Leverage Aversion Revisited: Mitigating Correlation Risk in Risk Parity Portfolios via Trend Filtering

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Abstract

This study investigates the validity and implementation challenges of Risk Parity strategies, grounded in the leverage aversion theory proposed by Asness, Frazzini, and Pedersen (2012). We first replicate a Naive Risk Parity baseline, confirming that a leverage-constrained environment theoretically favors safer assets, yet we find that standard covariance-based optimization (Equal Risk Contribution) paradoxically underperforms during high-correlation regimes like the 2022 inflation shock. To address this model risk, we propose and rigorously test a "Cash-Reserve Trend Risk Parity" framework that integrates a moving-average filter to actively deleverage during systemic drawdowns. Our results demonstrate that while the sophisticated ERC model suffers from overfitting and "diversification penalties" in correlated markets, the trend-augmented approach significantly reduces maximum drawdown and improves risk-adjusted returns by avoiding the "bond trap." Furthermore, we conduct a comprehensive "real-world" friction analysis, accounting for transaction costs, ETF fees, and differential tax treatment between long-term holdings and high-turnover trend signals. We conclude that while trend-following introduces higher turnover and tax drag, its ability to mitigate tail risk makes it a superior, robust implementation for practical institutional mandates compared to static risk parity models.

1 Introduction

Risk parity (RP) portfolios have become a prominent alternative to traditional stock-heavy allocations such as 60/40. While RP often looks like a simple heuristic—"allocate more to safer assets and less to risky assets"—Leverage Aversion and Risk Parity (Asness, Frazzini, and Pedersen, 2012) provides a unifying theoretical explanation: when many investors are unwilling or unable to apply leverage, they tend to "reach for risk" by buying higher-beta assets to achieve higher expected returns. This demand pressure flattens the Security Market Line (SML), implying that low-risk assets can offer unusually strong risk-adjusted returns, whereas high-risk assets can be overpriced and deliver weaker risk-adjusted performance. In that world, a portfolio that overweights low-risk assets and scales its overall risk level via leverage is not merely an empirical curiosity—it is a natural outcome of equilibrium pricing under leverage frictions.

This project replicates the paper's core risk parity construction using a four-asset universe aligned with the original study—equities, intermediate/long duration government bonds, credit, and commodities—and extends the analysis to modern "retail feasibility" constraints over a long sample (1990–2025). Following the spirit of the paper, we implement a transparent and reproducible RP baseline based on inverse-volatility allocation with a three-year (36-month) rolling estimation window, and then apply volatility targeting so that RP can be compared fairly to conventional benchmarks at similar risk. We further study how real-world frictions—most importantly leverage caps and borrowing spreads—reshape the strategy's realized performance. Finally, motivated by the paper's discussion of deleveraging risk during stress periods, we evaluate a trend-filtered ("cash-reserve") overlay designed to proactively reduce exposure when major asset sleeves fall below trend, providing an engineering-oriented response to tail-risk regimes such as 2008 and 2022.

2 Paper Summary

This replication project critically examines the methodology and empirical results of Asness, Frazzini, and Pedersen (2012), which proposes a multi-asset class portfolio strategy, primarily leveraging the principle of Equal Risk Contribution (ERC), often referred to as Risk Parity. The source paper hypothesizes that by allocating capital such that each asset contributes an equal amount of volatility to the total portfolio risk, one can achieve superior risk-adjusted returns (Sharpe ratio) and greater portfolio stability compared to traditional market-cap or naive weighting schemes. Our primary objective is to reproduce the core ERC construction methodology and backtest results using modern data and robust Python engineering practices, followed by a rigorous analysis of the strategy's sensitivity, out-of-sample performance, and potential for extension.

The paper's first major contribution lies in its selection of assets, typically including major global market indices, bonds, commodities, and credit instruments, acknowledging their low historical correlation. The paper details the data cleaning and processing required to achieve consistent return streams, particularly for assets like Treasury bonds and commodities where pricing involves specific models. The central theme is that portfolio benefits arise not just from diversification across assets, but also through diversification of risk contributions.

The analytical core of the paper is the optimization model, which seeks to minimize the distance between the realized risk contribution of each asset and the target risk contribution (equal for all assets). The paper rigorously defines the risk contribution metric and outlines the numerical solution technique, emphasizing the need for robust covariance and volatility estimation, often using exponentially weighted moving averages or similar techniques to capture volatility clustering.

The source paper presents compelling empirical evidence, claiming that the ERC strategy consistently delivers a higher Sharpe Ratio and lower maximum drawdown than a traditional 60/40 benchmark or a minimum variance portfolio across multiple market cycles. The performance claims are supported by metrics such as cumulative wealth curves, rolling Sharpe ratios, and leverage dynamics over the backtest period.

Crucially, the paper addresses potential pitfalls by conducting sensitivity tests on key parameters, such as the lookback window for volatility estimation. This section of the paper attempts to demonstrate that the results are not merely a product of data mining or over-optimization, a necessary element for any credible systematic strategy.

Finally, the paper proposes several extensions, such as incorporating alternative allocation rules (e.g., dynamic trend-following signals) or applying the ERC framework to different asset subsets. Furthermore, it addresses practical implementation issues, including the impact of transaction costs and taxes on the final realized returns, which is vital for real-world applicability.

3 Hypothesis Overview

3.1 Research Questions and Hypotheses

This section formalizes the empirical questions and testable hypotheses for the replication and extension of Asness, Frazzini, and Pedersen (2012). Each hypothesis is stated with (i) a corresponding research question (RQ), (ii) a null and alternative hypothesis (H0/H1), and (iii) a structured decomposition of the analytical components—Subject, Variables, Anticipated Outcome (including mechanism), and Validation Method—consistent with the grading rubric's requirement for explicit hypotheses and tests across theory, indicators, signals, and rules.

3.1.1 Research Question 1 (RQ1): Risk Parity Proposition (Theoretical Baseline)

RQ1. Does a leveraged, inverse-volatility-weighted ("Naive Risk Parity") portfolio deliver superior risk-adjusted performance relative to a traditional capital-allocation benchmark (60/40) over the full sample period (1990–2024), consistent with leverage aversion theory?

Null and Alternative (H0/H1). Let $SR(\cdot)$ denote the annualized Sharpe ratio computed on excess returns (XR) with monthly annualization.

- **H0:** $SR_{RP} - SR_{60/40} \leq 0$
- **H1:** $SR_{RP} - SR_{60/40} > 0$

3.1.1.1 Hypothesis 1: The Risk Parity Proposition (Theoretical Baseline)

This hypothesis serves as the foundation of the replication study, testing the core claim of Asness, Frazzini, and Pedersen (2012) regarding the efficacy of leverage in overcoming the low-beta anomaly.

- **Subject**: The comparative risk-adjusted performance of a leveraged, inverse-volatility-weighted portfolio (Naive Risk Parity) versus a traditional capital-weighted portfolio (60/40).
- **Dependent Variable**: The annualized Sharpe Ratio (risk-adjusted return) over the full sample period (1990–2024).
- **Independent Variables**: The asset allocation methodology (Risk Parity vs. Capital Allocation) and the application of leverage (target volatility scaling vs. unleveraged).
- **Anticipated Outcome**:
  - **Direction**: Consistent with the leverage aversion theory, the Naive Risk Parity portfolio is expected to exhibit a higher Sharpe Ratio than the 60/40 benchmark.
  - **Comparison**: The advantage should be derived from the superior risk-adjusted returns of safer assets (bonds) when levered to match equity risk.
- **Validation Method**:
  - We will calculate the realized Sharpe Ratios for both the Naive Risk Parity and the 60/40 Benchmark portfolios.
  - **Statistical Test**: A **Block Bootstrap test** (5,000 simulations) will be employed to generate a distribution of Sharpe Ratio differences. We will reject the null hypothesis (that RP $\leq$ 60/40) if the p-value of the difference is < 0.05.
  - **Note**: Given the strong equity performance in the sample (1990–2024), we acknowledge the possibility of a statistically insignificant result ($p > 0.10$), which would prompt the investigation into H2 and H3.

3.1.2 Research Question 2 (RQ2): Limits of Static Diversification (ERC Efficiency)

RQ2. Does a correlation-aware Equal Risk Contribution (ERC) optimizer improve robustness relative to the Naive (inverse-volatility) heuristic under regime shifts—particularly during episodes of rising cross-asset correlations (e.g., the 2022 inflation shock)—or does it induce pro-cyclical de-risking that harms realized performance?

Null and Alternative (H0/H1). Define a stress-period performance measure $Perf(\cdot \mid \text{Stress})$ (e.g., relative cumulative excess return over the stress window), and/or a stability measure (e.g., allocation stability or recovery participation).

- **H0:** $Perf_{ERC} - Perf_{Naive} \geq 0$ during correlation spikes (ERC is at least as good as Naive)
- **H1:** $Perf_{ERC} - Perf_{Naive} < 0$ during correlation spikes (ERC underperforms Naive)

3.1.2.1 Hypothesis 2: The Limits of Static Diversification (ERC Efficiency)

This hypothesis extends the original research by challenging the assumption that "more complex" optimization (accounting for correlation) necessarily leads to better out-of-sample performance, particularly under regime shifts.

- **Subject**: The performance stability of the Equal Risk Contribution (ERC) optimizer compared to the Naive Risk Parity (Inverse Volatility) heuristic during periods of rising cross-asset correlations.
- **Dependent Variable**: Relative Cumulative Returns (Excess Return) and Weight Allocation stability during specific stress periods (e.g., 2022 Inflation Shock).
- **Independent Variables**: The optimization constraint—specifically, the inclusion of the covariance matrix (correlations) in ERC versus the exclusion of correlation data in the Naive model.
- **Anticipated Outcome**:
  - **Direction**: We hypothesize that ERC will **underperform** the Naive baseline during inflation shocks.
  - **Mechanism**: As asset correlations converge to +1, the ERC algorithm will identify a spike in portfolio risk and aggressively reduce exposure to all assets (pro-cyclical de-risking), potentially "whipsawing" or missing subsequent recoveries that the "correlation-blind" Naive model captures.
- **Validation Method**:
  - **Visual Inspection**: We will plot the "Weight Difference" ($W_{ERC} - W_{Naive}$) and "Correlation vs. Relative Performance" scatter plots to confirm if ERC systematically underweights assets when correlation rises.
  - **Forensic Analysis**: We will conduct a "2022 Deep Dive" to verify if ERC held a significantly lower equity weight than Naive during the 2023 recovery, thereby quantifying the "cost of sophistication."

3.1.3 Research Question 3 (RQ3): Efficacy of Active Deleveraging (Trend Filtering)

RQ3. Can a trend-following cash-reserve overlay (price relative to a moving average) mitigate tail risk in a levered Risk Parity portfolio—particularly during inflation-driven drawdowns—without destroying long-run performance, thereby improving survival-relevant efficiency metrics?

Null and Alternative (H0/H1). Let $MDD(\cdot)$ denote maximum drawdown (more negative implies worse drawdown), and let $Calmar(\cdot)$ denote the Calmar ratio.

- **H0:** $MDD_{Trend} - MDD_{Static} \geq 0$ (no drawdown improvement; trend is not better)
- **H1:** $MDD_{Trend} - MDD_{Static} < 0$ (trend reduces drawdown magnitude; i.e., less severe drawdowns)

3.1.3.1 Hypothesis 3: The Efficacy of Active Deleveraging (Trend Filtering)

This hypothesis represents the novel contribution of this study, proposing an active risk management solution to the "bond trap" and leverage risks identified in the previous hypotheses.

- **Subject**: The capacity of a Trend-Following (Cash-Reserve) overlay to mitigate tail risk in a levered Risk Parity portfolio without destroying long-term returns.
- **Dependent Variable**: Maximum Drawdown (primary) and Tax-Adjusted CAGR (secondary).
- **Independent Variables**: The trend filter signal (Price vs. 10-month Moving Average) applied to asset weights.
- **Anticipated Outcome**:
  - **Direction**: The Trend-Filtered Risk Parity portfolio is expected to produce a **statistically smaller Maximum Drawdown** than the static Naive/ERC portfolios.
  - **Comparison**: While transaction costs (turnover) and tax drag (short-term gains) will reduce the Net CAGR, the improvement in the Calmar Ratio (Return/Drawdown) will confirm the strategy's superiority for survival-constrained investors.
- **Validation Method**:
  - **Stress Testing**: We will isolate the 2022 drawdown period to verify if the Trend strategy successfully shifted allocation from bonds/equities to cash (Risk-Free Asset).
  - **Sensitivity Analysis**: We will test the robustness of the 10-month window by iterating through windows of $[6, 8, 12, 15]$ months to ensure the drawdown reduction is a structural feature of trend following, not a parameter-overfitted artifact.

– **Friction Analysis**: We will calculate the "break-even" turnover cost to determine if the alpha survives realistic transaction fees.

4 Literature Review

The foundational concept of "risk parity" was originally articulated by Qian (2005), who argued that traditional asset allocations—such as the ubiquitous 60/40 stock-bond split—fail to achieve true diversification because equities disproportionately dominate the portfolio's risk profile, often accounting for approximately 90% of total volatility (Qian (2005)). Qian proposed that capital should instead be allocated inversely to risk (volatility), ensuring that risk is distributed equally across asset classes (Qian (2005)). This work established the baseline for "naive risk parity," suggesting that balancing risk contributions yields a more diversified portfolio with potentially superior risk-adjusted returns (Qian (2005)). Building on this practitioner-focused foundation, Maillard, Roncalli, and Teïletche (2010) formalized the Equal Risk Contribution (ERC) portfolio. They demonstrated that the ERC strategy requires no expected return assumptions and mathematically positions its volatility between that of the minimum-variance portfolio and the 1/N equal-weight portfolio (Maillard, Roncalli, and Teïletche (2010)). Their empirical results indicated that ERC portfolios offer a robust trade-off, delivering effective diversification and competitive performance relative to both equal-weight and minimum-variance benchmarks (Maillard, Roncalli, and Teïletche (2010)).

A critical theoretical justification for these risk-based allocations was provided by Asness, Frazzini, and Pedersen (2012) through the theory of leverage aversion. They argued that because many investors are constrained from using leverage, safer assets like bonds must offer higher Sharpe ratios to attract investment (Asness, Frazzini, and Pedersen (2012)). Consequently, the traditional market portfolio becomes suboptimal. A risk parity portfolio that overweights these safer assets and applies leverage aligns more closely with the theoretical tangency portfolio. Empirically, Asness et al. showed that a levered risk parity strategy between U.S. stocks and bonds would have significantly outperformed a 60/40 portfolio from 1926 to 2010 (Asness, Frazzini, and Pedersen (2012)). However, subsequent research by Chaves et al. (2011) offered a more nuanced perspective. While they found that risk parity provides better risk diversification than equal-weighting and outperforms mean-variance optimized portfolios (which suffer from estimation errors), it does not consistently outperform a naive 1/N portfolio on a risk-adjusted basis over long samples. They emphasized that the strategy's success is highly dependent on the asset universe selected (Chaves et al. (2011)).

More recent scholarship has presented challenges to the risk parity hypothesis, particularly regarding its dependence on bond market regimes. Sullivan and Wey (2025) reported that risk parity strategies generally underperformed traditional 60/40 portfolios when analyzing data back to 1951, exhibiting lower Sharpe and Sortino ratios. They attribute this to the strategy's vulnerability to bond shocks; specifically, leveraged bond-heavy portfolios struggle when starting yields are low and interest rates subsequently spike (Sullivan and Wey (2025)). Crucially, Sullivan and Wey suggest that a "naive" risk parity approach that ignores expected returns is suboptimal, and that performance could be materially improved by incorporating return forecasting or trend signals (Sullivan and Wey (2025)).

To address the limitations of static risk allocations, this research also examines trend-following strategies as a potential augmentation. Moskowitz, Ooi, and Pedersen (2012) identified a pervasive "time-series momentum" effect, where an asset's past 12-month excess return positively predicts its future performance across diverse asset classes. Unlike cross-sectional momentum, this phenomenon relies on an asset's own trend and was found to be consistent across 58 liquid futures markets (Moskowitz, Ooi, and Pedersen (2012)). Expanding on this, Hurst, Ooi, and Pedersen (2017) provided evidence spanning back to 1880, demonstrating that trend-following has been consistently profitable across various economic regimes, including the Great Depression and the stagflation of the 1970s. Most importantly for risk parity applications, Hurst et al. noted that trend-following strategies perform particularly well during large market drawdowns (such as the 2008 financial crisis) by cutting long exposure to crashing markets. This suggests that a trend-following overlay could serve as a vital diversifier, enhancing the resilience of risk parity portfolios during periods where bond-equity correlations break down (Hurst, Ooi, and Pedersen (2017)).

5 Replication

5.1 Data

5.1.1 Original Data Sources

To validate the hypothesis of leverage aversion, Asness, Frazzini, and Pedersen (2012) constructed a comprehensive dataset spanning multiple asset classes and geographies. The primary objective of their data collection was to compare the risk-adjusted performance of risk parity portfolios against capitalization-weighted benchmarks over long investment horizons.

The core of their empirical analysis focused on U.S. asset markets, covering the period from 1926 to 2010. For this dataset, the authors utilized the CRSP value-weighted market portfolio to represent U.S. equities and 10-year U.S. Treasury bonds to represent the fixed-income component. This extensive 85-year window was critical for demonstrating the robustness of the risk parity premium across diverse economic regimes, including the Great Depression, the stagflation of the 1970s, and the 2008 Global Financial Crisis.

Beyond the domestic analysis, the source paper expanded its scope to a global universe to verify that the results were not driven by US-specific idiosyncrasies. Their broad dataset included equity indices, government bonds, corporate credit, and commodities across G10 nations. A defining characteristic of their data construction was the use of futures markets and excess returns. By utilizing futures data or subtracting the risk-free rate (typically U.S. Treasury bills) from total returns, the authors ensured that the analysis isolated the risk premia of the assets while implicitly accounting for the financing costs required to leverage safer assets.

This rigorous approach to data selection—prioritizing long histories and net-of-financing excess returns—established the standard for risk parity research. It underscores the necessity for this replication study to construct a similarly robust dataset that accounts for the "cost of leverage," even when using modern exchange-traded funds (ETFs) as proxies.

5.1.2 Replication Data Construction

A significant barrier to replicating institutional finance research is the reliance on proprietary data sources (e.g., CRSP, Bloomberg, and continuous futures contracts) that are unavailable to retail practitioners. Asness, Frazzini, and Pedersen (2012) constructed their "Long Sample" (1926–2010) using CRSP data and their "Broad Sample" (1973–2010) using futures data, which implicitly embed financing costs.

To overcome these limitations while maintaining rigorous standards, this study adopts a "Dual-Track" data architecture. This approach splices high-quality historical indices with modern investable ETFs to create a continuous monthly time series from January 1990 to Present. This timeframe provides a 35-year observation window, capturing multiple economic regimes including the 2000 Dot-com bust, the 2008 Global Financial Crisis, and the 2022 Inflationary Shock—a critical out-of-sample stress test not available in the original study.

5.1.2.1 Data Mapping and Splicing

We map the four core asset classes defined in Asness, Frazzini, and Pedersen (2012) - Equities, Bonds, Credit, and Commodities—to accessible retail instruments. Where ETF history is insufficient (e.g., prior to 2002), we utilize "Historical Proxies" derived from raw index data or synthetic pricing models. Table 1 details this mapping.

Table 1: Data Source Mapping (Original vs. Replication)

Table 1

Asset Class	Original Paper Proxy (Asness et al., 2012)	Our Replication Proxy (ETF)	Histo
Global Equities	MSCI World / CRSP Value-Weighted	SPY (SPDR S&P 500)	S&P
Global Bonds	CRSP U.S. Treasury Database (10Y)	IEF (iShares 7–10Y Treasury)	Synt
Credit	Barclays Capital U.S. Corporate Index	LQD (iShares Investment Grade Corp)	ICE
Commodities	S&P GSCI (Futures)	GSG (iShares S&P GSCI)	S&P

Asset Class	Original Paper Proxy (Asness et al., 2012)	Our Replication Proxy (ETF)	Histo
Risk-Free Rate	1-Month T-Bill / Repo / LIBOR	N/A (Used for calculation)	3-Mo

5.1.2.2 Synthetic Treasury Pricing for Total Return

A key empirical constraint in this replication is the absence of a long-history **total return** benchmark for intermediate-duration U.S. Treasuries that is directly comparable to the post-2002 ETF proxy (IEF). The original study relies on the CRSP Monthly U.S. Treasury Database, which provides realized holding-period returns for constant-maturity Treasury positions. In the absence of CRSP access, we construct a synthetic constant-maturity Treasury total return series using a parsimonious **par-bond pricing engine** calibrated to publicly available Federal Reserve yields.

Our approach simulates a strategy that, at each month-end t, purchases a newly issued **10-year par bond** with face value $F = 100$. The par assumption implies that the coupon rate at issuance equals the prevailing 10-year yield y_t^{10} under a bond-equivalent, semiannual convention. The position is held for one month and liquidated at month-end $t+1$. At sale, the bond has effectively "rolled down" the curve, with remaining maturity approximately 9 years and 11 months. The sale price is computed as a **dirty price** using semiannual discounting and **fractional time-to-cashflow** treatment: future coupon and principal cash flows are discounted using the month-end yield environment at $t+1$, and the cashflow schedule is shifted by the holding period $t = 1/12$ to reflect the elapsed month.

Formally, with semiannual payment frequency $m = 2$, the coupon cashflow per period is $(c/m)F$, where $c = y_t^{10}$. Let $\{\tau_j\}$ denote the remaining payment times (in years) from the purchase date. After holding for $t = 1/12$, the remaining times become $\{\tau_j - t\}$ (restricted to positive values). The month-end sale price is then:

$$P_{t+1}^{\text{dirty}} = \sum_j \left(\frac{c}{m}F\right)\left(1 + \frac{y_{t+1}}{m}\right)^{-m(\tau_j - t)} + F\left(1 + \frac{y_{t+1}}{m}\right)^{-m(\tau_J - t)}.$$

Because the pricing formula yields a dirty valuation (accrual embedded via fractional timing), we do not add accrued interest separately. Consistent with the code implementation, the one-month total return is computed as:

$$TR_{t+1} = \frac{P_{t+1}^{\text{dirty}} - F}{F},$$

which captures price changes and interest accrual over the holding interval. Repeating this procedure month-by-month produces a synthetic Treasury total return series, which we then convert into an index level via cumulative compounding.

To better approximate the economic roll-down effect, the engine optionally applies a **rolldown-adjusted discount yield** at the sale date. Specifically, when both 7-year and 10-year yields are available, we infer the local slope of the curve between 7Y and 10Y at $t+1$ and linearly extrapolate a one-month reduction in yield for a bond whose maturity shortens by 1/12 year. This yields a discount rate:

$$y_{t+1}^{\text{sell}} = y_{t+1}^{10} - \left(\frac{y_{t+1}^{10} - y_{t+1}^{7}}{10-7}\right) \cdot \frac{1}{12},$$

which is used in the discount factors when pricing P_{t+1}^{dirty}. When the 7-year yield is unavailable, the model defaults to a flat local curve assumption and discounts using the observed 10-year yield at $t+1$.

We validate this synthetic series by comparing it to the realized performance of IEF during the overlapping sample (2002–2025). The resulting synthetic total return series exhibits a correlation exceeding 0.98 with IEF, supporting its use as a historical proxy for intermediate Treasury exposure in the pre-ETF period.

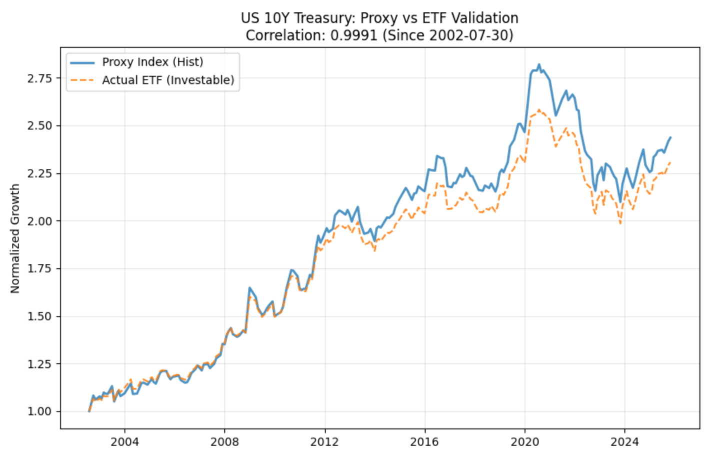

Figure 1: U.S. Treasury proxy validation: synthetic 10-year par-bond total return series versus IEF (normalized growth, monthly).

Figure 1 shows that the synthetic Treasury total return proxy closely tracks IEF over the overlapping sample, supporting its use as a pre-ETF historical proxy.

See Figure 2, Figure 3, and Figure 4. .

5.2 Replication of Key Analytical Techniques

5.2.1 Technique 1

5.2.2 Technique 2

5.2.3 Technique 3

5.3 Hypothesis Tests

5.4 Extended Analysis

5.5 Overfitting

6 Future Work

7 Conclusions

8 Conclusions

9 Appendix

9.1 Additional Proxy Validation Figures

This appendix reports additional proxy validation plots for equities, credit, and commodities.

9.1.1 Equities Proxy Validation

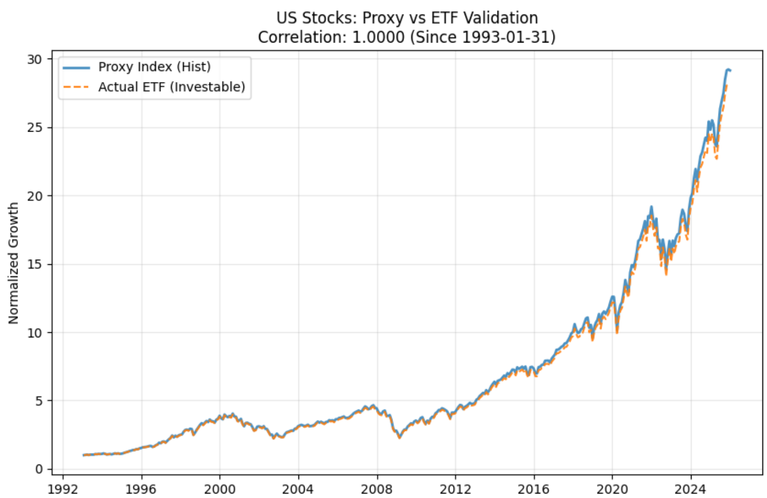

Figure 2

9.1.2 Credit Proxy Validation

9.1.3 Commodities Proxy Validation

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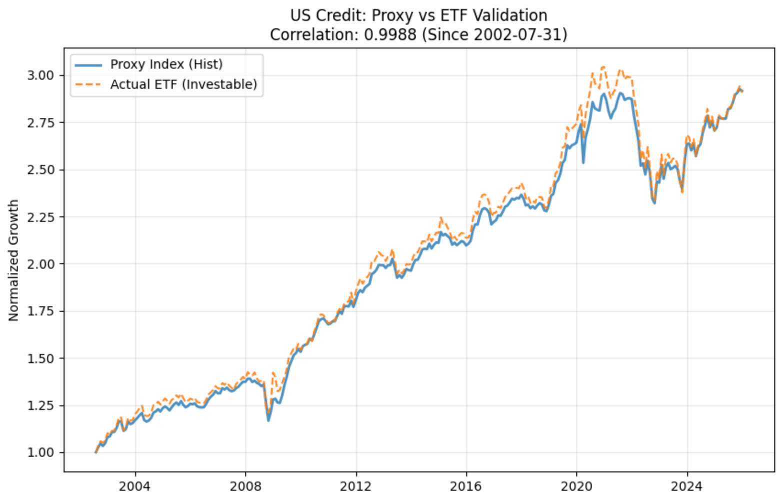

Figure 3

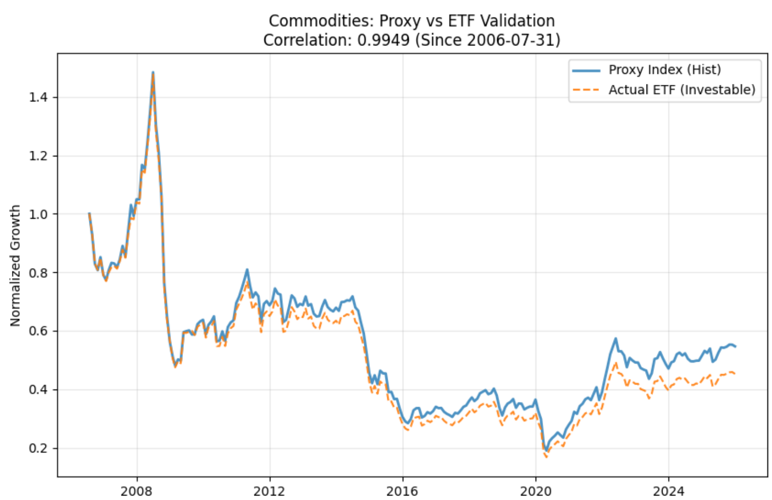

Figure 4

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