Understanding Momentum: A Review and Preview of an Alternative Investment Strategy

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ABSTRACT

Momentum stands as the pinnacle of simplicity in investment strategy—buying winners and selling losers. With a historical track record spanning over two centuries, this approach has emerged as the ultimate challenge to the Efficient Market Hypothesis (EMH). The persistent behavioral biases inherent in many investors lead them to become momentum traders, while professionals aiming to exploit this strategy encounter constraints within the marketplace. In a world where human beings struggle with behavioral biases, overreaction to negative news, and underreaction to positive news, prices possess the inherent potential to deviate from fundamentals. Throughout history, momentum strategies have consistently delivered substantial profits (Jegadeesh & Titman, 1993), attributed to delayed overreactions that eventually reverse. This research explores the complex dynamics of determining the efficacy of momentum investment strategy in the equities market. By exploring the historical context, behavioral dynamics, and challenges faced by professionals, this study sheds light on the enduring effectiveness of momentum strategies. As the financial market changes, investors who want to manage the market's complexities must first understand the secrets driving momentum. This study not only contributes to the academic discourse but also serves as a practical guide for investors and professionals aiming to capitalize on the transformative potential of momentum in the dynamic world of equity markets.

Keywords: Momentum, Investment, Portfolio, Strategy, Returns, Stock market

INTRODUCTION

Throughout history, researchers have embarked on a quest to solve the mysteries of market behavior, presenting various theories to explain and predict the complex dynamics of financial systems. Among these, the Efficient Market Hypothesis (EMH), put forward by Fama (1970), stands as a prominent theoretical framework guiding empirical studies in finance. The EMH posits a crucial principle: past prices, in an efficient market, should not be predictive of future success. However, a paradox emerges as past prices seemingly contradict this principle, often exhibiting an incredible ability to forecast future expected performance — a phenomenon termed "momentum."

A pivotal milestone in the exploration of momentum came with the groundbreaking study of Jegadeesh and Titman (1993). Their comprehensive study of the U.S. marketplace spanning from 1965 to 1989 provided compelling evidence of the momentum effect. It revealed that stocks with robust past performance consistently outperformed those with poor past performance in subsequent periods, showcasing approximately the monthly one percent of average excess returns. This discovery prompted a vigorous debate, questioning whether the persistent and robust momentum effect contradicts the principles of the EMH. The discourse surrounding momentum extended outside U.S. markets, encouraging international studies to corroborate and extend these findings. Momentum, it turned out, exhibited remarkable robustness not only across U.S. and foreign equity markets but also within diverse industries, countries, and various asset classes (Geczy & Samnov, 2012). The driving force behind this enduring phenomenon, according to researchers in financial economics, can be attributed to cognitive biases embedded in behavioral economics (Barberis et al., 1998; Devkota et al, 2023). The rationale behind this phenomenon is that investors, driven by irrationality, do not promptly integrate new information into their transaction prices due to their underreaction to it. Even in scenarios where traders are assumed to be perfectly rational, recent research contends that momentum can persist, adding a layer of complexity to the understanding of this phenomenon (Crombez, 2001).

Academic researchers studying into the momentum effect examined stock data spanning over two centuries, revealing a significant and robust historical performance record (Geczy & Samnov, 2012). The sustainability of momentum as an active investment strategy is dependent on the returns being driven by inherent human bias, making it a compelling subject of exploration. The objective of the momentum investing strategy is to profit from the persistence of current market trends. This strategy involves a speculator initiating a long position in an asset whose price is rising, or initiating a short sale of a security whose price has been falling. The fundamental assumption is founded on the belief that a trend is more likely to persist than to reverse once it has become established. Diverging from the long-term focus of value investing, momentum emerges as a short-term strategy, indifferent to operational performance from a pricing perspective. The framework of momentum investing interacts with the area of technical trading analysis, which has received substantial study. Past studies offer divergent perspectives, with some asserting that past information is insufficient for predicting future prices, while others argue that technical analysis, particularly when non-public information is taken into account, can yield substantial gains. considered, can yield substantial profits (Jensen & Bennington, 1970; Neftci, 1991; Treynor &

Ferguson, 1985; Bessembinder & Chan, 1995). The collision of these viewpoints emphasizes the multifaceted nature of momentum investing.

Recognizing the inherent biases in human decision-making processes, Gray and Vogel (2016) advocate for automation, contending that a systematic approach, as exemplified by technical analysis, can mitigate these biases and protect investors from their own behavioral errors (Gray & Vogel, 2016). Moving Average (MA), Moving Average Convergence Divergence (MACD), and Relative Strength Index (RSI) are the most commonly utilized technical trading rules. Despite their popularity in practical trading scenarios, these tools have received remarkably little attention in academic literature, leaving their empirical performance unexplored.

Viewed through this comprehensive lens, the empirical research on the momentum effect emerges as a compelling subject for further investigation. This study thus focuses on the use and efficacy of the momentum investment strategy in equity markets. By exploring this complex phenomenon, the article hopes to provide comprehensive insights that deepen our understanding of market dynamics, investor behavior, and the role of momentum in changing financial markets.

Momentum Investment Strategy

In finance, the momentum investing strategy captures the empirically known propensity for increasing asset values to continue increasing, whilst dropping values tend to remain in drop. The concept of momentum is central to behavioral finance, a field that studies the psychological factors influencing financial markets. Specifically, momentum in finance refers to the continuation of short-term stock price series, wherein prices tend to move consistently in the same direction throughout specific time horizons, typically ranging from 3 to 12 months.

Scholars have examined momentum in specific stocks and discovered that their potency is strong at the beginning of a trend, gradually declining as the trend progresses. This discovery emphasizes the dynamic of market behavior and provides a foundation for the momentum investing theory. This investment approach is grounded in the belief that market trends generally persist for a relatively short period, challenging the Efficient Market Hypothesis (EMH).

The Efficient Market Hypothesis, particularly in its weak form, posits that stock prices completely integrate all past market information, including past price movements and trading volumes. According to this perspective, new market information is quickly integrated into stock prices, making it impossible for investors to gain excess risk adjusted return by relying on historical market data. Though, Jegadeesh and Titman (1993) documented compelling

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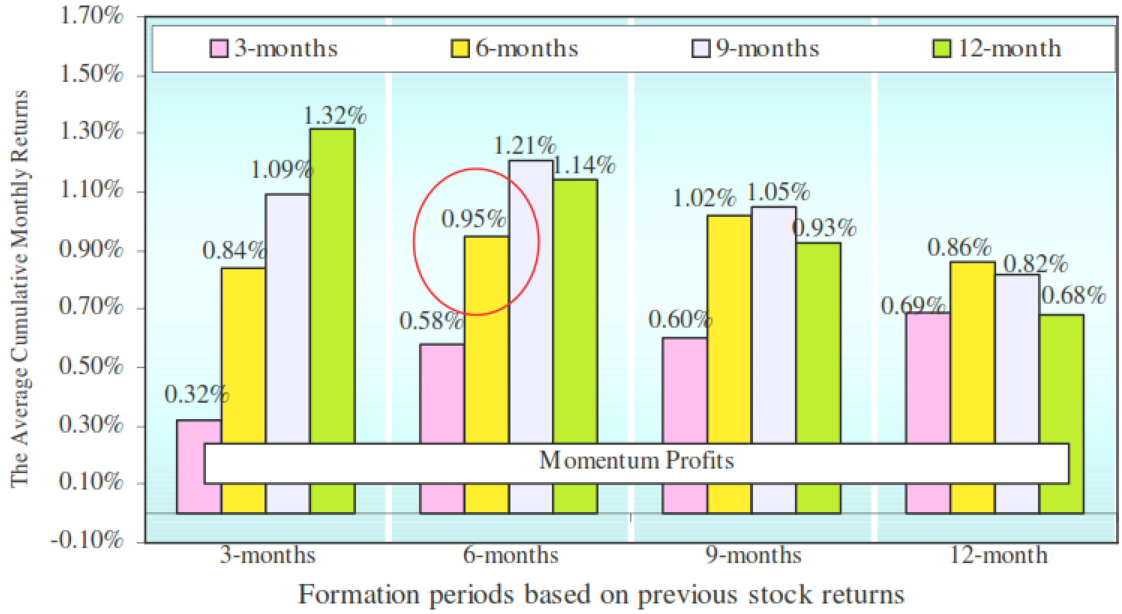
findings that contradict the EMH in its weak form. Their research identifies momentum patterns in stock prices, creating an opportunity for investors to attain significant profits.

Figure 1: Momentum Strategies of Jegadeesh and Titman (1993).



Note: This figure is derived from Journal of Finance volume 48, page 70, Table I, extracted from Jegadeesh and Titman (1993) article, '*Returns to buying winners and selling losers: implications for stock market efficiency*.'

Jegadeesh and Titman's (1993) momentum strategies, as illustrated in Figure 1, reveal zero-cost momentum strategies that produce positive returns. These strategies involve forming winning and losing stock portfolios based on returns over specific periods (3, 6, 9, and 12 months) and holding them for corresponding durations. For instance, the momentum portfolio created on stock return over the preceding six months and held for the subsequent six months produced excess returns of 0.95% per month from 1965 to 1989. The profitability of the zero-cost trading approach arises from the variation between the returns of the loser and winner portfolios during the investment horizon.

The short-term momentum arbitrage trading strategy, as described by Jegadeesh and Titman, entails transactions with only positive cash flows, involving a short position in the loser portfolio and a long position in the winner portfolio. This strategic approach leverages the examined patterns of momentum in equity prices to exploit potential market inefficiencies. It is noteworthy that over longer-term horizons, the dynamics shift toward reversal patterns rather than momentum. According to DeBondt and Thaler (1985, 1987), over the next 3 to 5 years, long-term past losers typically outperform long-term past winners. This reversal phenomenon emphasizes the need to consider different time frames when formulating investment strategies. The literature provided below offers evidence that supports the continued presence of short-term momentum trends in the stock market.

REVIEW OF LITERATURE

History of Momentum Investment Strategy

The momentum investment strategy has become a focal point of financial literature due to its persistent profitability, challenging the foundations of the efficient markets hypothesis (EMH). A historical exploration reveals the evolution of momentum and its challenges to established investment philosophies.

The Market's Oldest Religion: Technical Analysis

The origins of momentum can be drawn to the 17th century with the publication of "Confusion De Confusiones" in 1688 by the prosperous Dutch merchant Joseph de la Vega. This work was one of the oldest in the field of stock trading, and described phenomena such as excessive trading, overreaction, under-reaction, and the disposition effect, establishing the foundation for behavioral finance. The discoveries of Vega (1688) reflected concepts that were later published in current finance journals.

The Dojima Rice Market in Japan, founded in 1697, was one of the first futures markets, demonstrating the convergence of market forces and agricultural products. Homma (1755) in his book "*The Fountain of Gold- The Three Monkey Record of Money"*, highlighted the significance of emotions in influencing the fluctuations of rice prices by analyzing historical pricing patterns to make forecasts about the future. In the early 1900s, Edwin Lefevre's "*Reminiscences of a Stock Operator*" showcased Jesse Livermore's effective utilization of technical indicators.

However, in the early 20th century, doubts emerged regarding the efficacy of technical analysis. Investors initiated the process of examining fundamental analysis, carefully analyzing a company's financial statements to make more informed decisions. This shift gave rise to value investing, advocated by Benjamin Graham. Graham (1949) argued that buying stocks beneath their intrinsic value, computed through fundamental analysis, could yield higher risk-adjusted returns. His philosophy emphasized the direct link between a company's performance and its stock's future price patterns.

A New Religion Emerges: Fundamental Analysis

Benjamin Graham's influence strengthened fundamental analysis as a prominent investment philosophy. Graham (1973) argued that the performance of a stock is closely linked to the success or failure of the underlying firm. Gonedes (1972) expanded on this perspective, claiming that investors exhibit a predictable response to accounting figures, such as earnings and dividend announcements. Klarman (1991) challenged the idea of predicting market movements, considering it to be pointless. The author emphasized that investing based on predictions is speculative and likely to lead to losses over time. Klarman advocated for fundamental analysis, emphasizing that the underlying fundamentals of the company are the sole valid indicators for gaining an understanding of future stock prices. He disregarded price action as aimless and insignificant, emphasizing the irrationality of attempting to forecast the behavior of market participants. Malkiel (1996) also criticized technical analysis, arguing that the central proposition of charting is fundamentally flawed. Fundamental analysts, he argued, possess superior information and rationality. Notably, the prophetic aspect of stock pricing has gained attention from both academics and practitioners (Karki, 2018). In the context of evolving financial markets, Dahal et al. (2020) and Karki et al. (2021) have emphasized the importance of digital literacy and the adoption of management tools to rationalize decisions.

Fundamentalists tend to ignore technical analysis, despite its historical efficacy and the abundance of scholarly evidence confirming its merits (Karki et al., 2023). The value-investing ideology, advocated by fundamental analysts, remained consistent in its belief that thorough analysis of a company's fundamentals would guide prudent investment decisions. This perspective, although widely held among value investors, has initiated a continuous discussion between fundamental and technical analysts.

The Age of Evidence-Based Investing

In the field of investment strategies, a basic dichotomy exists between value investors, who prioritize fundamentals with the belief that prices will follow, and technical investors, who believe that prices lead and potentially even drive fundamentals. This dichotomy, however, is not a hard line, as an emerging body of academic research suggests that both fundamental and technical strategies can be effective. The age of evidence-based investing acknowledges that these strategies, including value and quality (fundamental) and momentum and trend-following (technical), may coexist and contribute to investment success.

Earnings-related strategies, rooted in the works of Graham and Dodd (1940), advocate for investing in stocks with low earnings multiples. The theoretical relationship between financial statements and equity prices (Nicholas & James, 2004) emphasizes the significance of earnings in determining share value. Empirical evidence consistently explores the impact of earnings on stock returns, forming a cornerstone of evidence-based investing. Contrary to viewing fundamental and technical analyses as conflicting, an evidence-based investor recognizes them as complementary approaches aiming to exploit market inefficiencies resulting from biased decision-making (Karki, 2020; 2022). In this evolving era of investing, a prominent focus is on constructing effective active momentum strategies. However, the term "momentum strategies" can be confusing, given the diverse approaches to measuring momentum. Two distinct categories help clarify the complexities of momentum strategies:

1) Time-series momentum (Also known as absolute momentum): This approach calculates momentum based on a stock's past returns, independently evaluated without considering other stocks' returns.
2) Cross-sectional momentum (Initially termed relative strength): Cross-sectional momentum measures a stock's performance relative to other stocks, providing a comparative measure within the market.

In simple terms, evidence-based investing believes that fundamental and technical analysis, along with some additional strategies such as momentum, can be used effectively. It emphasizes a comprehensive understanding of market dynamics, in which diverse methodologies combine to exploit inefficiencies and capitalize on the decisions of market participants.

Empirical Evidences on Momentum Investing

The discourse surrounding momentum investing constitutes a persistent debate, questioning the drivers of profit and challenging the efficient market hypothesis. This multifaceted discussion could be characterized into three streams of explanations: data-snooping effects, risk-based explanations, and behavioral factors influencing investor decisions.

- *Data-Snooping Effects:* Early skepticism in the momentum literature raised concerns about potential data-snooping effects, where observed returns might be artifacts of mining large datasets. Lo and MacKinlay (1990a) highlighted this concern, emphasizing the need to distinguish actual momentum from statistical noise. This signifies the importance of rigorous empirical methodologies to differentiate between true momentum effects and spurious correlations in historical data.
- *Risk-Based Explanations:* A second stream of explanations posits that momentum profits could be compensations for inherent risks. In this context, Levy's (1967) relative strength strategy, focusing on selling past losers and buying past winners, gained attention. However, Jensen and Bennington (1970) introduced skepticism by reevaluating Levy's trading rule over a prolonged period, finding that it did not consistently outperform a

simple buy-and-hold strategy. This led to a broader exploration of the risk factors associated with momentum, challenging traditional models like the Capital Asset Pricing Model (CAPM).

- *Behavioral Explanations:* The third stream of explanations explores the behavioral aspects of investors, suggesting that irrational behavior could drive the continuation of stock returns. Grinblatt and Titman (1989) observed a tendency among mutual funds to favor stocks that had increased in price over the previous quarter, indicative of a behavioral bias toward relative strength. This behavioral inclination was first overshadowed by the scholarly debate in the 1990s, which was largely concerned with contrarian rather than momentum strategies.

The notion shifted with the pioneering work of Jegadeesh and Titman (1993), who documented significant returns on trading strategies based on historical prices. Their study marked a turning point, bringing momentum strategies into the limelight. Jegadeesh and Titman ranked and sorted stocks on the NYSE and Amex between 1965 and 1989, forming deciles based on past returns over one to four quarters. The resulting momentum strategy, buying the top decile (winners) and selling the bottom decile (losers), demonstrated substantial profits over subsequent holding periods.

In addition to empirical evidence supporting the profitability of momentum strategies, Jegadeesh and Titman (1993) challenged traditional risk models. Their work highlighted that the traditional CAPM (Sharpe, 1964; Linter, 1965) could not fully account for stock returns, prompting the exploration of additional risk factors associated with the momentum effect. This expansion of risk considerations is essential for refining models and enhancing their explanatory power in the context of momentum investing.

The pioneering work of Jegadeesh and Titman (1993) on momentum investing has sparked an extensive body of research, expanding our understanding of this phenomenon across different markets and time frames. Subsequent studies have built upon their findings, shedding light on the global and historical applicability of momentum strategies. Rouwenhorst (1998) extended Jegadeesh and Titman's work, discovering similar momentum profits in European markets. Moskowitz and Grinblatt (1999) identified momentum profits across industry-sorted portfolios, while Grundy and Martin (2001) documented consistent profitability of momentum strategies in the United States dating back to the 1920s. These cumulative findings reinforce the robustness of momentum effects across geographic and sectoral boundaries.

Despite the overwhelming empirical evidence supporting momentum profits, consensus remains elusive on the underlying explanations. Traditional risk-based theories, aiming to attribute momentum to compensations for risks, have not received unanimous acceptance among researchers. Consequently, the momentum literature has shifted its focus toward behavioral theories, which argue that investor irrationality is a driving force behind the observed momentum effect. One prominent behavioral model presented by Barberis et al. (1998) is rooted in the psychological phenomena of 'conservatism' and the 'representativeness heuristic'. Conservatism induces overreaction, while self-attribution causes under-reaction in prices. However, a critique arises from the lack of specificity in terms of the time horizon or period of bias within their model, leading to challenges in explaining the time interval of momentum strategies found in empirical studies.

Daniel et al. (1998) introduced an alternative model that focused on the psychological biases of overconfidence and self-attribution. Their quasi-rational investor framework assumes investors confidently value securities, underestimating errors. The model posits that positive news reinforces confidence, whereas unfavorable information marginally reduces it. Jegadeesh and Titman (2001) empirically tested these behavioral theories, discovering a significant return reversal in a two to five-year post-holding period, supporting the idea that overconfidence and self-attribution biases drive short-term momentum and long-term reversals. Chui et al. (2010) investigated the impact of cultural differences on momentum profitability, using Hofstede's (2001) individualism index to relate individualism to overconfidence and self-attribution bias like Daniel et al. (1998). Their findings suggested that cultural differences influence investor behavior and, consequently, momentum profitability. Moreover, the level of education and awareness possessed by users emerged as a pivotal factor influencing the adoption of specific strategies and decision-making (Maharjan et al., 2022; Ghimire & Karki, 2022). However, behavioral theories face challenges, primarily stemming from the assumption that investors are inherently irrational. This skepticism revolves around the limited predictive power of these models, particularly in out-of-sample tests, and their ability to explain not just momentum effects, but other anomalies in financial markets.

In response to behavioral biases, technical analysis tools have been explored as potential mitigators. Sullivan et al. (1995), Gunasekarage and Power (2001), Kwon and Kish (2002), and Chong and Ng (2008), among others, reported significant excess returns to technical trading rules. Chong and Ip (2009) demonstrated the effectiveness of momentum strategies using technical tools, particularly the MACD and RSI rules. The application of these tools to historical data yielded returns surpassing the buy-and-hold strategy. The general consensus is that the momentum effect remains a mystery, challenging both rational and behavioral theorists alike. As acknowledged by Eugene Fama (2012), momentum stands out as a primary embarrassment to the efficient market hypothesis, preserving its status as a puzzle that continues to attract researchers and practitioners alike.

Momentum and Market Anomalies

The existence of momentum in financial markets poses a captivating anomaly that challenges traditional finance theories, particularly the efficient-market hypothesis (Fama, 1970). According to this hypothesis, changes in asset prices should be driven solely by changes in demand and supply or the incorporation of new information through fundamental analysis. However, momentum, characterized by the tendency for rising asset prices to continue rising and falling prices to persistently decline, stands as an anomaly that challenges conventional explanations. Eugene Fama, a Nobel Prize laureate in Economics in 2014 and a pivotal figure behind the efficient-market hypothesis, along with his esteemed co-author Ken French, acknowledged momentum as a premier anomaly in financial markets. The assertion that momentum is a prominent anomaly has triggered significant interest among both academic researchers and practitioners. This recognition highlights the complexities of momentum, demanding further investigation into its underlying mechanisms.

Jegadeesh and Titman (1993) published the landmark study "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," which investigated what is known as cross-sectional momentum. This type of momentum is critical in asset pricing models, where relative performance is measured by comparing the return of an asset to the returns of other assets within the same class. In a cross-sectional momentum strategy, assets with the top relative performance are bought, while those with the poorest relative performance are short-sold. This approach remains indifferent to the overall direction of the market; even in a scenario where all assets are appreciated, a cross-sectional momentum strategy would still short the assets with the lowest returns.

Expanding on the cross-sectional momentum paradigm, Avramov et al. (2017) contributed significantly to the literature with their study titled "Scaling Up Market Anomalies." Traditional momentum strategies capitalize on the persistence observed in stock prices. The authors sought to explore whether this persistence extended to other well-documented anomalies, thus scaling up the scope of inquiry. The 15 anomalies under scrutiny included failure probability, net stock issuance, O-Score, composite equity issuance, net operating assets, total accruals, momentum, asset growth, gross profitability, return on assets, standardized unexpected earnings, abnormal capital investment, analyst dispersion, book-to-

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market ratio, and idiosyncratic volatility. The study, spanning U.S. stocks from 1976 to 2013, not only delves into the profitability of these strategies but also scrutinizes their robustness and applicability in varying market conditions. The three-factor alpha estimates for the 15 strategies are highlighted in Table 1 below:

Table 1: Descriptive Statistics for Anomaly Portfolios

Panel A presents characteristics of the monthly anomaly portfolio in our sample during the period from 1976 to 2013. At the beginning of each month *t*, all common stocks listed on NYSE, AMEX, and NASDAQ are independently sorted into deciles based on their lagged 15 anomalies, including 1) failure probability, 2) O-Score, 3) net stock issuance, 4) composite equity issuance, 5) total accruals, 6) net operating assets, 7) momentum, 8) gross profitability, 9) asset growth, 10) return on assets, 11) abnormal capital investment, 12) standardized unexpected earnings, 13) analyst dispersion, 14) idiosyncratic volatility, and 15) book-to-market ratio. We report the average monthly value-weighted holding period (month *t*) returns (long-leg minus short-leg) of each anomaly, as well as a combined return as the equal-weighted average of all 15 anomalies. The returns are further adjusted by Fama-French three-factor model to obtain 3-Factor Alphas. We also report the Sharpe ratio, Fama-French three-factor betas, shortfall probability, and the value at risk. Sharpe ratio is computed as the average monthly excess portfolio return divided by its standard deviation over the entire sample period. Shortfall probability is the probability of a negative return, based on the assumption that returns are normally distributed. Value at risk is the maximal potential loss in the value of the portfolio over one month with a 5% probability, based on the assumption that returns are normally distributed. Panels B and C report similar statistics in the long-leg and short-leg of the anomalies, respectively. Appendix A provides the detailed definition of each variable, and Newey-West adjusted t-statistics are reported in parentheses.

Panel A: Summary Statistics of the Anomaly Returns (Long minus Short)																
Anomaly	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Combination
Raw Return (in %)	0.542	0.684	0.549	0.577	0.459	0.528	0.459	0.395	0.285	1.721	0.587	1.217	0.165	0.428	0.727	0.625
	(1.92)	(2.81)	(3.42)	(2.52)	(3.23)	(3.23)	(1.24)	(2.44)	(1.19)	(6.18)	(3.22)	(8.77)	(.6)	(1.11)	(2.24)	(5.94)
Sharpe Ratio	0.024	0.061	0.047	0.037	0.016	0.031	0.006	-0.005	-0.028	0.227	0.042	0.269	-0.043	0.002	0.052	0.101
3-Factor Alpha (in %)	**1.056**	**1.203**	**0.631**	**0.666**	**0.487**	**0.587**	**0.756**	**0.621**	-0.044	**2.226**	**0.549**	**1.310**	**0.779**	**1.012**	0.145	**0.799**
	(4.39)	(6.86)	(4.54)	(3.62)	(3.38)	(3.29)	(2.17)	(4.05)	-(.23)	(9.21)	(2.97)	(8.72)	(3.63)	(3.68)	(.58)	(10.46)
β-MKT	-0.364	-0.222	-0.133	-0.310	0.018	0.033	-0.407	-0.185	-0.069	-0.249	-0.068	-0.105	-0.433	-0.587	0.154	-0.195
	-(6.26)	-(5.22)	-(3.3)	-(5.33)	(.58)	(.74)	-(3.34)	-(4.62)	-(1.09)	-(2.79)	-(1.4)	-(1.83)	-(7.8)	-(5.68)	(1.67)	-(6.73)
β-SMB	-0.774	-0.995	-0.164	-0.277	-0.003	0.066	0.217	-0.040	0.371	-0.903	0.324	-0.011	-0.975	-1.361	0.384	-0.276
	-(7.22)	-(15.1)	-(2.73)	-(3.)	-(.05)	(.88)	(.77)	-(.63)	(4.14)	-(5.67)	(3.68)	-(.16)	-(11.82)	-(9.64)	(3.41)	-(7.77)
β-HML	-0.260	-0.356	0.134	0.538	-0.117	-0.299	-0.337	-0.321	0.839	-0.341	-0.026	-0.085	-0.271	0.435	1.192	0.049
	-(2.41)	-(4.35)	(1.7)	(6.67)	-(1.71)	-(3.55)	-(1.12)	-(3.)	(7.43)	-(2.93)	-(.21)	-(1.01)	-(2.1)	(2.13)	(7.03)	(.86)
Shortfall Probability	46.088	43.883	42.615	44.800	43.675	44.404	47.699	45.532	47.491	38.246	44.420	34.213	48.852	47.915	45.195	38.297
Value at Risk	8.537	6.629	4.303	6.690	4.285	5.648	12.631	5.394	7.175	7.746	6.297	3.704	9.263	13.044	9.181	2.830

The authors structured their investigation by sorting stocks within each anomaly into deciles based on cross-sectional momentum. The strategy employed involves going long on the top decile (best performers) and shorting the bottom decile (worst performers) for each of the 15 anomalies, resulting in 30 portfolios. The key findings presented in the study (Table 1) offer valuable insights into the effectiveness of momentum strategies. The most remarkable finding is the substantial outperformance of the momentum strategy compared to a naive (1/N) benchmark of equal-weighted investments in each anomaly. This signifies the inherent profitability of the momentum approach across diverse market anomalies, challenging conventional wisdom. The Fama-French three-factor risk-adjusted returns provide a robust metric for evaluating strategy efficacy.

- Avramov et al. (2017) report that 13 out of the 15 long-short strategies generated significantly positive Fama-French three-factor adjusted returns throughout the entire sample period.
- The combined strategy exhibits a highly significant average monthly adjusted return of 0.80 percent, underlining the consistency and strength of momentum across the anomalies.
- The strategy conditioned on the past one-month return yields a monthly alpha increase of 59 percent to 84 percent compared to the naive strategy.

- Crucially, the momentum-trading strategy remains profitable even during the post-2000 period, showcasing its resilience across different market environments. This temporal robustness enhances the credibility of momentum as a viable investment strategy over extended periods.
- The study also addresses risk considerations, highlighting the potential pitfalls of relying solely on a single anomaly-based trading strategy. The strong cross-sectional variation in the Value at Risk across the 15 strategies emphasizes the importance of a diversified approach. The result demonstrated that the combined strategy significantly mitigates this risk, attaining a much lower Value at Risk (2.83%) compared to the VAR on individual strategies (ranging from 3.7% to 13%), due to the low correlation of returns among the anomalies.
- The authors further explore the role of investor sentiment in influencing momentum strategies. Their findings align with existing literature including Karki (2017), Joshi et al. (2023), Karki and Khadka (2022), among many others, showing that momentum performs optimally during periods of high investor sentiment. This in-depth analysis adds a behavioral dimension to the understanding of momentum, demonstrating its sensitivity to market sentiment fluctuations.

These results provide insights into the efficacy of these anomalies. Avramov et al. (2017) shed light on whether the persistence observed in traditional momentum strategies is mirrored in these diverse anomalies, opening avenues for a more comprehensive understanding of market dynamics.

Time Series Momentum: In the financial markets, the study of momentum goes beyond the traditional cross-sectional paradigm, offering a captivating dimension known as time-series momentum. Unlike its counterpart, time-series momentum, often known as trend-following, focuses on the absolute performance of assets, creating a narrative of independence from the larger stock and bond markets. Moskowitz et al. (2012) shed light on this unique phenomenon, highlighting its distinguishing features and underlying diversification benefits, particularly during times of market distress.

Time-series momentum, as elucidated by Moskowitz et al. (2012), operates on the principle of tracking an asset's trend in isolation, buying into those on an ascending pattern and short-selling those on a descending path. This inherent focus on absolute performance renders it distinct from cross-sectional momentum, where the relative performance of assets within the same class takes precedence. A noteworthy feature emerges when all assets rise in value; in this scenario, none are shorted, emphasizing the unique nature of time-series momentum. The research spans a substantial timeframe, from 1985 to 2009, and reveals an interesting finding: time-series momentum exhibits a low correlation with broad bond markets and a near-zero correlation with broad stock markets. This unique characteristic implies that the returns generated by a trend-following strategy are nearly independent of traditional stock and bond portfolios. However, the attractiveness of time-series momentum extends beyond mere independence, offering diversification benefits that transcend simple correlations.

Figure 2: The Time Series Momentum Smile.

Figure 2 shows a visual representation of time-series momentum that was derived from the original paper. This graph compares non-overlapping quarterly returns on the diversified 12-month time series momentum strategy, evenly weighted across all contracts, against comparable returns on the S&P 500.

Figure 2 shows a visual representation of time-series momentum that was derived from the original paper. This graph compares non-overlapping quarterly returns on the diversified 12-month time series momentum strategy, evenly weighted across all contracts, against comparable returns on the S&P 500. Figure 2 shows the "Time Series Momentum Smile," which occurs when equities market downturns cause time-series momentum strategies to rise. This smile, which spans from 1985 to 2009, exemplifies the counter-cyclical character of time-series momentum, demonstrating its potential as a hedge against market volatility.

Enduring Premia and Strategic Implementation: The combined examination of cross-sectional and time-series momentum reveals an array of enduring premia that persist throughout long time periods, geographical boundaries, and varied asset classes. The robustness of these strategies, surviving variations in definitions and transaction costs, ensures their applicability in practical investment contexts. Avramov et al. (2017) further add these findings by noting that the combined strategy not only sustains significantly positive risk-adjusted returns but also acts as an effective mitigator of noise and risk inherent in individual strategies.

Pervasiveness and Persistence: The empirical evidence presented in the literature review emphasizes the pervasiveness and persistence of the momentum premium. This insight, together with the distinct dynamics of cross-sectional and time-series momentum, positions momentum strategies as not only enduring anomalies but also as potential instruments for strategic diversification (Karki et al., 2023). The comprehensive review of these results invites further exploration and application, encouraging both researchers and practitioners to explore further the multifaceted world of momentum in financial markets.

CONCLUSION

In the ever-evolving field of investment philosophies, a persistent and compelling argument continues to shape the discourse. One focal point of this discourse centers around the momentum literature, a subject that has recently gained substantial attention due to its consistent profitability, presenting a major challenge to the efficient markets hypothesis. The significance of this challenge is shown by the noteworthy works of researchers such as Barberis et al. (1998) and Daniel et al. (1998), who, in their respective studies, propose models that deal with behavioral biases. These models serve as a theoretical framework, capturing and understanding the complex dynamics of momentum strategies in financial markets. The seminal contributions of Jegadeesh and Titman, spanning from their early work to more recent investigations in 2001, lay the foundation for understanding the implications of behavioral models in the context of momentum. Their pioneering studies provide empirical evidence that aligns with the theoretical underpinnings of behavioral biases, offering valuable insights into the complexities of stock price movements. Furthermore, the momentum literature continues to thrive with the corroborative findings of subsequent studies, including but not limited to the works of Lee and Swaminathan (2000) and Avramov et al. (2017). The comprehensive review of the literature reveals a rich web of evidence supporting the implications, affirming the existence and profitability of momentum strategies. This alignment between theory and evidence not only substantiates the persistence of momentum anomalies but also invites further exploration into the complex relationship between behavioral factors and market efficiency.

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