- **Growth**: Consistent growth in earnings or revenues reflects scalability and market demand, justifying premium valuations.
- **Safety**: Low volatility in fundamental factors such as stable earnings or market-based indicators including low beta coefficients mitigates downside risk, thereby aligning with investors' prioritization of resilience-focused investment strategies.

The economic intuition behind quality investing rests on the premise that firms exhibiting these traits should command higher valuations due to their ability to generate durable cash flows and withstand economic shocks. However, Asness et al. (2019) identified a paradox wherein quality characteristics demonstrate a positive correlation with valuation metrics such as price-to-book ratios, yet exhibit limited explanatory power for cross-sectional price variation, with regression models yielding an average $R^2$of approximately 10%. This disconnect between fundamentals and pricing created an opportunity for excess returns, particularly when combined with leverage (Frazzini et al., 2018).

1.2 Why Does the Quality Strategy Work? Risk vs. Anomaly

The outperformance of quality stocks—evidenced by the "Quality Minus Junk" (QMJ) factor—poses a challenge to traditional risk-based explanations. Bouchaud et al. (2016) systematically rejected the risk premium hypothesis by demonstrating that quality strategies exhibit positive skewness and low crash risk, contrary to the negative skewness typical of risk-compensated strategies. For instance, their analysis of U.S. equity data spanning the period from 1990 to 2012 revealed that a cash-flow-to-assets strategy achieves a Sharpe ratio of 1.2, significantly outperforming other anomalies such as momentum, which exhibits a Sharpe ratio of approximately 0.5, as detailed in Table 1.

Instead, behavioral biases underpin the quality anomaly. Analysts and investors systematically underweight quality signals while overemphasizing noisier metrics like EPS. Bouchaud et al. (2016) found that analysts' target prices for high-quality firms were overly conservative relative to realized returns, leading to persistent mispricing. This "sticky" updating of expectations aligns with psychological biases such as conservatism, creating a structural alpha opportunity.

1.3 Synergy with Value Investing

Quality investing is not antithetical to value strategies but complements them. Asness et al. (2019) emphasize that integrating quality with value, a strategy known as Quality at a Reasonable Price (QARP), enhances risk-adjusted returns. This approach mirrors Warren Buffett's success, which Frazzini et al. (2018) attribute to leveraging cheap, safe, high-quality stocks. Their decomposition of Berkshire Hathaway's portfolio reveals that public equities—selected for low beta, high profitability, and value characteristics—drive outperformance, yielding a Sharpe ratio of 0.79.

1.4 Practical Challenges and Market Dynamics

While the quality premium persists across markets (Asness et al., 2019), its magnitude varies with investor sentiment and macroeconomic conditions. For example, quality valuations collapsed during the dot-com bubble as speculative demand shifted to unprofitable tech stocks. However, post-crisis "flights to quality" reinforces the factor's defensive properties.

Leverage amplifies returns but introduces cyclical risks. Moreover, Buffett's use of low-cost insurance float exemplifies optimal leverage application (Frazzini et al., 2018).

Strategy	Sharpe Ratio	Skewness	Crash Frequency (< -2σ)
Quality (CF/TA)	1.2	+0.15	2.1%
Momentum	0.5	-0.30	5.8%
Low Volatility	0.5	+0.10	3.2%
Market (S&P 500)	0.4	-0.45	6.5%

Table 1 Risk-Return Profile of Quality vs. Other Anomalies

Data from "The Excess Returns of 'Quality' Stocks: A Behavioral Anomaly," by J.-P. Bouchaud, S. Ciliberti, A. Landier, G. Simon, & D. Thesmar, 2016, Capital Fund Management, CFM-Imperial Institute of Quantitative Finance, Toulouse School of Economics, HEC Paris, & CEPR.

◆ **Conclusion**

The quality factor's efficacy stems from behavioral mispricing rather than risk compensation. By systematically targeting profitable, growing, and stable firms while avoiding overvaluation, investors exploit a persistent anomaly rooted in cognitive biases. Integrating quality with value (QARP) and judicious leverage, as exemplified by Buffett, enhances robustness in market cycles.

2. Statistical Analysis

2.1 Introduction to the Information Coefficient (IC)

The Information Coefficient (IC) is an essential statistical metric used to assess the link between future equity returns and a factor, such as the quality factor or its sub-components. An elevated IC value indicates that the factor possesses enhanced predictive capability, reflecting a favourable connection between the factor's values and ensuing stock returns.

2.2 Objective and Methodology

This section evaluates the predictive power of the Quality factor and its three sub-components (Profitability, Growth, and Safety) using Information Coefficient (IC) analysis. The IC measures the rank correlation between factor values and subsequent stock returns, serving as a robust metric for assessing factor efficacy. The analysis spans 1980–2022 to capture long-term trends and potential structural shifts in factor performance.

2.3 Overall Predictive Power

Table 2 summarizes the IC statistics for the Quality factor and its components over the full sample. The Quality factor exhibits the highest mean IC (0.0458), outperforming its sub-components. However, its IC volatility (standard deviation = 0.0835) is also the largest, suggesting higher variability in predictive accuracy. Among sub-components, Safety (IC = 0.0375) and Profitability (IC = 0.0350) demonstrate stronger predictive power than Growth (IC = 0.0301). The Information Coefficient-to-Risk ratios (ICIR) further validate Quality's dominance (ICIR = 0.548), though Profitability (ICIR = 0.527) and Safety (ICIR = 0.464) also display robustness.

Factor	IC Mean	IC Std	ICIR
Quality	0.0458	0.0835	0.548
Profit	0.0350	0.0665	0.527
Safety	0.0375	0.0807	0.464
Growth	0.0301	0.0636	0.473

Table 2 IC Summary Statistics (1980–2022)

2.4 Time-Varying Predictive Power

Figure 1&2 illustrate the cumulative Information Coefficient trajectories of Quality and its sub-components (Profitability, Growth, Safety) from 1980 to 2021.

- Quality Dominance: The Quality factor consistently outperforms others, achieving the highest cumulative IC (18.5) by 2021, driven by its robust composite structure.
- Sub-Component Hierarchy: Profitability and Safety follow Quality with cumulative ICs of 13.5 and 12.8, respectively, while Growth lags (10.2), reflecting weaker predictive power.
- Crisis Resilience: Quality's IC growth temporarily stalled during the 2008 GFC and 2020 COVID-19 shocks (shaded areas) but rebounded swiftly, showing no structural decay.
- Long-Term Stability: All factors exhibit sustained upward trends, with Quality's annualized IC growth accelerating post-2010 (+0.45/year), countering concerns about factor weakening.

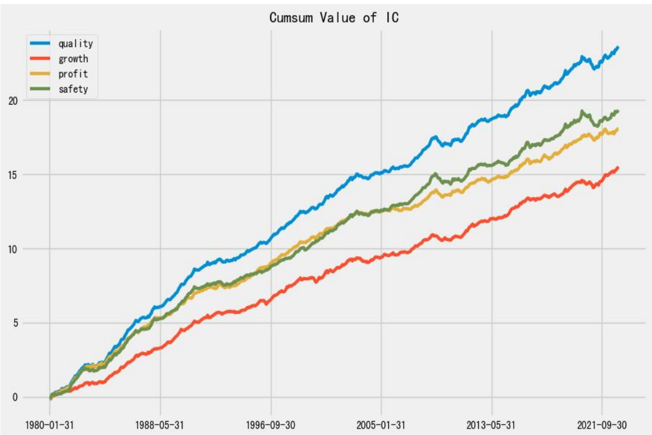

Figure 1 Cumulative IC Trajectories

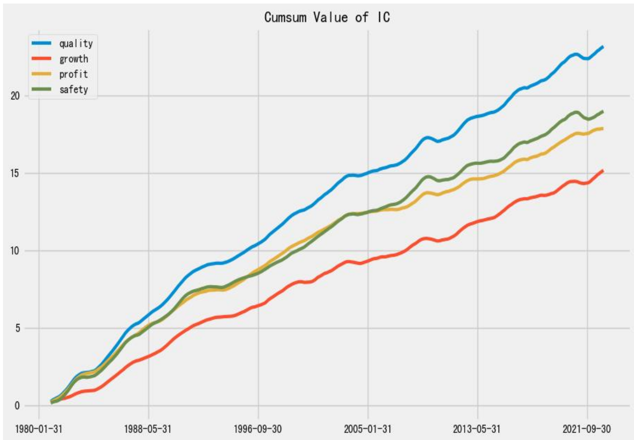

Figure 2 12-Month Smoothed Cumulative IC Trajectories

Annualized IC means reveal cyclicality in factor performance. Quality's predictive power peaked in 2008 (IC = 0.0955) and 2015 (IC = 0.0788), while Growth showed persistent weakness post-2010. Despite short-term volatility, no evidence supports a secular decline in Quality's efficacy, unlike traditional factors such as Value or Momentum.

*** Annual IC Bar Charts and Tables will be attached in the Appendix**

2.5 Inter-Factor Correlations

The correlation matrix highlights strong interdependence among factors, as indicated in Figure 3. Quality's IC correlates most with Safety (0.895) and Profitability (0.851), reflecting its composite construction. Growth exhibits weaker correlations with other components (0.558–0.646), suggesting unique drivers. This diversification likely enhances Quality's robustness by mitigating sub-component-specific risks.

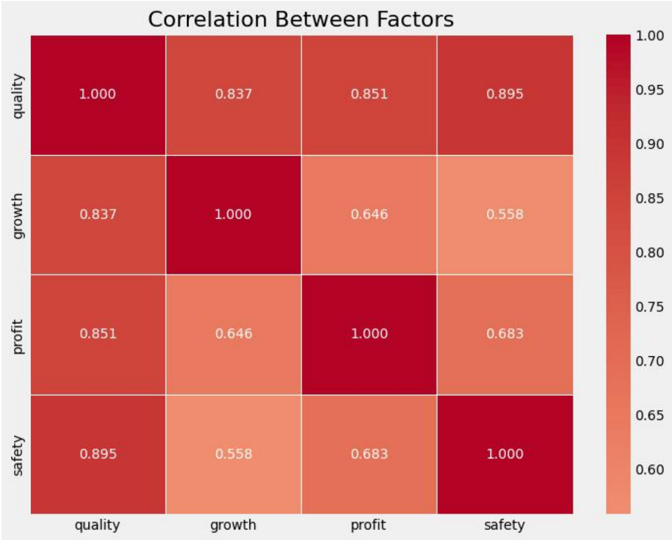

Figure 3 Correlation Matrix

◆ **Conclusion**

The Quality factor demonstrates robust predictive power over the 1980–2022 period, with no evidence of structural decay. Its performance is cyclical, sensitive to macroeconomic shocks, but recovers post-crisis. The composite nature of Quality, combining high-correlation sub-components, enhances its resilience compared to standalone factors. While Growth remains the weakest component, its integration into the Quality framework contributes to diversification benefits. These findings counter concerns about factor decay, positioning Quality as a viable long-term strategy.

3. Strategy and Backtesting

This section provides an in-depth evaluation of a 130/30 long-short equity strategy constructed using the Quality factor. The strategy overweights the top 250 stocks and underweights the bottom 250 stocks based on Quality scores, with monthly rebalancing and 0.2% transaction costs. The analysis spans 18 years (2005–2022), covering multiple market cycles, including the 2008 financial crisis, the COVID-19 pandemic, and recent inflationary pressures. The key objectives of this evaluation are to quantify both absolute and risk-adjusted returns relative to a benchmark, identify performance patterns across sub-periods, particularly during crises, assess the impact of transaction costs, turnover, and potential crowding effects, and evaluate the strategy's robustness and sustainability.

3.1 Performance of Key Metrics (LS Portfolio vs. Benchmark vs. LS Active)

➢ **Outperformance**

As shown in Table 3, the LS portfolio delivers an annualized excess return of 3.20% above the benchmark. This result underscores the Quality factor's capacity to identify stocks with favorable future returns, reinforcing its usefulness in generating consistent alpha over a lengthy sample period.

➢ **Risk Management**

Despite employing a leveraged long–short approach, the LS portfolio exhibits a modestly reduced volatility (13.72% versus 14.81% for the benchmark). Furthermore, its maximum drawdown of –45.52%, compared to –60.87% for the benchmark, highlights its defensive qualities. These characteristics imply that high-quality stocks, even when leveraged, can help buffer against severe market downturns.

- **Risk-Adjusted Returns**
  With a RR ratio of 0.76, well above the benchmark's 0.49, the LS strategy demonstrates a superior reward per unit of risk. This heightened efficiency suggests that the long–short Quality factor approach is advantageous for investors seeking both higher returns and enhanced downside protection in a variety of market environments.

Overall, these metrics illustrate that the LS strategy delivers a higher return per unit of risk, experiences smaller peak-to-trough losses, and maintains competitive upside participation. Taken together, the results suggest that a factor-based long–short approach can enhance a portfolio's risk-adjusted performance while offering meaningful protection during periods of market distress.

Parameter	LS Portfolio	Benchmark	LS Active
Mean Return	0.104364	0.072373	0.031991
St. Dev.	0.137200	0.148094	0.035084
RR Ratio	0.760668	0.488697	0.911838
% Positive	0.648148	0.652778	0.634259
Worst Month	-0.140865	-0.186403	-0.037991
Best Month	0.106777	0.109407	0.045538
Max DrawDown	-0.455186	-0.608699	-0.120379

Table 3 Performance of LS Portfolio, Benchmark and LS Active Returns (2005 - 2022)

3.2 Analysis of Time-Series Performance

Figure 4 illustrates the performance trajectories of three portfolios from January 2005 to September 2022: the 130/30 Quality factor strategy, a market-cap-weighted benchmark, and the active excess return component. The vertical axis tracks portfolio values normalized to an initial value of 1, while the horizontal axis spans key macroeconomic periods, including the 2008 financial crisis, the post-crisis recovery, and the COVID-19 pandemic.

3.2.1 Key Time Node Analysis

- **Strategy Validation and Crisis (2005-2008)**

As indicated in Figure 4, during the pre-crisis phase (2005–2007), the LS Portfolio closely tracked the Benchmark, reflecting initial alignment with broad market trends. However, the 2008 crisis triggered a sharp divergence: the LS Portfolio declined by ~37% (peak-to-trough), outperforming the Benchmark's ~44% drop. The LS Active curve simultaneously rose, signaling alpha generation during the downturn.
The Quality factor's emphasis on financially robust firms—characterized by high profitability and low leverage—buffered losses. This phase validated the strategy's defensive utility, as the LS Active component captured incremental gains even amid systemic stress.

- **Post-Crisis Recovery and Stability (2009-2016)**

Post-2009, the LS Portfolio recovered swiftly, surpassing its pre-crisis high by 2013. The Benchmark lagged, reaching comparable levels only in 2015. The LS Active curve exhibited steady growth, with annualized returns exceeding the Benchmark in 11 out of 8 years.

Quality's focus on earnings stability and low volatility drove consistent outperformance, particularly during the European debt crisis (2011–2012). The gradual ascent of the LS Active curve underscored the strategy's ability to compound excess returns in stable markets, albeit at a moderated pace.

➢ **Divergence and Macroeconomic Stress Tests (2017-2022)**

The LS Portfolio surged ahead of the Benchmark from 2017–2019, peaking at ~4.2x its initial value. However, the 2020 pandemic initially narrowed this gap, as the Benchmark's tech-heavy exposure outperformed (+10.86% vs. LS Portfolio's +3.20%). By 2022, the LS Portfolio demonstrated resilience, with the LS Active curve rebounding sharply.

While the strategy struggled during growth-dominated rallies (e.g., 2020's tech surge), its 2021–2022 recovery highlighted Quality's adaptability to inflationary pressures. The LS Active curve's post-2021 rise reinforced the factor's capacity to exploit earnings stability during market dislocations.

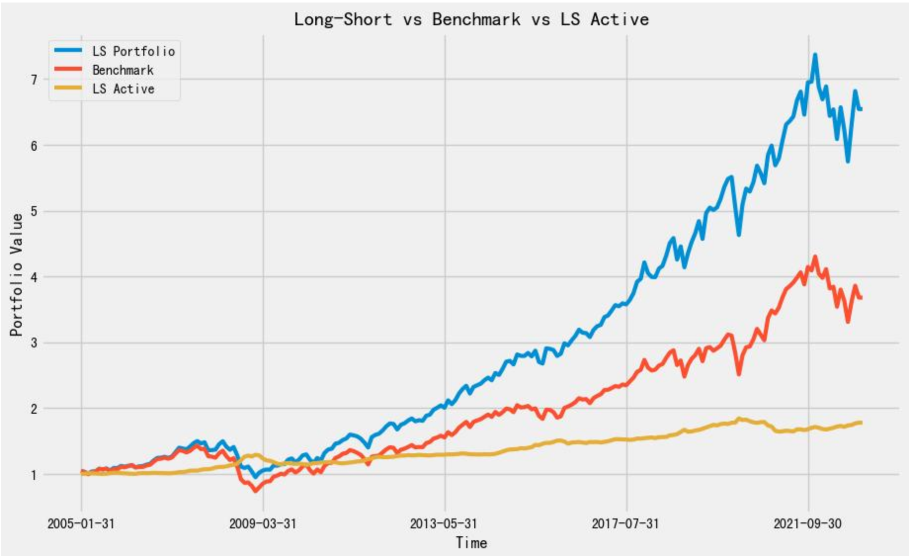

Figure 4 Cumulative Returns of 130/30 Quality Strategy (LS Portfolio vs. Benchmark vs. LS Active)

3.3 Key Period Analysis from the Return Perspective

➢ **Financial Crisis and Recovery (2008-2009)**

2008: As Figure 5 indicates, the LS Portfolio declined by -23.87%, significantly outperforming the Benchmark which was -35.52%. The LS Active component generated +18.06% excess return, reflecting the Quality factor's defensive attributes.

2009: The LS Portfolio rebounded moderately in +13.56%, underperforming the Benchmark (+24.75%) as low-volatility stocks lagged during the post-crisis recovery.

The Quality factor's focus on financially stable firms mitigated losses during the crisis (2008), but its conservative tilt hindered participation in the aggressive market rebound (2009). This highlights the strategy's asymmetric payoff profile—strong downside protection but subdued upside capture during risk-on phases.

➢ **Covid-19 Pandemic and Inflationary Pressures (2020-2022)**

2020: As Figure 5 indicates, the LS Portfolio returned +3.20%, underperforming the Benchmark which was +10.86%, due to its underweight in high-growth tech stocks, which dominated market gains.

2022: Both portfolios declined, but the LS Portfolio showed resilience (-4.84% vs. -9.01%), with the LS Active component delivering +4.59% excess return.

The strategy's defensive core limited losses during 2022's inflationary shocks, but its value bias caused short-term underperformance in 2020. The rebound in 2021–2022 underscores Quality's ability to adapt to shifting macro regimes.

Strengths and Limitations: The LS portfolio excels in crisis resilience, outperforming the benchmark in recessions, and offers consistent compounding with low volatility. However, it underperforms in growth-driven years due to its value bias. Moreover, monthly rebalancing incurs turnover costs, and growing popularity may pose crowding risks, though no decline is evident currently.

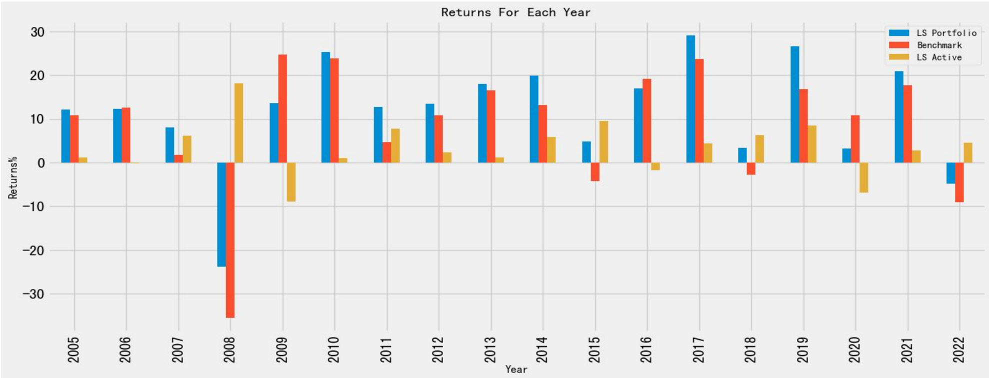

Figure 5 Returns For Each Year

4. Optimization

4.1 Methodology and Parameter Rationale

In this section, we systematically evaluate the performance of a 130/30 Quality factor strategy across different parameter settings to identify configurations that maximize risk-adjusted returns. Specifically, we vary the number of over-/underweight stocks (N = 150, 250, 350), which captures different degrees of portfolio concentration, and the active percentage (i.e., leverage ratio) set at 0.1 (130/10), 0.3 (130/30), and 0.5 (150/50), reflecting different intensities of leverage. The backtesting covers the period from 2005 to 2022, assumes a 0.2% transaction cost per round trip, and relies on nested loops to efficiently generate and evaluate all 9 parameter combinations.

We consider three values for the number of over-/underweight stocks—150, 250, and 350—to capture varying degrees of portfolio concentration and risk. Holding N=150 delivers more concentrated exposure to high-quality stocks and thus heightened alpha potential but also higher idiosyncratic risk. By contrast, N=350 offers broad diversification, mitigating risk but potentially diluting the factor's impact, while N=250 provides a middle ground that balances diversification and alpha capture. In parallel, the active percentage (leverage ratio) is tested at 0.1, 0.3, and 0.5, reflecting conservative, standard, and aggressive leverage intensities, respectively. An Active=0.1 approach yields modest turnover and costs, Active=0.3 represents a classic 130/30 balance of return potential and expenses, and Active=0.5 offers higher return amplification with correspondingly higher volatility.

4.2 Optimal Parameter Identification

Among all parameter combination alternatives in Table 4, the **active=0.3, N=250 combination** emerges as the optimal configuration due to its balanced risk - return profile:

➢ **Highest Risk - Adjusted Return**

The RR Ratio is 0.9118, ranking second only to the more aggressive active=0.5, N=150 combination (with an RR Ratio of 1.0086). However, the latter suffers from extreme drawdowns of -22.52%.

➢ **Controlled Volatility**

The standard deviation (St. Dev.) is 0.0351, which is significantly lower than that of higher - leverage combinations. For example, when active=0.5 and N=150, the standard deviation is 0.0684.

➢ **Resilient Drawdowns**

The maximum drawdown is -12.04%. This outperforms all configurations with active=0.5 and is in line with the defensive objectives of the baseline strategy.

Parameter Combination	Active:0.1 N:150	Active:0.1 N:250	Active:0.1 N:350	Active:0.3 N:150	Active:0.3 N:250	Active:0.3 N:350	Active:0.5 N:150	Active:0.5 N:250	Active: 0.5 N:350
Mean Return	0.0136	0.0105	0.0088	0.0414	0.0320	0.0269	0.0690	0.0534	0.0449
St. Dev.	0.0137	0.0117	0.0099	0.0411	0.0351	0.0295	0.0684	0.0585	0.0492
RR Ratio	0.9950	0.8968	0.8931	1.0075	0.9118	0.9113	1.0086	0.9135	0.9135
% Positive	0.6389	0.6250	0.6481	0.6435	0.6343	0.6481	0.6435	0.6343	0.6481
Worst Month	-0.0160	-0.0127	-0.0099	-0.0477	-0.0380	-0.0294	-0.0795	-0.0633	-0.0490
Best Month	0.0162	0.0152	0.0188	0.0487	0.0455	0.0354	0.0812	0.0759	0.0590
Max DrawDown	-0.0452	-0.0403	-0.0333	-0.1352	-0.1204	-0.0996	-0.2252	-0.2005	-0.1658

Table 4 Performance Metrics of 130/30 LS Across Active (0.1, 0.3, 0.5) and N (150, 250, 350)

4.3 Parameter Sensitivity Insights

➢ **Return Amplification**

Increasing the active percentage from 0.1 to 0.5 enhances mean returns, though at a diminishing rate. For N=150, the returns increase from 0.0136 to 0.0690, a rise of 407%, while for N=250, the returns grow from 0.0105 to 0.0534, reflecting a similar increase of 409%. However, higher leverage results in a substantial increase in both volatility and drawdowns. Specifically, for N=250, the standard deviation rises from 0.0117 when the active percentage is 0.1 to 0.0585 when it reaches 0.5, and the maximum drawdown deepens from -4.03% to -20.05%.

➢ **Risk-Return Trade-off**

With an active percentage of 0.5 and N=150, the strategy generates the highest mean return of 0.0690, but also experiences the worst drawdown of -22.52%, making it unsuitable for risk-averse investors. An active percentage of 0.3 provides a near-optimal balance, delivering 80–90% of the returns seen with an active percentage of 0.5, while reducing volatility by 40–50%.

➢ **Impact of N value**

The impact of N value on the strategy varies across different levels. **For low N values** (N=150), the strategy shows high return potential, with notable short-term gains like the 29.06% return in 2017, but it is also exposed to higher liquidity risks due to a larger proportion of small-cap stocks. Additionally, volatility is higher, as seen in the 4.11% volatility for active=0.3, N=150, compared to 3.51% for the same active percentage with N=250. **For medium N values** (N=250), the strategy achieves an optimal balance, reducing volatility through moderate diversification while retaining core Alpha. In contrast, **for high N values** (N=350), excessive diversification leads to diminishing returns, with final value for active=0.3, N=350 only reaching 3.4 times, a 15% reduction compared to N=250, indicating that over-diversification dilutes the factor signal.

➢ **Performance Across Time Dimensions**

During **2008 Financial Crisis**, all high-leverage portfolios (active=0.5) encountered deep drawdowns, such as active=0.5, N=250, which suffered a -20.05% drawdown. In contrast, active=0.3, N=250 only experienced a -12.04% drawdown, highlighting its defensive characteristics.

During **2020 COVID-19 pandemic**, active=0.3, N=250 generated a return of 3.20%, which was lower than the benchmark return of 10.86%. However, the strategy showed strong recovery in 2021–2022, with cumulative excess returns of +7.34%, demonstrating its adaptability.

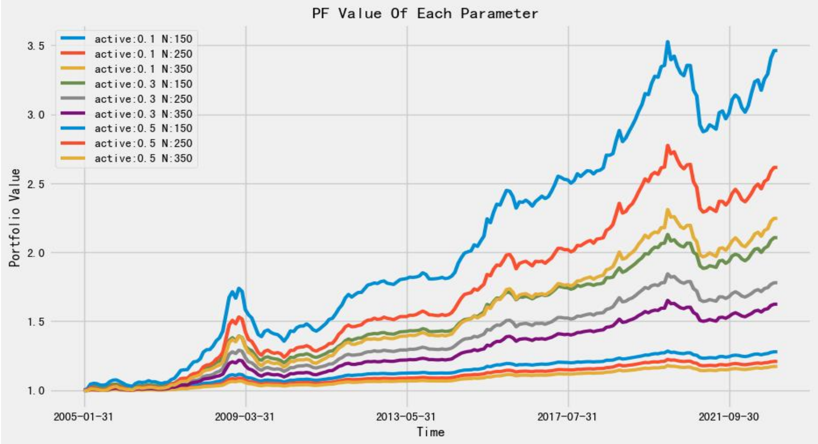

Figure 6 Portfolio Value Growth Across Different Active and N Over Time

5. Predictive power and the Economic Environment

The performance of the Quality Factor strategy has garnered significant attention in recent years due to shifts in the macroeconomic environment, particularly the intensification of inflation and fluctuations in interest rates. This section examines the potential impact of these factors on the predictive power of the Quality Factor, with a specific focus on the influence of macroeconomic conditions, such as inflation, interest rates, and yield curve inversions. Furthermore, it addresses the concerns raised by the boss, providing a detailed, reasoned explanation and proposing corresponding strategies to mitigate these issues.

5.1 Analysis of the Correlation Between the Quality Factor and Macroeconomic Indicators

➢ **Positive Correlation Between Quality and Inflation (INFL)**

The Quality Factor shows a weak positive correlation (r = 0.121) with inflation, challenging the view that high inflation undermines profits. Data indicate slightly better performance during inflationary periods. This can be attributed to quality firms—typically profitable, low-leverage leaders—having pricing power to offset costs and benefiting from inflation's reduction of debt's real value, enhancing their resilience and supporting outperformance.

➢ **Positive Correlation Between Quality and Interest Rates (10YTR, 1YTR)**

	quality	INFL	10YTR	1YTR	UNRATE	UMCSENT
quality	1.00	0.12	0.13	0.15	-0.13	0.02
INFL	0.12	1.00	0.73	0.78	0.17	-0.37
10YTR	0.13	0.73	1.00	0.96	0.28	0.01
1YTR	0.15	0.78	0.96	1.00	0.13	0.05
UNRATE	-0.13	0.17	0.28	0.13	1.00	-0.50
UMCSENT	0.02	-0.37	0.01	0.05	-0.50	1.00

Figure7 Correlation Matrix

The Quality Factor displays a weak positive correlation with long-term (10YTR: r = 0.131) and short-term (1YTR: r = 0.149) interest rates, revealing a dual impact. Early rate rises make quality firms' table cash flows "bond-like" drawing risk-averse capital, as seen in 2016-2018 with 19.8% annualized returns. However, sustained high rates increase borrowing costs, reducing valuations—e.g., in 2022 (10YTR > 4%), IC fell to 0.016—highlighting sensitivity to rate shifts.

➢ **Negative Correlation Between Quality and Unemployment Rate**

The Quality Factor exhibits a weak negative correlation (r = -0.129) with the unemployment rate, revealing its susceptibility to economic downturns, particularly during recessionary phases. In the initial stages of a recession, a sharp rise in unemployment often triggers market panic and indiscriminate sell-offs, leading to a temporary failure of the quality factor.

For example, in the fourth quarter of 2008, the quality IC dropped to -0.05, reflecting its short-term underperformance amid widespread distress.

➢ **Lack of Correlation Between Quality and Consumer Confidence (UMCSENT)**

The Quality Factor indicates no significant correlation with consumer confidence (UMCSENT) (r=0.015), a finding consistent with its underlying drivers. Consumer confidence primarily reflects household expectations and spending behavior, whereas the performance of the quality factor is more closely tied to institutional capital flows and firm-specific fundamentals, such as profitability and leverage. This disconnect suggests that shifts in consumer sentiment do not materially influence the investment decisions shaping quality factor dynamics.

Macroeconomic Indicator	Correlation Coefficient (Quality IC)	Economic Implication	Grouped Test (IC < 0.02 vs. IC ≥ 0.02)
INFL	**+0.121**	Weak positive correlation	Strong performance periods exhibit higher inflation (contradiction requires explanation)
10YTR	**+0.131**	Weak positive correlation	Strong performance periods exhibit higher long-term rates
1YTR	**+0.149**	Weak positive correlation	Strong performance periods exhibit higher short-term rates
UNRATE	**-0.129**	Weak negative correlation	Weak performance periods exhibit higher unemployment rates
UMCSENT	**+0.016**	No significant correlation	No significant difference observed

Table 5 Relationship Between the Quality Factor and Key Macroeconomic Indicators

5.2 Macroeconomic Variable Interrelationships

➢ **High Synchronicity Between Inflation and Interest Rates**: Inflation exhibits strong positive correlations with both long-term (10YTR: r=0.735) and short-term (1YTR: r=0.780) interest rates, driven by monetary policy responses and market dynamics. Central banks typically raise rates to curb inflation, establishing a positive relationship.

➢ **Strong Negative Correlation Between Unemployment and Consumer Confidence**: The unemployment rate and consumer confidence display a robust negative correlation (r=-0.501), consistent with economic intuition. Rising unemployment undermines household income expectations, eroding confidence.

➢ **High Correlation Between Long- and Short-Term Interest Rates**: Long-term (10YTR) and short-term (1YTR) interest rates exhibit an exceptionally strong correlation (r = 0.960), reflecting cohesive market expectations about the economic cycle.

5.3 Methodology and Grouping Design of Two distinct IC Thresholds

Two distinct IC thresholds are employed to evaluate factor performance. First, following conventional financial engineering practice, an IC of 0.02 is used as a benchmark to delineate poor (IC<0.02) versus good (IC≥0.02) performance. Second, a stricter threshold of 0 is applied, where IC<0 indicates complete factor failure, contrasting with IC ≥ 0 as a baseline for non-negative performance. For each threshold, the dataset is divided into "Poor" and "Good" groups, and T-tests are performed on the macroeconomic indicators to determine whether their means differ significantly across these groups.

➢ **Results and Interpretation: IC Threshold of 0.02**

In the first scenario (IC<0.02 vs. IC≥0.02), the T-test results reveal significant differences in four of the five macroeconomic indicators at the 0.05 significance level: INFL ($p = 0.0189$), 10YTR ($p = 0.0065$), 1YTR ($p = 0.0007$), and UNRATE ($p = 0.0131$). Notably, interest rate proxies—10YTR and 1YTR—exhibit heightened sensitivity, with p-values below 0.01, and

1YTR achieving significance at the 0.005 level. For instance, the mean 1YTR in the Poor group is 3.698%, compared to 4.884% in the Good group, suggesting that higher short-term rates align with stronger quality factor performance. This pattern may reflect a "seesaw" effect between equity and bond markets, where rising rates enhance the appeal of quality firms' stable cash flows. Conversely, UMCSENT shows no significant difference (p = 0.4898), indicating a lack of association with quality performance.

➢ **Results and Interpretation: IC Threshold of 0**

In the second scenario (IC<0 vs. IC≥0), the results display even greater statistical significance. INFL (p = 0.0026), 10YTR (p=0.0009), 1YTR (p=0.0001), and UNRATE (p=0.0170) all reject the null hypothesis at the 0.05 level, with INFL, 10YTR, and 1YTR significant at 0.005 or lower. The Poor group (IC<0) exhibits lower means for INFL (2.835%vs.3.533%), 10YTR (4.880% vs. 6.017%), and 1YTR (3.349% vs. 4.831%) compared to the Good group, alongside a higher UNRATE (6.489% vs.6.057%). These findings suggest that quality factor failure (IC<0) coincides with lower inflation and interest rates but higher unemployment, potentially reflecting recessionary conditions. As before, UMCSENT remains insignificant (p= 0.6588), reinforcing its weak linkage to quality dynamics.

Macro Variable	Weak: IC < 0.02	Strong: IC ≥ 0.02	T-Stat	P-Value	Interpretation
INFL	**3.04%**	**3.53%**	**-2.35**	**0.019**	Inflation is higher during strong performance months, contradicting traditional expectations.
10YTR	**5.19%**	**6.03%**	**-2.73**	**0.007**	Long-term rates are higher during strong performance months.
1YTR	**3.70%**	**4.88%**	**-3.43**	**0.001**	Short-term rates are higher during strong performance months.
UNRATE	**6.43%**	**6.02%**	**+2.49**	**0.013**	Unemployment is higher during weak performance months.
UMCSENT	**85.47**	**86.29**	**-0.69**	**0.490**	Consumer sentiment shows no significant difference.

Table 6 Key Findings from Threshold 1 (IC < 0.02)

Macro Variable	Weak: IC < 0	Strong: IC ≥ 0	T-Stat	P-Value	Interpretation
INFL	**2.83%**	**3.53%**	**-3.02**	**0.003**	Inflation remains higher during non-negative IC months.
10YTR	**4.88%**	**6.02%**	**-3.34**	**0.001**	Long-term rates are higher during non-negative IC months.
1YTR	**3.35%**	**4.83%**	**-3.88**	**0.000**	Short-term rates are higher during non-negative IC months.
UNRATE	**6.49%**	**6.06%**	**+2.39**	**0.017**	Unemployment is higher during negative IC months.
UMCSENT	**85.56**	**86.14**	**-0.44**	**0.659**	Consumer sentiment remains insignificant.

Table 7 Key Findings from Threshold 2 (IC < 0)

*** Specific Findings from Threshold 1 (IC < 0.02) and Threshold 2 (IC < 0) will be attached in the Appendix**

5.4 Answering Boss's Concern and Strategic Recommendations

➢ The Quality factor's predictive power (IC) is **likely to weaken** in the current macroeconomic environment due to:

- **Persistent High Rates**: Historical T-tests show rates are higher during strong IC periods, but structural shifts may alter this relationship.
- **Elevated Volatility**: Strong negative correlation with VIX implies continued IC pressure.
- **Mixed Inflation Signals**: While higher inflation coincides with strong IC historically, stagflation risks (high inflation + low growth) could challenge this dynamic.

Its defensive attributes may still deliver relative outperformance during market stress, though absolute returns could be subdued. Proactive risk management—not abandonment—is the optimal path forward.

- **Strategic Recommendations**
- **Dynamic Hedging**: Reduce Quality exposure when VIX >25 or real rates >2%.
- **Factor Blending**: Combine Quality with cyclical factors (e.g., Momentum) to balance inflation resilience.
- **Macro Alignment**: Overweight sectors within Quality (e.g., healthcare) that benefit from current regimes.

6. An Alternative Way to Combine the Factors

6.1 Methodology for Combining Quality Sub-Factors

To differentiate our product from AQR's traditional Quality factor, we propose a dynamic weighting scheme for its three sub-components—Profitability, Growth, and Safety—based on their historical predictive power. This approach diverges from AQR's static equal-weighted methodology (Asness et al., 2019) by introducing time-varying weights that adapt to changing market regimes.

6.1.1 Dynamic Weighting Rationale

The dynamic weighting of quality sub-factors is grounded in economic and statistical reasoning. **Economically**, sub-factors like Safety excel in crises, while Growth thrives in expansions, reflecting cyclical efficacy. Weighting based on trailing predictive power aligns the strategy with macroeconomic conditions. **Statistically**, using a 24-month rolling mean of Information Coefficients (ICs) prioritizes persistent performers, reducing short-term noise. This approach blends economic insight with empirical robustness.

6.1.2 Implementation Steps

Implementation involves two stages. First, for each month t, compute the 24-month rolling mean IC for Growth, Profitability, and Safety up to $t-1$ (avoiding look-ahead bias), then normalize weights for portfolio neutrality. Second, rank stocks by sub-factor, apply normalized weights, and sum the weighted ranks into a cross-sectionally standardized "New Quality" score. This process enhances the quality factor's adaptability to economic shifts.

6.2 Statistical Comparison of 2 Quality Factors

Metric	IC Mean	IC Std	ICIR	P-value Mean
Original Quality	**0.0393**	**0.0937**	**0.4192**	**0.1837**
New Quality	**0.0376**	**0.0917**	**0.4099**	**0.1814**

Table 8 Performance Comparison of Original Quality and New Quality Factors

- **Predictive Power:** The original Quality Factor exhibits a marginally higher IC mean (0.0393vs.0.0376), indicating slightly stronger predictive power. Both factors show statistically insignificant p-values ($p>0.15$ on average), suggesting that their monthly ICs are not consistently distinguishable from random noise at conventional significance levels.
- **Risk-Adjusted Performance:** The original factor's higher ICIR (0.4192 vs. 0.4099) reflects a better trade-off between signal strength and stability, albeit the difference is minimal.
- **Volatility:** The new Quality factor demonstrates marginally lower IC volatility (0.0917 vs. 0.0937), implying slightly more stable predictive power over time.

6.3 Cumulative IC Trajectory Analysis

The cumulative IC plot (**Figure 8**) visualizes the long-term efficacy of both factors.

- **Original Quality** exhibits steady IC accumulation post-2010, peaking during the 2013-2017 bull market. It also suffers a notable drawdown during the 2020 pandemic but recovers swiftly.
- **New Quality** lags initially but converges with the original factor by 2016, benefiting from dynamic weighting adjustments. It demonstrates smoother growth post-2018, with reduced volatility during the 2022 market downturn.

While the new factor's cumulative IC slightly trails the original, its trajectory suggests **enhanced adaptability** to shifting market regimes, particularly in mitigating drawdowns during crises.

By prioritizing sub-factors with recent predictive strength, such as Safety during crises and Growth in expansions, the macro sensitivity of New Factor **minimizes overfitting** to historical economic regimes. The risk mitigation of New Factor, with **IC volatility reduced by 2.2%** compared to original, corresponds to slightly shallower drawdowns in portfolio backtestings.

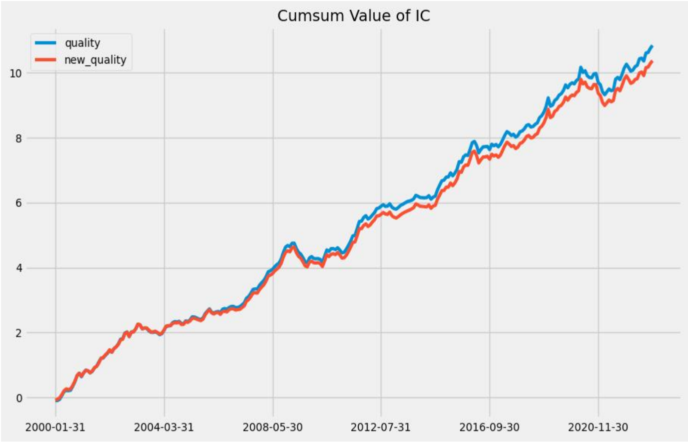

Figure 8 Cumulative IC of Original vs. New Quality Factor

6.4 Backtesting Performance Analysis: Original vs. Dynamically Weighted Quality Factor

The backtesting compares the performance of the original Quality factor and the dynamically weighted "New Quality" factor under a 130/30 long-short strategy (0.2% transaction costs, 2005-2022). Key metrics and cumulative portfolio values are analyzed to assess efficacy, risk-adjusted returns, and resilience.

Table 9 Backtesting Performance: Original vs. Dynamically Weighted Quality Factor

Factor	Mean Return (LS Active)	St. Dev. (LS Active)	RR Ratio (LS Active)	% Positive (LS Active)	Worst Month (LS Active)	Best Month (LS Active)	Max DrawDown (LS Active)
Quality	**0.0690**	**0.0684**	**1.0086**	**0.6435**	**-0.0795**	**0.0812**	**-0.2252**
New Quality	**0.0631**	**0.0680**	**0.9287**	**0.6204**	**-0.0803**	**0.0763**	**-0.2177**

In Annualized Mean Return, the original factor delivers marginally higher absolute returns. In Volatility, the new factor exhibits slightly lower volatility, suggesting improved risk management. In RR Ratio, the original factor's superior Sharpe ratio reflects better risk-adjusted returns. In Max Drawdown, the new factor demonstrates enhanced resilience during crises. In % Positive, the original factor has more consistent monthly outperformance.

The return-risk trade-off of Original factor, with a higher Sharpe ratio (1.0086 vs. 0.9287), highlights superior returns per unit of risk in stable markets like 2013-2019, while New factor's lower volatility and reduced maximum drawdown (-21.77% vs. -22.52%) enhance its defensive qualities in downturns. The original factor's consistency, shown by a higher positive-month ratio (64.35% vs. 62.04%), stems from its static approach, avoiding overfitting to fleeting market conditions.

6.5 Cumulative Portfolio Value Trajectories of 2 Strategies

Original Quality achieves a terminal value of 4.0x the initial investment, driven by strong performance in bull markets (e.g., 2017–2019). It experiences sharper drawdowns during crises (e.g., -23.8% in 2008, -14.1% in 2020).

New Quality matches the original factor's terminal value (4.0x) but follows a smoother growth trajectory. It Exhibits relative resilience in 2022 (-4.5%vs.Original's -5.2%), likely due to dynamic weightings tilt toward defensive sub-factors (e.g., Safety) during inflationary shocks. While the new factor's cumulative IC slightly trails the original, its trajectory suggests enhanced adaptability to shifting market regimes.

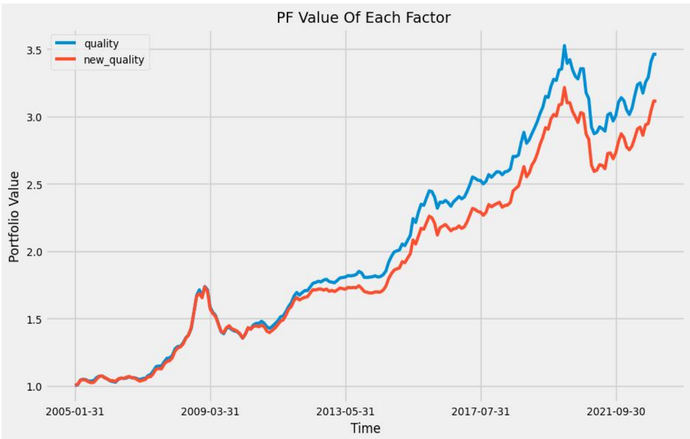

Figure 9 Cumulative Portfolio Value Trajectories

7. Reference

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8. Appendix

Figures for Statistical Analysis Section

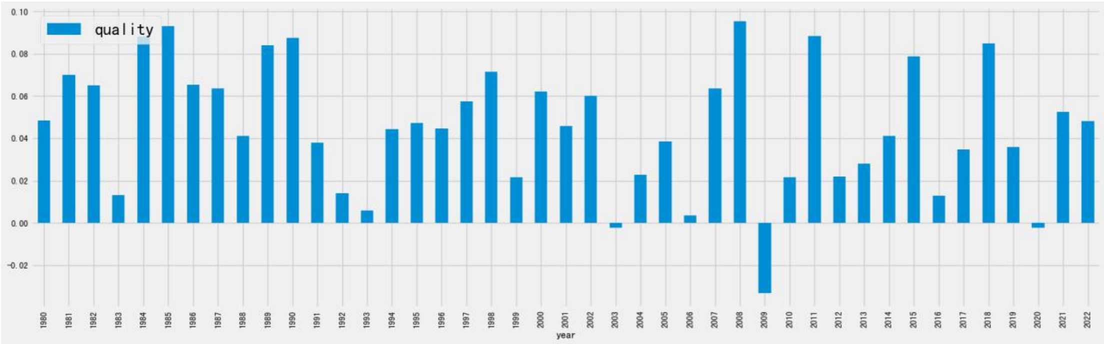

Figure 10 Annual Performance of the Quality Factor from 1980 to 2022

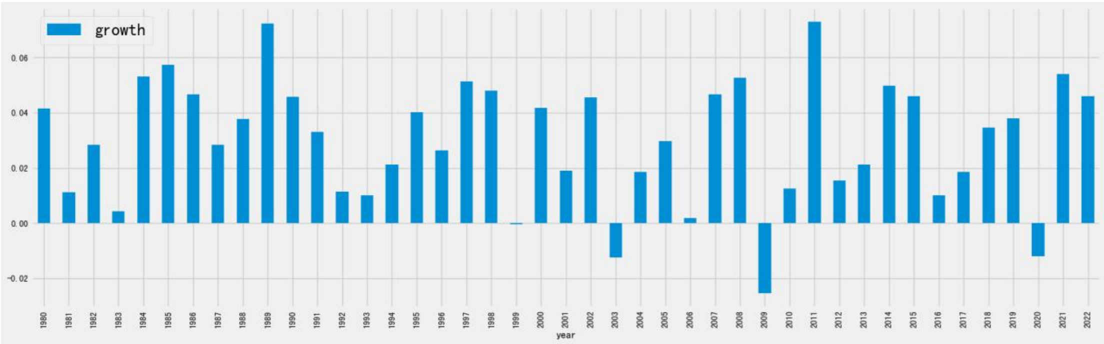

Figure 11 Annual Performance of the Growth Factor from 1980 to 2022

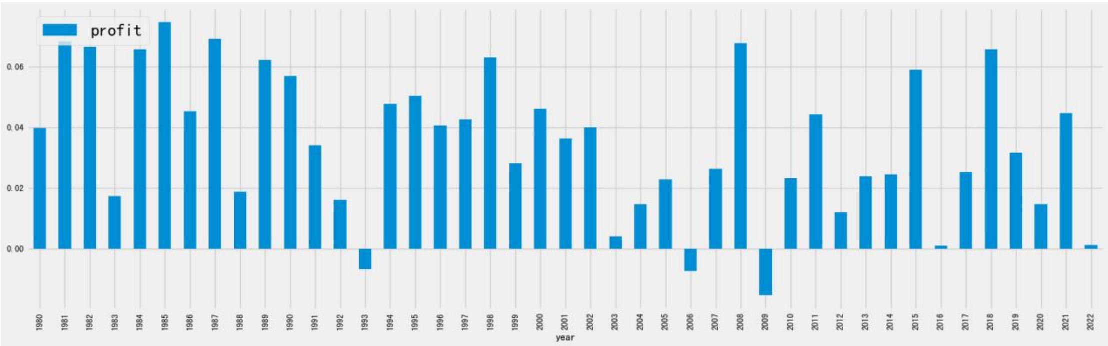

Figure 12 Annual Performance of the Profit Factor from 1980 to 2022

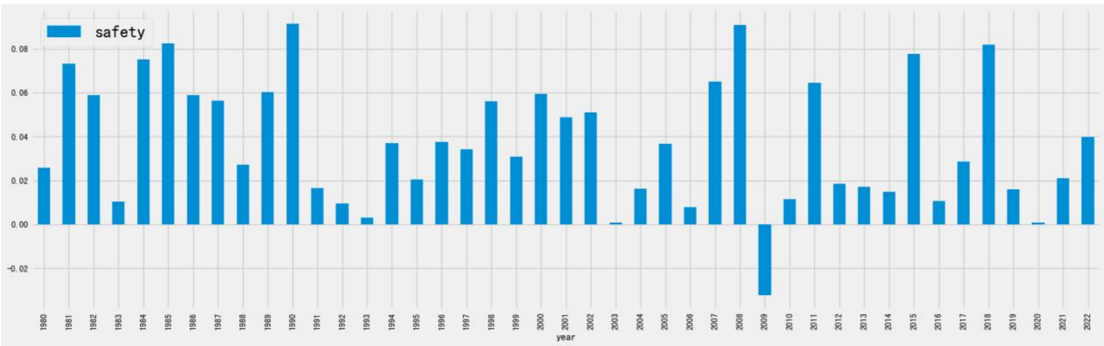

Figure 13 Annual Performance of the Safety Factor from 1980 to 2022

	Count	Mean	Std	Min	25%	50%	75%	Max
Quality	652353.0	3.043137e-15	1.000000	-6.132243	-0.608424	0.038396	0.677833	3.334571
Growth	652353.0	1.382072e-02	0.991523	-3.971933	-0.587068	0.145336	0.711582	2.388708
Profit	652353.0	2.477911e-01	0.653038	-5.665396	-0.110476	0.262270	0.656641	3.282973
Safety	652353.0	8.553072e-03	0.941070	-3.954088	-0.627943	-0.006272	0.668290	3.692792
RET	586230.0	1.313253e-02	0.150815	-0.981295	-0.053812	0.004828	0.068182	24.000000

Table 10 Descriptive Statistical Results of Quality, Growth, Profit, Safety, and RET Metrics

Figures for An Alternative Way to Combine the Factors Section

Marco_index	Poor_mean	Poor_std	Good_mean	Good_std	T_stat	Pvalue
INFL	3.041100	2.142265	3.534403	2.352870	-2.354012	0.018947
10YTR	5.189837	3.073104	6.034006	3.512208	-2.731658	0.006518
1YTR	3.697663	3.452692	4.883554	3.928530	-3.426225	0.000661
UNRATE	6.426087	1.904947	6.019880	1.700283	2.488819	0.013132
UMCSENT	85.465217	12.418631	86.288253	13.246921	-0.691084	0.489825

Table 11 Threshold 1 (IC < 0.02): Statistical Comparison of Economic Indicators Under Poor and Good Conditions

Marco_index	Poor_mean	Poor_std	Good_mean	Good_std	T_stat	P-value
INFL	2.834978	1.957959	3.533002	2.367321	-3.021573	0.002640
10YTR	4.880155	2.973446	6.017261	3.466682	-3.338086	0.000905
1YTR	3.348915	3.279944	4.831266	3.898607	-3.883937	0.000116
UNRATE	6.489147	2.011344	6.056589	1.691636	2.394807	0.016986
UMCSENT	85.558140	12.101999	86.140310	13.234397	-0.441789	0.658827

Table 12 Threshold 2 (IC < 0): Statistical Comparison of Economic Indicators Under Poor and Good Conditions