Backtesting Factor-Based Trading Strategies

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Abstract

This report explores factors from Momentum, Investment, Profitability, and Value vs Growth categories, and tests the effectiveness of factor-based trading strategies through the traditional Fama-MacBeth cross-sectional regression and a machine learning algorithm, Random Forest. The backtesting results reveal that Tax Expense Surprise, On-Balance-Volume, and Asset-to-Market demonstrate robust performance in predicting stock returns. By leveraging Fama-MacBeth t-statistics, Random Forest feature importances, and categorization, the trading strategy incorporates Tax Expense Surprise, On-Balance-Volume, Asset-to-Market, Liquidity Adjusted Debt, and Stochastic Oscillator. Performance analysis on hedge portfolios generated among the Fama-MacBeth cross-sectional regression, Random Forest, and the ensemble approach, indicates that the best results are achieved by the ensemble approach of linear regression and Random Forest, with a strong Sharpe ratio of 3.1838 and an Information ratio of 1.0989.

1. Introduction

With a rich landscape of investment strategies and the changing trend in portfolio management methods, this study aims to apply factor investing and develop a novel model to improve portfolio outcomes. The research builds on the framework of factor investing models to discover and test factors that support better predictions about the effectiveness and robustness of investment portfolio returns. By leveraging Fama-MacBeth cross-sectional regression and machine learning models such as Random Forest, the paper will test the predictive ability of factors chosen and backtest the portfolio strategy over long periods of history that cover decades of market data. The main objective is to develop and refine portfolio strategies that exploit market inefficiencies and adapt to changing market dynamics. The aim is also to introduce new knowledge about asset returns by integrating ML models into the backtesting process, thus providing investors with actionable insights for efficient and forward-looking navigation through financial markets. This unique approach aspires to enhance portfolio management methodologies, enabling sustainable wealth creation for investors.

2. Factors

This project discusses Momentum, Investment, Profitability, and Value vs Growth factors.

2.1 Momentum

2.1.1 Tax Expense Surprise (TES)

TES measures the difference between a company's actual tax expenses and the market's expectations. Thomas and Zhang (2011) suggested TES as a dependable indicator of future stock returns. High TES values signal better tax management and potentially lead to increased investor confidence and stock price; low TES values, on the other hand, signal an overestimation and may bring skepticism and a stock value drop.

2.1.2 On-Balance-Volume (OBV)

OBV tracks cumulative buying and selling pressure by subtracting down volume from from up volume. A rising OBV indicates the probable continuation of the current price trend, while a falling OBV signals a potential price trend reversal. Ijegwa et al. (2014) uncovered OBV's ability to predict price movements and identify volume trends.

2.1.3 Stochastic Oscillator (STO)

STO reflects the relationship between volume flow and stock price movements by comparing the closing price of a stock to its price range over a period. STO ranges from 0 to 100, where above 80 when overbought and below 20 when oversold. High STO values signal a potential reversal in its price trend. This underscores its predictive utility in reflecting the market's evaluation of stock conditions over time (Ijegwa et al., 2014).

2.2 Investment

2.2.1 Change in Net Operating Assets (DNOA)

DNOA evaluates shifts in a company's operating efficiency by finding the 1-year-lagged Net Operating Assets (NOA), where NOA is the difference between Operating Assets and Operating Liabilities. An increase in DNOA signifies a firm is expanding its operational base faster than its growth in total assets, which may reflect aggressive growth strategies or underutilized assets. Conversely, a decrease suggests improved asset efficiency or tightening operational focus. The work by Hirshleifer et al. (2004) provides empirical evidence of the influence of operational efficiency on stock returns.

2.2.2 Net Stock Issues (NSI)

NSI measures the net change in a company's outstanding shares due to stock issuances and repurchases over a specified period. It is calculated by taking the natural log of the ratio of the split-adjusted shares outstanding at t-1 to that at t−2. Pontiff and Woodgate (2008) showed that NSI exhibits a strong cross-sectional ability to predict stock returns. If more shares are issued than repurchased, NSI is positive: signaling a dilution of existing shareholders' ownership and a potential stock return drop. In contrast, a negative NSI reflects confidence in the company's prospects or a desire to return excess cash to shareholders, which enhances stock returns.

2.2.3 Tobin’s Q Ratio (ToQ)

ToQ ratio discerns a firm’s market valuation relative to its asset base (Gharaibeh and Qader, 2017). A ratio greater than 1 suggests that the market values the company more than its replacement cost, indicating potential bad financial health and overvaluation. An increasing ToQ ratio may indicate improving market sentiment and confidence in a firm’s prospects. As such, the ratio can be a factor in predicting investment opportunities and influencing investor decisions and stock returns.

2.3 Profitability

2.3.1 Gross Profit Over Asset (GPOA)

GPOA measures how efficiently a firm utilizes its assets to generate earnings. It is calculated by dividing the difference between Total Quarterly Revenue and Cost of Goods Sold by Total Assets. Asness et al. (2019) highlighted GPOA’s use in evaluating a firm’s operational efficiency. Generally, a higher ratio indicates better operational efficiency and higher profitability, which can increase stock returns as investors may perceive the company as more valuable and efficient.

2.3.2 DuPont Analysis

DuPont Analysis assesses the operational and financial strengths of a firm and identifies areas for improvement (Chang et al. 2014). It deconstructs a company’s Return on Equity (ROE) into 3 distinct components which reveal profitability, asset efficiency, and financial leverage to shape shareholder returns. Firms valued high from DuPont analysis are perceived as financially robust and potentially have higher stock prices and returns. In contrast, weaknesses detected through DuPont analysis may predict poorer stock performance.

2.4 Value-vs-Growth

2.4.1 Asset-to-Market (AM)

The AM ratio reflects the relationship between a company's total assets and its market value. High AM ratios suggest undervaluation of firms (i.e., value stocks), while low ratios indicate overvaluation (i.e., growth stocks) (Obreja, 2013). Research by Pontiff and Schall (1998) provided empirical evidence of the enduring relevance of the AM ratio in predicting stock returns over extended periods: high ratios predict market and small firm excess returns, reflecting investors' preferences for undervalued stocks. This predictive power is attributed to the market's mispricing of stocks and the relation between book value and future earnings.

2.4.2 Liquidity Adjusted Debt (LIQ)

LIQ ratio assesses a company's ability to meet its debt obligations by considering both its liquid assets and its debt. A lower LIQ suggests that the company has a stronger ability to cover its debt obligations with its liquid assets. Such ability is perceived as attractive by investors and potentially leads to higher stock returns (Chabachib et al., 2020). A higher LIQ signals higher financial risk as the company may have limited liquidity to cover its debt obligations and, thus, may negatively affect the stock price.

2.4.3 Debt-to-Market (DM)

DM ratio measures a company's financial leverage by comparing its total debt to its market capitalization. A high DM underlies that the company is leveraging debt to finance growth opportunities. If these investments yield returns higher than the cost of the debt, the firm's stock price will rise; if these investments fail to yield the expected return, the stock returns may decrease (Kamar, 2017).

3. Trading Strategy

The trading strategy is developed based on the analysis of factor premia from the Fama-MacBeth cross-sectional regression during the in-sample period, as detailed in Exhibit 1. Factors TES, OBV, and AM demonstrate strong significance in predicting stock returns with t-statistics substantially exceeding 1. LIQ and STO exhibit moderate predictive power with t-statistics around 0.9. In contrast, t-statistics for other factors, GPOA, DNOA, NSI, ToQ, DM, and Dup, are low, indicating a weak correlation with stock returns. Feature importances derived from Random Forest further validate the predictive strengths of OBV, STO and AM, as presented in Exhibit 2.

Extended to factor categories and investment preference, the trading strategy focuses on momentum and value versus growth as strong historical performance demonstrates the effectiveness of momentum strategies and value stocks typically outperform growth stocks in long-term investment. Research by Robert et al. (2023) emphasized the robust performance of the cross-sectional factor momentum strategy with an average monthly alpha of 0.62 and a t-value of 5.95. Additionally, Hou, Xue, and Zhang (2018) documented a momentum strategy replication rate of 63.2%, over the other five categories, and a moderate replicate rate of 42% for value versus growth strategies.

Furthermore, the chosen factors are independent yet complementary, AM focuses on capitalizing on growth opportunities, while LIQ aims to reduce exposure to potential financial distress. TES, a forward-looking indicator, signals changes in profitability and financial efficiency and offers deeper insights into a company's operational and financial health when combined with AM and LIQ. In addition, the volume-based indicator OBV and the price-based metric STO provide comprehensive insights into market sentiment and potential price movements.

Therefore, considering t-statistics, signal signs, and categories, the trading strategy is constructed by longing factors including **TES, OBV, AM, LIQ, and STO**. By leveraging factors from diverse categories, this strategy offers a multifaceted view of potential stock returns, allowing for diversified risk management and the ability to capitalize on different aspects of the market and company performance.

4. The Experimental Methodology

4.1 Data Overview

This research assesses the performance of various factors and trading strategies using common stocks from the NYSE and Nasdaq from January 1985 to December 2019, accessed via the WRDS CRSP database. The analysis excludes illiquid stocks, specifically those with a price below $5 or a market capitalization under $100 million at the start of each January in the forecasting period. The dataset includes a training period from January 1985 to December 2009 (300 months), and a testing period from January 2010 to December 2019 (120 months). To ensure data consistency, stocks that were continuously listed throughout the entire study period from 1983 to 2019 were selected, starting two years before the beginning of the training period for a sufficient look-back period. ß

4.2 Data Preprocessing

Factor-related metrics were extracted from the WRDS Compustat quarterly database from 1983 to 2020. Each factor was standardized by the industry, using the mean and standard deviation to normalize the data in each month, to mitigate the impact of differing units across factors.

Market-related metrics, including market return, risk-free rate, SMB, HML, and UMD, were sourced from the WRDS Fama-French 5-factor dataset, aligning with widely accepted finance models and benchmarks.

4.3 Factor Selection

Factors considered at the initial stage included TES, OBV, STO, DNOA, NSI, ToQ, GPOA, DuP, AM, LIQ, and DM. This study utilized Fama-Macbeth cross-sectional regressions to evaluate factor premia and a Random Forest algorithm to assess feature importances. Factors such as DNOA, NSI, ToQ, GPOA, DuP, and DM were excluded based on their low t-statistics(i.e. not significant in stock returns).

4.4 Portfolio Construction

Stocks were ranked according to predicted returns derived separately from linear regression and Random Forest models, as well as an ensemble approach that considers results from both methods. Three equal-weighted hedge portfolios (linear regression portfolio, Random Forest portfolio, and linear regression & Random Forest portfolio) were constructed by longing on the top 10% and shorting on the bottom 10% of stocks, based on their respective predicted returns. Portfolios were rebalanced monthly to reflect updated rankings and predictions.

4.5 Portfolio Performance Testing

The performance of three hedged portfolios throughout the out-of-sample period (2010-2019) was evaluated using several metrics: Raw return (total returns over these 10 years), Sharpe ratio (risk-adjusted performance), CAPM alpha (returns relative to the broader market), 4-Factor alpha (returns against a multi-factor risk model), and Information Ratio (effectiveness of the active strategies). These metrics collectively provide a comprehensive evaluation of the effectiveness of the selected trading strategies under various market conditions and risk scenarios.

5. Results and Discussion

5.1 Linear Regression Portfolio

As depicted in Exhibit 3, the linear regression portfolio achieved a raw return of 1.1353% and a Sharpe ratio of 1.1499 from 2010 to 2020, indicating commendable risk-adjusted performance. CAPM and the 4-Factor Fama-French model alphas of 0.006359 and 0.006912, respectively, suggest that the portfolio outperforms both the market and the multi-factor risk model. However, a negative information ratio of -0.1695 indicates the portfolio failed to surpass the benchmark.

Exhibit 6 reveals that the returns of the linear regression portfolio consistently trailed the market returns during peaks of the overall market (i.e. bull market). This trend is attributed to the portfolio's long position in value stocks, primarily driven by AM and LIQ, while value stocks typically underperform growth stocks in such conditions. Conversely, during recessions, the factors OBV and STO effectively captured downward trends, allowing for timely exits during rebalancing that enabled the portfolio to outperform the market. This pattern of underperformance in bull markets and overperformance in bear markets reduces the portfolio's volatility. Additionally, the strong pre-COVID-19 bull markets and the relatively stable recovery following the 2008 financial crisis contributed to the negative information ratio.

However, the portfolio exhibited significant volatility in 2016 and 2017, as shown in Exhibit 6, coinciding with consecutive interest rate increases. This volatility can be attributed to the portfolio's sensitivity to interest rates, which is influenced by debt-related factors LIQ and TES.

Overall, the linear regression portfolio is particularly suitable for investors anticipating market downturns or impending recessions.

5.2 Random Forest Portfolio

The Random Forest Portfolio demonstrates significant outperformance relative to the market, as well as the CAPM and FF4 models, as illustrated in Exhibit 4. Key performance metrics include a raw return of 2.7614%, a Sharpe ratio of 2.9992, and an information ratio of 0.8873, with CAPM and FF4 alphas of 0.02256 and 0.02305, respectively.

Furthermore, the Random Forest portfolio markedly surpasses the linear regression portfolio, suggesting the presence of strong non-linear relationships between factors and stock returns and the Random Forest model captures these non-linear relationships effectively. Exhibit 7 highlights the portfolio's enhanced performance during bull markets while maintaining low volatility. This performance suggests the Random Forest model's ability to leverage complex interactions among variables in various market conditions.

5.3 Linear Regression & Random Forest Portfolio

The linear Regression & Random Forest Portfolio showcases the best performance among these three portfolios, as detailed in Exhibit 5. This ensemble approach yields a raw return of 3.0102%, a Sharpe ratio of 3.1838, a CAPM alpha of 0.02371, an FF4 alpha of 0.02484, and an information ratio of 1.0989. This superior performance is attributed to the combination of the strengths of both linear regression and the Random Forest model.

Exhibit 8 illustrates that the Linear Regression & Random Forest portfolio maintains stability during market fluctuations and achieves consistent returns in stable market conditions. This dual-strategy approach effectively harnesses the predictive accuracy of Random Forest while leveraging the explanatory power of linear regression, resulting in enhanced performance across various market scenarios.

6. Conclusion

The research demonstrates the effectiveness of integrating machine learning techniques with traditional factor investing strategies to enhance portfolio management. The empirical analysis, which included Fama-MacBeth regression and Random Forest models, highlighted the predictive power of selected factors like TES, OBV, AM, LIQ, and STO. The study also confirmed that machine learning models capture non-linear relationships that traditional models might miss, offering a more robust framework for predicting stock returns. Portfolios constructed using these insights not only achieved better returns but also provided resilience during various market conditions, particularly downturns. This approach empowers investors with a more nuanced understanding of market dynamics and asset valuation, facilitating more informed decision-making in portfolio construction. Future research could explore different machine learning models and a broader array of factors to further validate and refine these findings.

Exhibit

Exhibit 1: Average of Lambda and T-statistics of Factors

	Factor	Average	t-statistics	abs(t-statistics)
1	TES	-0.0772	-1.3385	1.3385
2	OBV	0.0121	1.3048	1.3048
3	AM	0.0083	1.2317	1.2317
4	LIQ	-0.0104	-0.9212	0.9212
5	STO	0.0526	0.9045	0.9045
6	GPOA	0.0155	0.7416	0.7416
7	DNOA	-0.0306	-0.6600	0.6600
8	NSI	-0.0268	-0.5827	0.5827
9	ToQ	0.0080	0.3940	0.3940
10	DM	0.0044	0.3291	0.3291
11	Dup	0.0057	0.1416	0.1416

Exhibit 2: Future Importance of Factors

	Factor	AVG
1	ToQ	0.1160
2	OBV	0.1131
3	STO	0.1111
4	AM	0.0971
5	DM	0.0958
6	DNOA	0.0816
7	NSI	0.0793
8	TES	0.0787
9	Dup	0.0784
10	GPOA	0.0750
11	LIQ	0.0736

Exhibit 3: Performance Statistics of Linear Regression Portfolio

Raw Return	Sharpe Ratio	CAPM Alpha	FF4 Alpha	Information Ratio
1.1353%	1.1499	0.006359	0.006912	-0.1695

Exhibit 4: Performance Statistics of Random Forest Portfolio

Raw Return	Sharpe Ratio	CAPM Alpha	FF4 Alpha	Information Ratio
2.7614%	2.9992	0.02256	0.02305	0.8873

Exhibit 5: Performance Statistics of Linear Regression & Random Forest Portfolio

Raw Return	Sharpe Ratio	CAPM Alpha	FF4 Alpha	Information Ratio
3.0102%	3.1838	0.02371	0.02484	1.0989

Exhibit 6 Return-Linear Regression Model

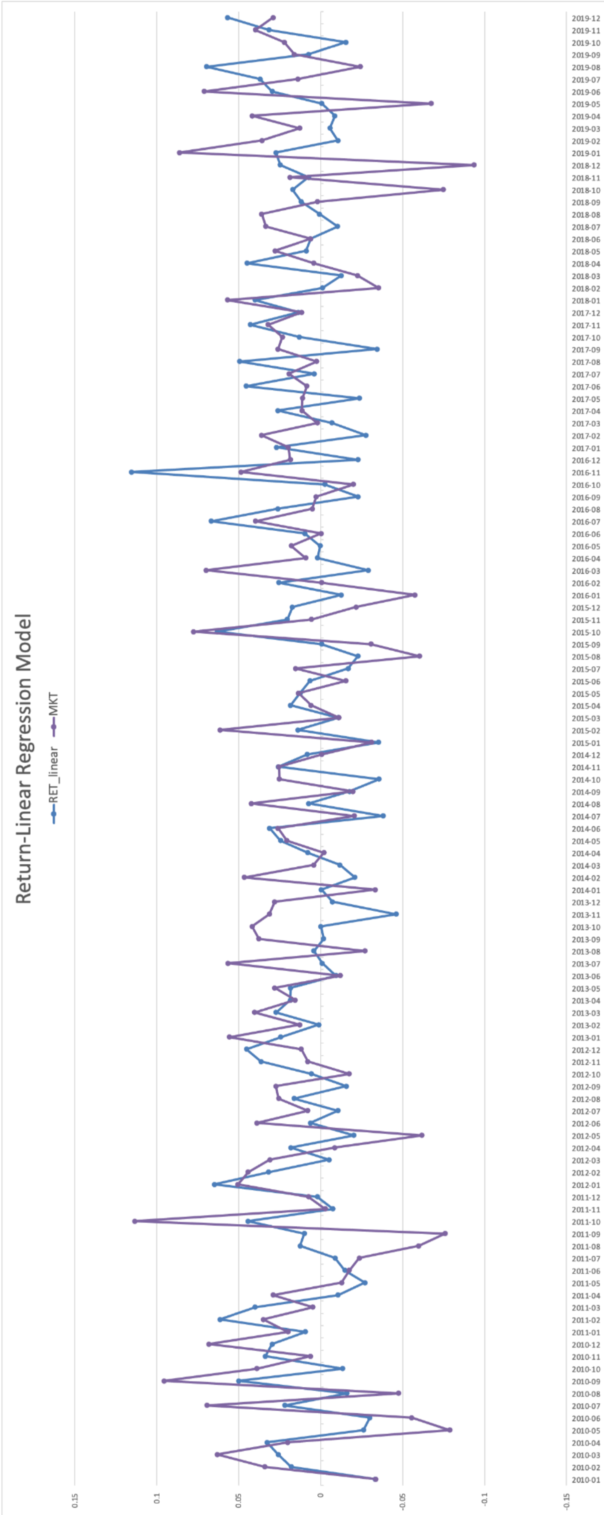


Exhibit 7 Return-Random Forest Model

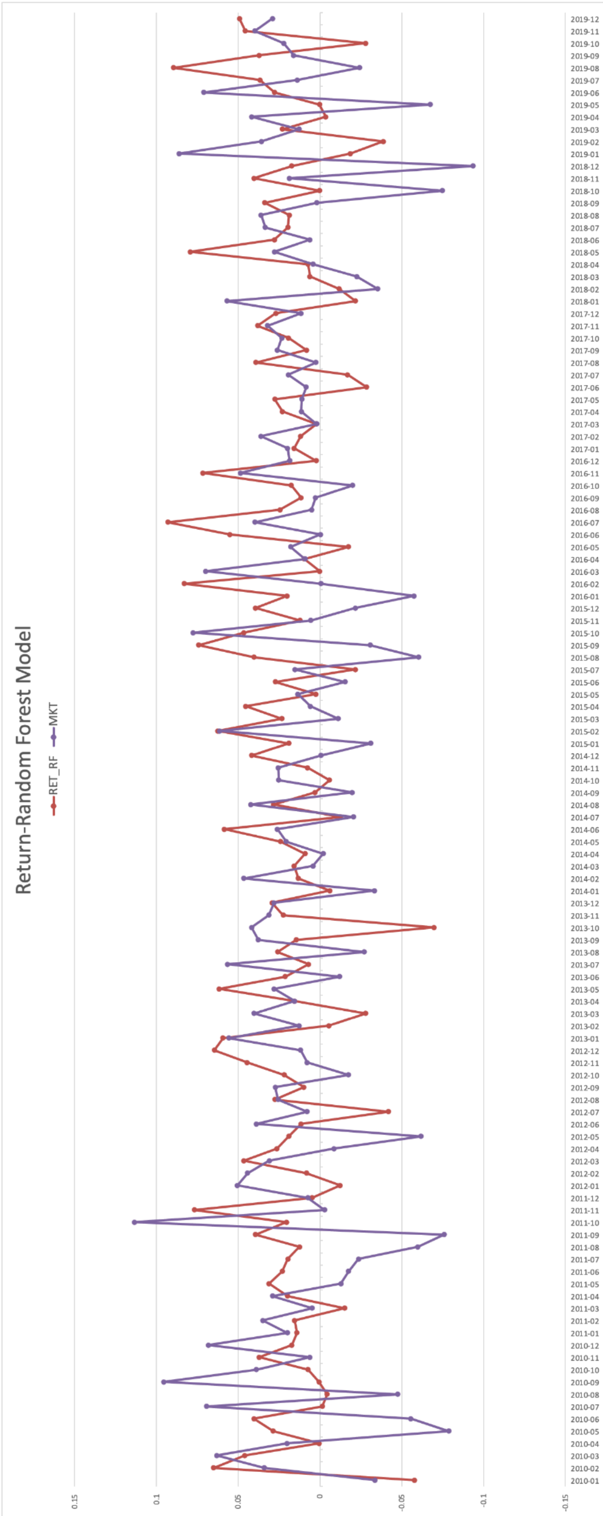
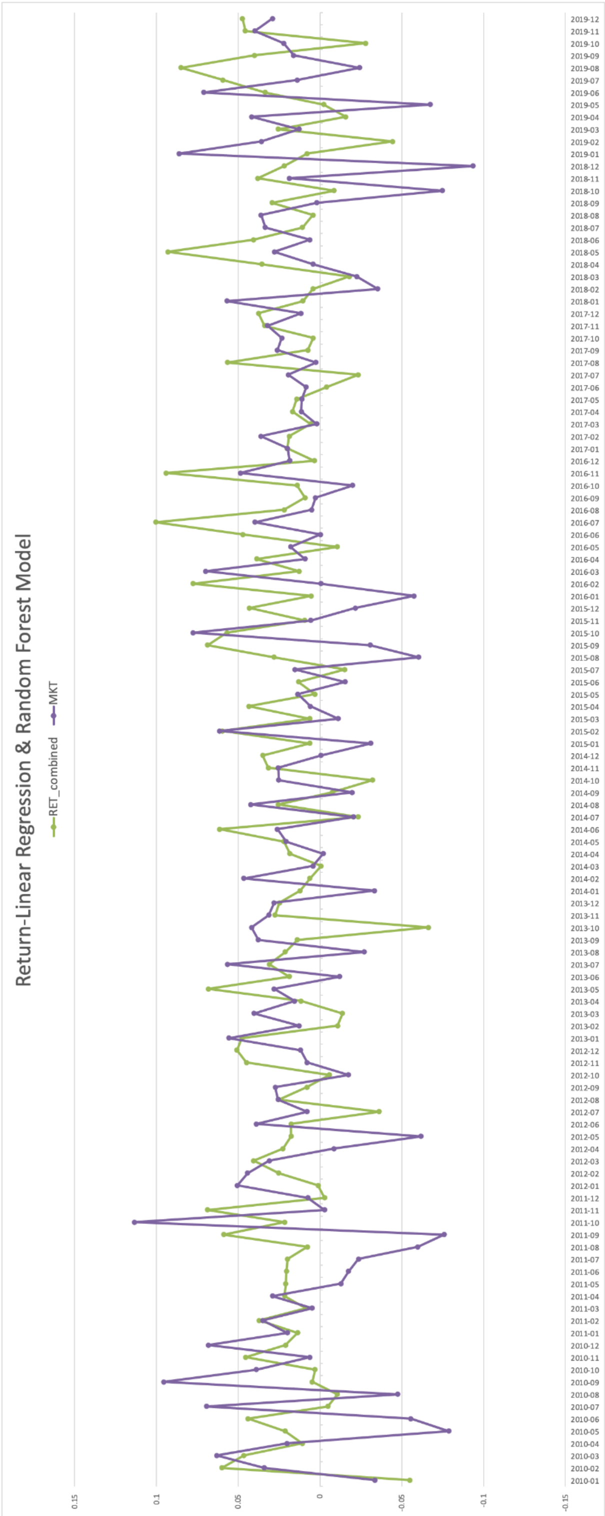


Exhibit 8 Return-Linear Regression & Random Forest Model



Detailed returns of the hedge portfolios of linear regression, Random Forest, and linear regression & Random Forest are appended as Excel attachments.

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