Residual Reversal as an independent anomaly: A risk-adjusted approach to return consistency

Nicola Belli

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Abstract

This study analyzes residual reversal strategies as an independent alternative to conventional reversal methods, extensively studied in prior literature. Despite broad evidence supporting short-term conventional reversals, the robustness and global factor-neutrality of residual reversal strategies remain partially underexplored. We investigate whether these residual-based strategies exhibit greater return stability across regions and reduced exposure to global factors compared to the conventional counterparts. Using US, European, and Asian monthly equity returns from 1973 to 2023, conventional reversal methods are compared with their residual versions, which temper their exposures to the CAPM, Fama–French three-factor, and five-factor models. The residual strategies are constantly generating higher risk-adjusted returns in short-horizon, equal-weighted portfolios, among the different regions implemented. Those findings do not hold for the long-term horizon implementation. Additional regressions verify the residual reversal's partial statistical independence from the conventional counterpart, generating stable alphas. These results are also confirmed for factor exposure in the short term, demonstrated to be a factor-neutral anomaly with cross-market stability. However, the fading reversal performance over time demonstrates the presence of a sensitivity to changing market liquidity conditions.

Keywords: Asset allocation, Reversal Strategies, Momentum Anomalies, Factor Models, Market efficiency.

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Resumo

Este estudo analisa estratégias de reversão residual como uma alternativa independente aos métodos convencionais de reversão, extensivamente estudados na literatura anterior. Apesar das amplas evidências que apoiam as reversões convencionais de curto prazo, a robustez e a neutralidade em relação a fatores globais das estratégias de reversão residual permanecem parcialmente inexploradas. Investigámos se essas estratégias baseadas em resíduos exibem maior estabilidade de retorno entre regiões e menor exposição a fatores globais em comparação com as contrapartes convencionais. Utilizando retornos mensais de ações dos EUA, Europa e Ásia de 1973 a 2023, os métodos convencionais de reversão são comparados com as suas versões residuais, que atenuam as exposições ao CAPM, aos modelos de três fatores de Fama–French e de cinco fatores. As estratégias residuais geram consistentemente maiores retornos ajustados ao risco em horizontes de curto prazo, em portfólios igualmente ponderados, entre as diferentes regiões implementadas. Estes resultados não se mantêm, porém, para a implementação em horizonte de longo prazo. Regressões adicionais verificam a independência estatística parcial da reversão residual em relação à contraparte convencional, gerando alfas estáveis. Esses resultados residuais são confirmados para exposição a fatores no curto prazo, demonstrando ser uma anomalia neutra a fatores com maior estabilidade entre mercados. No entanto, a enfraquecida significância do desempenho da reversão ao longo do tempo demonstra a presença de uma sensibilidade às condições de liquidez do mercado em mudança.

Palavras-chave: Alocação de ativos; Estratégias de reversão; Anomalias de momentum; Modelos de fatores; Eficiência de mercado.

Título: Reversão residual como anomalia independente: uma abordagem ajustada ao risco para a consistência das rendibilidades.

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1. Introduction

Lehmann and Jegadeesh (1990) first introduced the concept of a short-term reversal. They found that stocks with the lowest past-month returns tend to outperform those with the highest past-month returns in the following periods. The strategy exploits the tendency of stock performance to reverse over time. The reversal phenomenon contrasts with momentum; Jegadeesh and Titman (1993) demonstrate that investing in past winners and selling past losers can generate considerable abnormal returns. However, the two anomalies may co-exist since the momentum is calculated on the previous 12 months before the strategy, excluding the most recent month, thereby creating space for the potential occurrence of short-term reversal effects. Furthermore, the positive returns are found over holding periods of 3 to 12 months, after which a portion of these gains tends to reverse. The reversion on the long-term is first identified by De Bondt and Thaler (1985), who discover that stocks with the poorest performance over 3 to 5 years typically outperform past high-performance stocks in subsequent years.

Medhat and Schmeling (2022) also find that short-term reversal and short-term momentum can co-exist at the 1-month horizon. They reveal the tendency of low turnover stocks, characterized by low trading volume compared to their outstanding shares and low liquidity, to exhibit short-term reversal phenomena given transitory price pressures or liquidity shocks. When large trades are executed in low-turnover stocks, often their trading price shows great drops, creating short-term mispricings that reverse when the selling pressure abates. Conversely, high-turnover stocks, which are more liquid and have greater trading volumes, can demonstrate short-term momentum caused by slower incorporation of new information or underreaction by investors. This possible simultaneous occurrence of momentum and reversal effects challenges the conventional view that these phenomena are mutually exclusive, highlighting instead that stock-specific attributes, such as turnover levels or liquidity, influence whether momentum or reversal prevails, even within identical time frames. Also, Nagel (2012) argues that reversal strategies in equity markets can be interpreted as a proxy for the returns from liquidity provision.

The strategy using the conventional reversal, as intended by Lehmann and Jegadeesh (1990) has historically brought significant and consistent returns. Nevertheless, the phenomenon frequently exhibits significant exposure to systematic risk and global factors, raising concerns about the robustness of the obtained results, as other elements can largely influence. Previous studies first investigate the issue in the context of momentum. Moskowitz and Grinblatt (1999) find that momentum shows a strong and persistent relation with industry effects. Industries that have historically performed positively tend to continue doing so in the future, indicating that certain factors can significantly influence this type of strategy. Grundy and Martin (2001) later demonstrate that such momentum strategy consistently shows relations and exposures to common risk factors as those to the Fama and French (1993) three-factor model. The described phenomenon also extends to reversal strategies, as Blitz et al. (2013) mention. However, Grundy and Martin (2001) also identify that when it comes to hedging the realized factor exposures of the strategy, controlling for the size and market factors, the effect directly attributable to momentum earns an average risk-adjusted return of 1.34% per month. The hedging removes the implicit bet on momentum in the factors, avoiding great losses when this doesn't happen. The finding suggests that it would be possible to refine the strategy by carving out risk-related components influenced by global factor performances. Building on these informations, Blitz et al. (2011) refine the strategy by isolating risk-adjusted components, introducing the concept of Residual Momentum. It is characterized by the definition of past winners and losers based on residuals between real returns and predicted returns. Predicted returns are produced depending on stocks' past exposures to factors over an estimation window that can differ between strategies. By doing so, they demonstrate not only that the described implementation led to better returns compared to conventional momentum but also less exposure to the Fama and French factors. Blitz et al. (2013) extend the approach of residuals to the short-term reversal strategies using the Fama and French three-factor model to define the residuals. The findings are consistent with the previous investigation on momentum, with the strategy delivering better risk-adjusted returns and less exposure to factors compared with the conventional short-term reversal.

The purpose of this research is to answer the question of a possible independence of the reversal principle from other factors' influence, considering its ability to deliver returns, on different equity markets, and to have uncorrelated risk with those. This is answered by investigating the alternative model of the residual reversal that can generate superior risk-adjusted performances, showing less exposure to systematic risk factors. Also demonstrating its independence from the conventional reversal. Both the conventional and the residual reversal in the short-term and long-term are implemented to do so. The long-term residual reversal is a new element not present in previous literature. I compute the residuals using various regression models to test exposure to multiple risk factors. Specifically, I apply the Fama and French

(1993) three-factor model, the Fama and French (2016) five-factor model, and the Sharpe (1964) CAPM model.

Initially, I examine the returns generated by these strategies over time. The dataset spans from January 1972 to December 2024, providing a total of 636 monthly return observations per selected stock. The existence of reversal is investigated over different datasets, searching over stock clusters and regions. The examined regions are the United States, Europe, and Asia. The first one contains stocks from the three main stock exchanges in the USA: NYSE, AMEX, and NASDAQ. The European dataset is composed of French (EURONEXT Paris), German (Deutsche Börse AG), and UK (London Stock Exchange) stocks. The Asian dataset is composed of Japanese (Tokyo Stock Exchange) and Chinese (Shanghai Stock Exchange) stocks. More details are given in the Data section of this research. The findings indicate that significant positive returns are obtained in all regions. The strongest and economically most significant results are often obtained when reversal portfolios are constructed based on Fama–French three-factor residuals. Among the regions, the short-term residual strategy performs better than its traditional counterpart consistently, with higher average returns and superior Sharpe ratios. By contrast, the long-horizon strategy is not always profitable, particularly in the United States and Japan, where traditional long-horizon reversals have negative returns. Europe is a comparatively notable exception, but even within Europe, the short-term residual strategy continues to dominate.

Secondly, I compare conventional and residual strategies regarding exposures to risk factors to test the correlation between the performance of global factors and the returns generated by the reversals. Using different regression models allows for controlling these variables and attributing uncorrelated, risk-adjusted returns to my strategies. The empirical models applied are adapted from Grundy and Martin (2001) and Blitz et al. (2013); they are detailed in the Empirical Research section. Results confirm more considerable factor-independent performances of Residual reversals, compared to their conventional counterpart. After regression, the residual portfolios continue to have large and significant alphas of approximately 1% per month, whereas alphas of conventional strategies shrink considerably. Residual portfolios have much smaller loadings on RMRF[1], SMB[2], HML[3], and their cross-products (see Eq. 18 and 19), resulting in a reduction of approximately two-thirds in

[1] Market risk premium, Market Factor
[2] Small minus Big, Size Factor
[3] High minus Low, Value Factor

explanatory power (R-squared) relative to conventional models. This suggests that Residual Reversal returns are less correlated to standard factor exposures. However, findings from Arnott et al. (2023) show that the explanatory power of common risk factors appears limited even when using comprehensive factor models. The suggestion is such that a portion of stock returns remains attributed to idiosyncratic risk. Also, the relation between systematic and idiosyncratic returns is a significant limitation as systematic components negatively predict future idiosyncratic returns, creating potential errors when estimating factor exposures for reversal strategies. Therefore, my methodology should account for Arnott et al. (2023) research, so that the results from the regression models should be interpreted carefully.

Lastly, to demonstrate residual reversal as a distinct strategy from the conventional, this study implements a regression model comparing returns from residual reversal strategies with those of conventional strategies. The objective is to determine whether the two exhibit minimal correlation. The findings attest to the fact that correlations fall off steeply as the number of factors covered increases by the residual strategy definition. This phenomenon is common to all geographic regions, suggesting diversification potential. Together, the findings imply that residual reversals remain partially related to the traditional reversal effect but with less factor exposure and more consistent performance over longer horizons and across markets.

2. Data

The dataset used includes equity data for the United States, Japan, China, the United Kingdom, France, and Germany. The time frame of stock retrieval is within a period that starts from 01/1972 until 12/2024, using monthly data. Because of the different availability of records among regions, especially regarding factor parameters, the strategies begin in different periods on the described time frame, but all end on 12/2024. Moreover, the strategies themselves require different periods to implement them effectively, resulting in different starting dates also within the same dataset of a specific region. Table 1 gives an overview of the different portfolios time spans.

For equities in Japan, Datastream was used for data that screened active stocks on the Tokyo Stock Exchange, excluding ETFs and closed-end funds. The same procedure was applied to China from the Shanghai Stock Exchange, the UK from the London Stock Exchange, France from the Euronext Paris Exchange, and Germany from Deutsche Börse AG. For all regions, Datastream's Return Index (RI) in USD dollars base was used to compute monthly returns. To avoid potential distortions of the strategy resulting from price fluctuations, common in securities with low prices, the dataset was further filtered to exclude stock returns for which the underlying stock price fell below $5 in any given month. These were consequently omitted in that specific month from the portfolio construction. For the United States, the data was sourced from the CRSP database with ticker codes classified as types 10 and 11 trading on the NYSE, AMEX, or NASDAQ, respectively, with exchange codes 1,2, and 3, including the same price filter as above. The USA dataset finally resulted in 4,498 stocks. The Asian dataset, which included Japan and China, resulted in 3,234 total stocks. The European dataset, which included the UK, France, and Germany, yielded a total of 1292 stocks. This last dataset was further filtered for some securities (15), which were delisted from the stock exchanges and showed peculiar behaviours of extreme results (Monthly returns over 100% and great volatility throughout consecutive months). Indeed, in the end, the European dataset counted 1277 stocks. The described datasets define three different regions that will be analysed throughout the research to test the robustness of the portfolio strategies among different markets, countries, and company dynamics.

Data on factors necessary for the execution of residual reversal strategies were retrieved from the Fama-French data library, following the return data by geographic region. For the U.S. analysis, the U.S. Fama-French 5-Factor (5FF) monthly data were used, along with the

European 5FF monthly data for the European analysis. For the Asian region, different procedures were taken because the Japanese stocks were matched with the Japanese 5FF monthly factors, and the Chinese st5ocks were matched with the Asia Pacific (Japan Excluded) 5FF monthly factors. As the timing of when the factors' data became available on the Fama-French library is different by region, there were some restrictions on the inception dates of the residual strategies. The data for Europe and Asia are only available from July 1990 onwards, resulting in differences in the start of the first portfolio return of residual strategies for each region. So, the lag between returns data and factor data meant that the residual strategies are starting from different periods depending on the region. Table 1 indicates the starting point of each dataset to give a more specific view of the portfolios.

Table 1: Dataset statistics[4]

Region:	USA	Europe	Asia
# of Variables			
Factors	5	5	10
Stocks	4498	1277	3234
Starting Date			
Factors	31/01/72	31/07/90	31/07/90
Stocks	31/01/72	31/01/72	31/01/73

[4] *The Ending date is not reported as it is 31/12/2024 for all datasets.*

3. Empirical Analysis

3.1. Overview of the Strategy

The empirical Analysis part of this research defines the two distinct concepts of Conventional Reversal and Residual Reversal, how they are implemented, and what type of regression models were included to obtain residuals. The name “Conventional Reversal” relies on its definition from Blitz et al. (2013), which uses that terminology to indicate the strategy first built by Lehmann and Jegadeesh (1990), based solely on stock returns. Residual Reversal represents a different approach, relying on the reversal principle but defining allocations in percentiles based on residuals between stock returns and regression-estimated returns. These strategies will be implemented and assessed with comprehensive monthly return data for equities from the United States, Asia, and Europe, facilitating a larger analysis of their performance across varying market conditions and economic environments. By comparing these strategies', this thesis ultimately provides valuable insights regarding the reliability and effectiveness of residual (and conventional) reversal strategies in global financial markets, thereby enhancing the understanding of momentum-related anomalies and their potential exploitation for asset allocation decisions.

3.2. Conventional Reversals

The concept of conventional reversal was initially identified and empirically analyzed by Lehmann and Jegadeesh (1990). These studies highlighted the profitability of strategies that involve buying stocks exhibiting the lowest returns from the preceding period and shorting stocks that displayed the highest returns. Conventional reversal strategies are structured according to a systematic process that includes:

1. **Portfolio Formation**: Stocks are ranked based on their historical returns over a specified prior period, which differs between the short-term and long-term horizons.
2. **Decile Sorting**: Based on these rankings, stocks are sorted into deciles. The lowest decile (past losers) and the highest decile (past winners) are particularly relevant for constructing reversal portfolios.
3. **Strategy Execution**: Investors short the top decile (stocks that have recently performed positively) and simultaneously go long on the bottom decile (stocks that have performed negatively). This long-short portfolio, if the reversal anomaly persists, is expected to generate positive excess returns.

In general terms, the reversal parameter (RP) is defined on the past returns, and it is the variable that determines the division between deciles. The parameter can change based on the type of reversal implied, it will be shown how the strategy varies based on it. Finally, the stock weights in the extreme deciles (*D1-D10*) will be allocated on two different methods: equal weights (EW) and value weights (VW). The value weighting scheme has the purpose of enquiring if controlling for smaller companies, which can have more extreme returns due to their size, it is possible to achieve performances with less volatility. The schemes are applied as follows:

$$EW(i) = \frac{1}{Total\ N.of\ Stocks} \tag{1}$$

$$VW(i) = \frac{Market\ Cap._i}{Total\ Market\ Cap.} \tag{2}$$

3.2.1. Short-Term Conventional Reversal

The Short-Term Conventional reversal (*ST_CR*) is the shorter-term horizon that will be implemented in this research, Figure 1 shows an example of the timeline of the strategy. The Short-Term definition indicates the close horizon of time between variable definition and portfolio implementation. In this strategy, the reversal parameter (*RP*) of a stock *i* at time *t* is simply based on the previous month's return of that security at time *t-1*, resulting in:

$$RP_{i,t} = r_{i,t-1} \tag{3}$$

The defined parameters are then sorted in 10 deciles based on return performance at time *t-1*. *D1* (Losers Portfolio) and *D10* (Winners portfolios) are the ones of interest by the strategy, which buy "past losers" and sells "past winners". The stocks in those deciles then yield returns at time *t* , based on the weighting schemes applied, and are the ones that will shape the performance of the reversal portfolio.

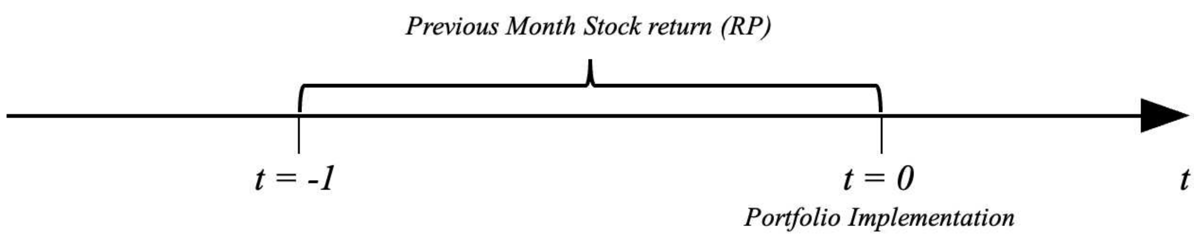
$$r_{D10,t} = \sum_{i=1}^{N} r_{i(10),t}\, w_{i,t-1} \tag{4}$$

$$r_{D1,t} = \sum_{i=1}^{N} r_{i(1),t}\, w_{i,t-1} \tag{5}$$

Where $r_{D1,t}$, $r_{D10,t}$ are the returns at time *t* of the stocks that were allocated respectively on the losers and winners deciles defined in the past month. By doing this, we create a zero-cost portfolio (p) that, if the reversal principle holds, should produce positive excess returns ($R_{p,t}$) in both legs with no initial investment needed.

$$R_{p,t} = r_{D1,t} - r_{D10,t} \tag{6}$$

Figure 1: ST_CR timeline representation



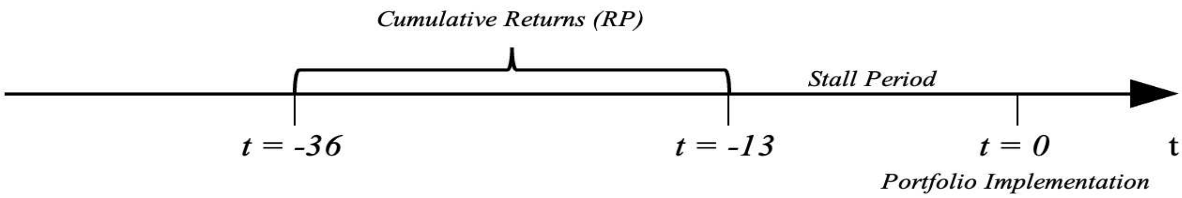
3.2.2. Long-Term Conventional Reversal

The Long-Term Conventional Reversal (*LT_CR*) strategy considers an extended historical horizon to capture price reversals. Unlike the Short-Term Conventional Reversal, the Long-Term horizon involves a more extensive timeframe between the definition of the reversal parameter and the execution of the investment portfolio. This strategy originated from foundational research by De Bondt and Thaler (1985), who first documented that stocks exhibiting prolonged poor performance tend to outperform subsequently, while those with sustained high returns subsequently underperform. In my research, the strategy is intended to perform in a three-year window, defining two years of *RP* definition and one year of stall, in which no action is taken. More precisely, the reversal parameter (*RP*) for a given stock *i* at time *t* is calculated by considering the cumulative past returns over an extended historical period, 24 months in this case, leading up to *t-13*, defined as follows:

$$RP_{i,t} = \sum_{k=t-36}^{t-13} r_{i,k} \tag{7}$$

After the calculation of the Reversal Parameters (*RPs*), stocks are divided into ten groups based on their previous performance. The trading strategy is based on the extreme deciles: a long position in previous "losers" and a short position in previous "winners". The following steps are already explained in Equations (4), (5), and (6). It is important to notice that the implementation of the portfolio happens 12 months after the *RP*s' definition, as indicated in Figure 2.

Figure 2: LT_CR timeline representation



3.3. Residual Reversals

The Residual Reversals (*RRs*) are distinct strategies from the conventional ones. They specify their reversal parameters in terms of residual returns, which are different to total stock returns. Residual returns are calculated by adjusting the return of each stock through a regression-based model, which commonly incorporates systematic risk factors. This research uses three different factor models as a proxy to determine residuals, which are expected to have less exposure to factor performances when used to implement the portfolios. The models indicated are the CAPM model, Fama-French 3 and 5 factor models, as follows:

$$CAPM \mid r_{i,t} = \alpha + \beta^1 \, RMRF_t + \varepsilon_{i,t} \tag{8}$$

$$FF3 \mid r_{i,t} = \alpha + \beta^1 \, RMRF_t + \beta^2 \, SMB_t + \beta^3 \, HML_t + \varepsilon_{i,t} \tag{9}$$

$$FF5 \mid r_{i,t} = \alpha + \beta^1 \, RMRF_t + \beta^2 \, SMB_t + \beta^3 \, HML_t + \beta^4 \, CMA_t + \beta^5 \, RMW_t + \varepsilon_{i,t} \tag{10}$$

Where $r_{i,t}$ is the return on stock i in month *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, HML_t, CMA_t and RMW_t are respectively the excess returns on factor-mimicking portfolios for the market, size, value, investment, and profitability in time *t*. The coefficients α and β^n are parameters to be estimated through the regressions. Lastly, $\varepsilon_{i,t}$ is the residual return of stock *i* in month *t*, which is then the type of residual used to form the *RPs* after determining the coefficient values obtained by the regressions. The regression period in my research is always 36 months and differs only in the point in time made before forming the portfolios, depending on the reversal strategy applied. As opposed to the conventional approach, which applies historical raw returns directly, residual reversal strategies employ the component of stock returns that is unexplained by familiar systematic factors. The main rationale for residual reversal is the isolation of stock-specific information, thus reducing exposure to common systematic risks and more accurately capturing reversal effects. This approach stands in contrast to conventional reversal strategies, which inherently carry dynamic exposures to systematic market factors. Thus, residual reversal strategies are designed to achieve improved risk-adjusted returns by appropriately minimizing factor-based noise that is inherent in traditional reversal strategies.

3.3.1. Short-Term Residual Reversal

The Short-Term Residual Reversal (*ST_RR*) extends and refines the traditional Short-Term Conventional Reversal by shifting the primary focus from total returns to residual returns. First formally introduced by Blitz et al. (2013), this strategy specifically leverages the reversal pattern observable within the residual component of stock returns, effectively filtering out systematic factor exposures. The strategy will be implemented in three different methods based on the factor models applied to determine coefficients and residuals. The factor models are reported by Eq. (8),(9), and (10), creating three portfolios defined respectively as *ST_RR_CAPM*, *ST_RR_FF3,* and *ST_RR_FF5.* Each of these variants will be formed for each of the countries examined in my research. The factor models are specifically used to implement a regression window of 36 months, with the dependent variables being the excess returns of each stock available on the dataset and eligible by conditions determined in the Data section.

Within the Short-Term Residual Reversal framework, the reversal parameter (*RP*) for each stock *i* at time *t* is computed by isolating the residual return at time *t-1*, derived from the coefficients defined on the regression window. The process described is notated as follows:

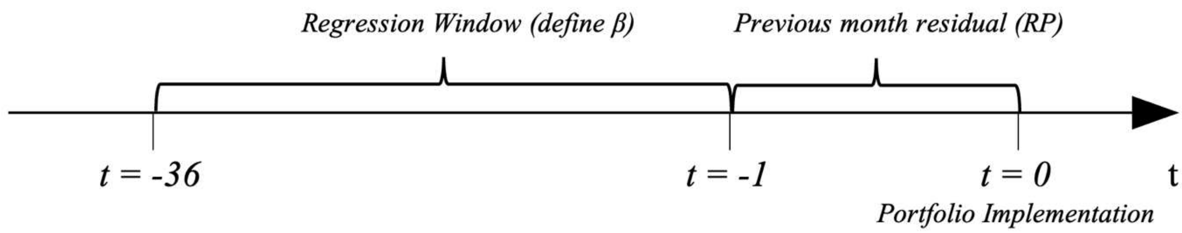
$$\varepsilon_{i,t-1} = r_{i,t-1} - \sum_{k=1}^{K} \beta_i^k f_{t-1}^k \tag{11}$$

$$RP_{i,t} = \varepsilon_{i,t-1} \tag{12}$$

where f_{t-1}^k is the excess return on a factor-mimicking portfolio at time *t-1.*
Upon computation, these residual parameters are ranked into deciles based on the prior month's residual return performance. Stocks within the lowest decile (D1) form the residual losers portfolio, while stocks in the highest decile (D10), displaying positive residual returns, constitute the residual winners portfolio. The portfolio is then formed following Eq. (4), (5) and (6). Figure 3 specifies the timeline events involved on this specific portfolio implementation.

This approach ensures that the strategy is directly based on stock-specific, idiosyncratic information, isolating and capturing reversals stemming solely from firm-specific movements. By filtering out systematic risk exposures inherent in total returns, the Short-Term Residual Reversal strategy seeks to improve the risk-return profile, yielding more robust and stable returns across different market environments.

Figure 3: ST_RR timeline representation



3.3.2. Long-Term Residual Reversal

The Long-Term Residual Reversal (*LT_RR*) is an alternative approach to the conventional long-term reversal. It effectively serve to isolate idiosyncratic effects in stock performance. New concept in recent literature, which mainly dealt with studies on long-term momentum effects, this approach operates based on the reversal effect to take place in a longer time-horizon by employing residual returns to differentiate between firm-specific information and overall systematic movement.

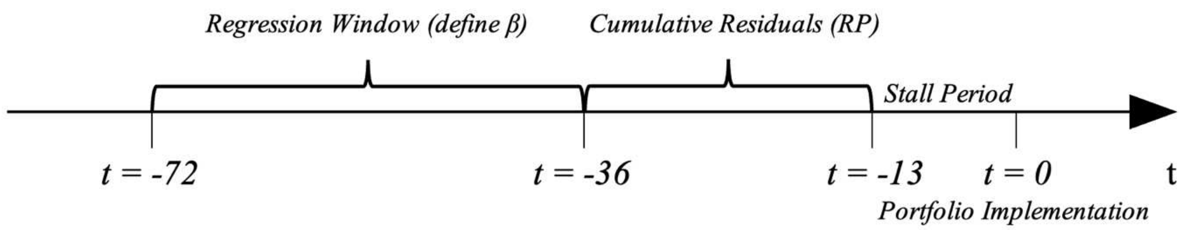
Apart from utilizing a 36-month regression period employed in computing the residual returns, the *LT_RR* strategy incorporates an extra 24-month window for the construction of the so called reversal parameters (*RP*s) , analogous to the conventional long-term reversal strategies (where returns were used instead of residuals). Followed by a 12-month holding period added as an interlude break prior to portfolio deployment. This step-by-step timeline therefore covers a duration of 72 months from the initiation of the process through to portfolio formation (see Figure 4). The structure guarantees a phased approach that well defines the residual calculation, cumulation, and portfolio implementation steps. The approach is outlined by three different factor models: *LT_RR_CAPM*, *LT_RR_FF3*, and *LT_RR_FF5*, which correspond respectively to the implementations of regressions on the models in equations (8), (9), and (10). The estimation of the reversal parameter in the *LT_RR* model relies on the cumulative residual returns over the 24-month residual defining window. Cumulative residual return is more formally described as the cumulation of monthly residual returns from factor-model regressions, as illustrated by the equation:

$$\in_{i,t}^{(cum)} = \sum_{\tau=t-36}^{t-13} \varepsilon_{i,\tau} = \sum_{\tau=-36}^{t-13} (r_{i,\tau} - \sum_{k=1}^{K} \beta_i^k f_{t-1}^k) \tag{13}$$

$$RP_{i,t} = \in_{i,t}^{(cum)} \tag{14}$$

where $\in_{i,t}^{(cum)}$ represent the cumulative residual returns generated in the 24-month window, which then define the *RPs.* After the calculation, securities are ranked into deciles based on their cumulative residual performance, thereby determining the extreme deciles *D1* and *D10*. The strategy involves taking long positions in the residual loser stocks and short positions in the residual winners. Portfolio returns for the deciles are computed as explained above using equations (4), (5), and (6), thus creating a zero-cost portfolio. As a result, the Long-Term Residual Reversal strategy provides investors with a robust analytical tool that can identify stock-specific reversal events over longer investment horizons, which can potentially provide stable and consistent risk-adjusted performance.

Figure 4: LT_RR timeline representation



3.4. Regression Analysis

To analyze the factor exposures of the different reversal strategies examined in this study, I conduct a series of regression analyses. These involve separate model specifications to provide a clear understanding of the underlying reversal dynamics. The analysis begins by comparing the performance of the Conventional Reversal (CR) strategy with that of the Residual Reversal (*RR*). This first comparison is meant to measure how much the *RR* strategy's performance can be explained by the *CR* model, thus critically assessing the uniqueness and autonomy of the *RR* methodology and checking whether it can exist independently as a standalone investment strategy or if it is simply an expression of the traditional method. The regression is applied as follows:

$$RR(\gamma)_t = \alpha + \beta_k \, CR(k)_t + \varepsilon_{i,t} \tag{15}$$

where the index k indicates the type of conventional reversal taken in examination, which differs between Short Term and Long Term. Index γ defines the type of residual reversal, which can vary from the ST and LT, but also the factor model implied in the specific portfolio (CAPM, FF3, FF5).

Then, the analysis will be complemented by applying regression models on the three Fama-French factors. Through decomposition of returns into risk-related factors pertinent to the identified factors, the degree to which such strategies actually exploit idiosyncratic opportunities or simply capture conventional systematic risks will be determinable. To distinguish the exposure to these variables of the strategies, I regress the conventional reversals and residual reversals as dependent variables against the FF3 Factors. Findings can be significant if the *RRs* show lower degrees of dependency on factors, regarding performance, compared to *CRs*. The regression models that will be applied are the following:

$$CR(k)_t = \alpha + \beta_k^1 \, RMRF_t + \beta_k^2 \; SMB_t + \beta_k^3 \; HML_t + \varepsilon_{k,t} \tag{16}$$

$$RR(\gamma)_t = \alpha + \beta_\gamma^1 \, RMRF_t + \beta_\gamma^2 \; SMB_t + \beta_\gamma^3 \; HML_t + \varepsilon_{\gamma,t} \tag{17}$$

where k and γ are the types of reversals taken into consideration, in the stance of this research, they will be respectively the *ST_CR_EW* and the *ST_RR_FF3_EW* for each of the regions taken in account. This analysis will not be extended to Asia since stocks in that are assigned to different regional factors, compromising the regression.

To further expand the analysis and examine dynamic risk exposures, the conditional regression method devised by Grundy and Martin (2001) and later modified by Blitz et al. (2013) will be utilized:

$$CR(k)_t = \alpha + \beta_k^1 RMRF_t + \beta_k^2 SMB_t + \beta_k^3 HML_t + \beta_k^4 RMRF\_UP_t + \beta_k^5 SMB\_UP_t + \beta_k^6 HML\_UP_t + \varepsilon_{k,t} \quad (18)$$

$$RR(\gamma)_t = \alpha + \beta_\gamma^1 RMRF_t + \beta_\gamma^2 SMB_t + \beta_\gamma^3 HML_t + \beta_\gamma^4 RMRF\_UP_t + \beta_\gamma^5 SMB\_UP_t + \beta_\gamma^6 HML\_UP_t + \varepsilon_{\gamma,t} \quad (19)$$

where $RMRF\_UP_t$, SMB_UP_t and HML_UP_t represent interaction terms capturing the excess returns associated with the RMRF, SMB, and HML factors during month *t* if, and only if, that factor exhibited a positive return during the preceding month (*t-1*); otherwise, they assume a value of zero.

The method is particularly designed to capture the possible shifts of factor exposures over different horizons through the use of interaction terms, such that it incorporates spans over which the factor returns had positive values last month. Under this conditional specification, the examination explicitly considers dynamic time-series shifts in factor exposures, with implications for how prior performances of factor returns condition subsequent exposures of reversal strategies negatively. Large negative coefficients on such interaction terms would affirm the inverse relationship between past and current factor returns and factor exposures, respectively, and highlight the key risk dynamics of reversal strategies. In addition to these techniques, this research hopes to create meaningful evidence regarding how systematic and dynamic factor exposures affect the risk-return profiles of both traditional and residual reversal strategies. Past literature has demonstrated that conventional reversals tend to show significant negative coefficients on factors' prior returns, such that a great part of the reversal effect is explained by the performance of those.

3.5. Strategy Construction

To implement the reversal framework described in the empirical analysis section, I construct sixteen types of portfolios for each of the three regions in our sample: the United States (*USA*), Europe (*EU*), and Asia (*Asia*). Every portfolio has a consistent monthly rebalancing protocol. The first type consists of short-term reversal portfolios, which we already labeled *ST*, which can be conventional (*CR*) or residual (*RR*). The same applies to the long-term reversal (*LT*). Every strategy is enacted according to two different weighting standards. One is called equal weight (*EW*), which in practice means that all stocks in each decile receive the same capital weight. At the other end of the spectrum is value weight (*VW*). Portfolios constructed as *VW* use market caps to scale individual positions in a manner that supposedly examines the effect of size-adjusted portfolios. The portfolios created are a total of 48, and they are noted as indicated in Table 2 in further parts of the research.

Table 2: Strategy's portfolios notations

Panel A: USA Strategies		Conventional Reversal (CR)	Residual Reversal (RR)		
			CAPM	FF-3	FF-5
Short-Term (ST)	Equal Weights (EW)	USA_ST_CR_EW	USA_ST_RR_CAPM_EW	USA_ST_RR_FF-3_EW	USA_ST_RR_FF-5_EW
	Value Weights (VW)	USA_ST_CR_VW	USA_ST_RR_CAPM_VW	USA_ST_RR_FF-3_VW	USA_ST_RR_FF-5_VW
Long-Term (LT)	Equal Weights (EW)	USA_ST_CR_VW	USA_LT_RR_CAPM_EW	USA_LT_RR_FF-3_EW	USA_LT_RR_FF-5_EW
	Value Weights (VW)	USA_LT_CR_VW	USA_LT_RR_CAPM_VW	USA_LT_RR_FF-3_VW	USA_LT_RR_FF-5_VW
Panel B: Europe Strategies		Conventional Reversal (CR)	Residual Reversal (RR)		
			CAPM	FF-3	FF-5
Short-Term (ST)	Equal Weights (EW)	EU_ST_CR_EW	EU_ST_RR_CAPM_EW	EU_ST_RR_FF-3_EW	EU_ST_RR_FF-5_EW
	Value Weights (VW)	EU_ST_CR_VW	EU_ST_RR_CAPM_VW	EU_ST_RR_FF-3_VW	EU_ST_RR_FF-5_VW
Long-Term (LT)	Equal Weights (EW)	EU_ST_CR_VW	EU_LT_RR_CAPM_EW	EU_LT_RR_FF-3_EW	EU_LT_RR_FF-5_EW
	Value Weights (VW)	EU_LT_CR_VW	EU_LT_RR_CAPM_VW	EU_LT_RR_FF-3_VW	EU_LT_RR_FF-5_VW
Panel C: Asia Strategies		Conventional Reversal (CR)	Residual Reversal (RR)		
			CAPM	FF-3	FF-5
Short-Term (ST)	Equal Weights (EW)	Asia_ST_CR_EW	Asia_ST_RR_CAPM_EW	Asia_ST_RR_FF-3_EW	Asia_ST_RR_FF-5_EW
	Value Weights (VW)	Asia_ST_CR_VW	Asia_ST_RR_CAPM_VW	Asia_ST_RR_FF-3_VW	Asia_ST_RR_FF-5_VW
Long-Term (LT)	Equal Weights (EW)	Asia_ST_CR_VW	Asia_LT_RR_CAPM_EW	Asia_LT_RR_FF-3_EW	Asia_LT_RR_FF-5_EW
	Value Weights (VW)	Asia_LT_CR_VW	Asia_LT_RR_CAPM_VW	Asia_LT_RR_FF-3_VW	Asia_LT_RR_FF-5_VW

4. Empirical Results

4.1. Main Results: USA

To start defining the performances of reversal strategies, summary statistics in Table 3 document how they perform in the USA sample. The United States region has been deeply analysed in previous literature, showing already consistent performances applying reversal strategies. This is also the case in my research.

Table 3: Summary Statistics Reversal Strategies USA

Table 3 summarizes the characteristics of reversal strategies in the USA sample. Across the page, it distinguishes short-term portfolios from long-term portfolios. It splits results for equal-weighted (Panel A) and value-weighted (Panel B) implementations. The first column reports the benchmark conventional reversal strategy , while the next three columns show the residual reversals that remove successively richer sets of factor exposures. For every specification, the table lists the key statistics of monthly returns: mean (annualised), t-statistic, p-value, Volatility (annual), Sharpe ratio[5], skewness, excess kurtosis, the smallest and largest returns, and percentiles. *,**,*** represent respectively significance levels of 10%, 5% and 1%.

	Short-Term				Long-Term			
Panel A: Equal Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	12.93%***	13.82%***	15.37%***	14.56%***	8.15%***	3.04%*	2.72%	3.15%**
t-stat	5.99	6.95	9.76	9.73	3.89	1.80	1.78	2.13
p-value	0.00	0.00	0.00	0.00	0.00	0.07	0.08	0.03
Std. Dev. (%)	15.71%	14.04%	11.13%	10.58%	14.83%	11.60%	10.48%	10.15%
Sharpe ratio	0.82***	0.98***	1.38***	1.38***	0.55***	0.26***	0.26***	0.31***
t-stat	17.93	19.76	24.19	24.14	12.55	6.12	6.06	7.20
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	0.40	-0.21	0.30	0.32	0.94	0.30	0.16	0.40
Excess kurtosis	6.13	10.25	1.90	1.08	4.27	1.57	0.79	1.78
Minimum (%)	-29.17%	-32.12%	-13.91%	-9.56%	-12.73%	-11.59%	-9.68%	-11.84%
Percentile 25 (%)	-1.51%	-1.08%	-0.71%	-0.83%	-2.00%	-1.75%	-1.59%	-1.51%
Median (%)	10.14%	11.10%	13.41%	12.81%	4.40%	-0.31%	1.19%	2.58%
Percentile 75 (%)	3.17%	3.13%	2.93%	2.90%	2.92%	2.12%	2.08%	1.82%
Maximum (%)	26.02%	24.35%	14.96%	13.13%	28.59%	15.45%	10.39%	12.56%

	Short-Term				Long-Term			
Panel B: Value Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	4.67%*	6.6%**	8.11%***	8.32%***	6.27%**	3.48%	2.33%	3.70%
t-stat	1.74	2.56	3.57	3.58	2.13	1.44	0.98	1.61
p-value	0.08	0.01	0.00	0.00	0.03	0.15	0.33	0.11
Std. Dev. (%)	0.20	0.18	0.16	0.16	0.21	0.17	0.16	0.16
Sharpe ratio	0.24***	0.36***	0.51***	0.51***	0.30***	0.21***	0.14***	0.23***
t-stat	5.95	8.58	11.66	11.68	7.22	4.94	3.38	5.51
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	-0.15	0.21	-0.24	0.05	0.79	0.52	0.13	-0.06
Excess kurtosis	1.67	2.54	2.29	1.41	3.17	2.05	2.31	1.93
Minimum (%)	-22.48%	-20.54%	-21.92%	-19.67%	-19.44%	-13.26%	-23.30%	-23.61%
Percentile 25 (%)	-2.74%	-2.60%	-1.84%	-1.91%	-3.43%	-2.77%	-2.32%	-2.24%
Median (%)	2.14%	3.39%	5.79%	6.64%	1.72%	1.06%	0.98%	2.47%
Percentile 75 (%)	3.97%	3.58%	3.43%	3.37%	3.81%	3.01%	2.64%	2.78%
Maximum (%)	23.95%	25.21%	17.47%	17.60%	34.29%	26.83%	20.07%	16.45%

[5] In the case of long-short strategies, Sharpe ratios are calculated using raw returns.

Within the results obtained, focusing first on the short-term with equal-weighted portfolios (Panel A, left), all four strategies deliver economically large and statistically significant average annualized returns. The magnitude of those increases once residual reversals are implied, particularly using the FF3 model (*ST_RR_FF3*). The conventional strategy (*ST_CR_EW*) records a mean of 12.93% per year. In comparison, the CAPM residual-based component boosts that figure to 13.82%, and accounting for the FF3 and 5 residuals, performance lifts it further to roughly 14.5 – 15.4 %. Volatility falls in the meanwhile, from 15.7% for *CR* to just above 10% for the five-factor residual variant, so the Sharpe ratio essentially doubles (0.82 for *ST_CR_EW* versus 1.38 for *ST_RR_FF3_E*W and *ST_RR_FF5_EW*). These improvements underline the core intuition of residual reversal: once systematic co-movements are controlled for through the residual method, remaining stock-specific appears to be both stronger and less noisy, yielding materially higher risk-adjusted pay-offs. However, Excess kurtosis tends to be positive in all of the portfolios, indicating leptokurtic distribution, with fatter tails compared to the normal distribution. Skewness is almost always positive in the table, which results in the tendency of left-skewed return distributions by the reversal strategies. The most negative performance figure reveals that the worst monthly performance is less negative on the residual reversals, especially on the FF3 and FF5 (from –29.17% for *CR* to -9.56% for *RR_FF5*), which could indicate the great exposure to factor performance of the *CR*, when factors perform positively the reversal tend to do the opposite. Even the *ST_RR_CAPM_EW* seems to have minimum performance close to the *CR*, which can suggest that the model is not accounting for enough factors to generate independent yields (as a matter of fact, only the *RMRF* factor is considered in that strategy). The same trend is shown in maximum performances, underlying the tendency of *CR* to show extreme results and higher excess kurtosis through the return distribution. Moving to the long-term, equal-weighted (Panel A, right), the outcome appears to be less significant. The conventional strategy generates the highest annualized return mean (8.1%), and the residual variants produce noticeably lower averages in the 2.7–3.2 % range. However, these lower means coincide with lower volatility as annualized standard deviations stand between 10.15 and 11.60 %. The significance of the findings is not robust, especially for the *LT_RRs,* as there is a low level of significance on returns (especially for *LT_RR_FF3_EW,* which is not significant for any level considered in the table). Such results will pose doubts on the persistence of long-term reversal through historical periods and different models, as will be shown by similar results for Asia and Europe presented in the following sections of my research. In other words, controlling for factor performances in a long-horizon doesn't seem to deliver higher risk-adjusted returns for the U.S.

The value-weighted results (Panel B) convey two additional themes. First, tilting weights toward market capitalisation compresses all performance metrics. Mean returns for short-term *CR* drop from 12.9 % to 4.7 %, reflecting the fact that reversal phenomena appear to have stronger effects among less capitalized companies. Even so, residual filters still matter: the ST_*RR_FF3_VW* and ST_*RR_FF5_VW* variants lift the average to 8.1 % and 8.3 %, respectively, and more than double the Sharpe ratio relative to ST_*CR_VW*. It is also remarkable that the residual reversal shows higher degrees of significance compared to the *CR*, especially the residuals based on the FF factor models. Secondly, in the long-term value-weighted setting, a similar pattern to the equal-weighted panel is shown. Returns overall are not significant.

Several conclusions emerge from the above empirical findings. Economic strength is especially strong for short-term reversals, suggesting that reversal effects are typically more stable in a short-term framework. Equal weighting strategies provide higher returns and Sharpe ratios, supporting the view that the anomaly might be due to smaller firms, usually characterized by lower liquidity. For these two points, it is particularly clear that residual reversals have better performance compared to their *CR* counterparts, especially after controlling for the Fama-French factors. Moreover, long reversals have weaker persistence and strength indicators and tend to be less statistically significant than short reversals. Their idiosyncratic components are less extreme; the factor-neutralizing approach attenuates upside and downside at roughly the same point, with very little alteration of the risk-adjusted shape. Lastly, value weighting reduces the headline figures of all methods; residual adjustments continue to yield gains, suggesting that even within larger capitalizations, factor noise removal is providing material efficiency gains.

4.2. Main Results: Europe

The reversal portfolio strategies have been applied to different datasets to further explore their consistency among different geographical regions. Research on reversal to this extent has been done only in a limited way in previous literature. In this section, I will introduce summary statistics and performance results for the European securities dataset.

Table 4: Summary Statistics Reversal Strategies Europe

Table 4 summarizes the monthly performance characteristics of all reversal strategies in the European sample after implementation exactly as defined in the data section. Similar to Table 3, the page distinguishes short-term portfolios from long-term portfolios. It splits results for equal-weighted (Panel A) and value-weighted (Panel B) implementations, so that the influence of firm size on the anomaly can be inspected. Within each block, the first column reports the benchmark conventional reversal strategy (*CR*), while the next three columns show the residual reversals that remove successively richer sets of factor exposures (*CAPM*, *FF-3*, *FF-5*). For every specification, the table lists the key distributional statistics of monthly returns: mean (annualised), t-statistic, p-value, Volatility (annual), Sharpe ratio, skewness, excess kurtosis, the smallest and largest single-month outcomes, and several percentiles that capture the shape of the return distribution. *,**,*** represent respectively significance levels of 10%, 5% and 1%.

	Short-Term				Long-Term			
Panel A: Equal Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	19.08%***	28.10%***	31.44%***	29.25%***	9.84%***	0.06%	-2.06%	2.09%
t-stat	6.38	9.24	10.49	9.86	3.91	0.02	-0.73	0.71
p-value	0.00	0.00	0.00	0.00	0.00	0.98	0.46	0.48
Std. Dev. (%)	21.72%	17.04%	16.79%	16.62%	17.78%	15.27%	14.96%	15.79%
Sharpe ratio	0.88***	1.65***	1.87***	1.76***	0.55***	0.00	-0.14**	0.13**
t-stat	18.78	20.84	21.91	21.40	12.61	0.07	-2.53	2.43
p-value	0.00	0.00	0.00	0.00	0.00	0.94	0.01	0.01
Skewness	1.42	2.11	2.44	2.33	0.33	0.59	0.21	1.77
Excess kurtosis	8.09	13.59	15.93	16.28	5.00	8.80	10.74	11.56
Minimum (%)	-20.17%	-10.99%	-11.84%	-13.55%	-30.31%	-22.64%	-25.56%	-13.62%
Percentile 25 (%)	-1.48%	-0.40%	-0.12%	-0.13%	-2.18%	-2.09%	-2.18%	-2.34%
Median (%)	13.73%	25.09%	27.97%	25.42%	4.44%	-3.03%	-2.04%	-1.23%
Percentile 75 (%)	4.00%	4.15%	4.50%	4.53%	3.69%	2.36%	1.96%	2.17%
Maximum (%)	40.27%	42.47%	43.34%	42.26%	30.70%	30.92%	30.27%	31.73%

	Short-Term				Long-Term			
Panel B: Value Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	6.91%*	6.04%	12.84%***	10.53%**	2.47%	-1.95%	-6.82%	-6.85%
t-stat	1.95	1.53	3.15	2.44	0.69	-0.46	-1.62	-1.53
p-value	0.05	0.13	0.00	0.01	0.49	0.65	0.10	0.13
Std. Dev. (%)	25.78%	22.17%	22.83%	24.20%	25.13%	22.74%	22.45%	23.89%
Sharpe ratio	0.27***	0.27***	0.56***	0.43***	0.10**	-0.09*	-0.30***	0.29***
t-stat	6.63	5.20	10.15	8.07	2.40	-1.59	-5.49	-5.19
p-value	0.00	0.00	0.00	0.00	0.02	0.11	0.00	0.00
Skewness	0.08	-0.25	-0.29	-0.56	0.12	0.33	0.36	0.43
Excess kurtosis	5.19	2.27	7.45	8.79	1.02	1.50	1.02	1.69
Minimum (%)	-47.83%	-27.51%	-43.87%	-49.56%	-24.52%	-24.17%	-23.52%	-23.09%
Percentile 25 (%)	-3.58%	-2.97%	-2.69%	-2.62%	-4.34%	-4.29%	-4.83%	-4.70%
Median (%)	3.77%	5.64%	17.47%	12.99%	0.08%	-6.74%	-8.75%	-9.05%
Percentile 75 (%)	4.44%	4.00%	4.55%	4.73%	4.54%	3.44%	3.14%	2.86%
Maximum (%)	38.40%	23.16%	34.41%	33.95%	27.47%	25.58%	23.39%	25.88%

Table 4 represents the main findings, in terms of statistics, for the European dataset portfolios. In the equal-weighted short-run panel, the traditional strategy has an annualised return of 19.08%, greater than the *US_ST_CR_EW*. This pattern appears even to the *RRs*, which give very high returns, up to about 29.25% yearly for the *ST_RR_FF5_EW*. At first glance, it appears that the reversal strategy performs more efficiently in the European environment, however, it needs to be cautiously interpreted. The portfolios have a fat-tailed return distribution with Excess Kurtosis between 8.09 and 16.28, increasing when *RRs* are added. These tails are not symmetrical: the highest monthly returns are always three to four times larger than the worst drawdowns, suggesting that the majority of the kurtosis is being generated by frequent negative returns, which are offset in terms of average yields by occasional great positive performances (positive skewness among the portfolios confirms it). This can explain the significantly greater returns observed relative to USA equities, which had a different trend of lower excess Kurtosis among the residual reversals. The shared return variation is unlikely to be solely attributable to the reversal signal per se; rather, it is more plausible that it is driven by other considerations not captured in this investigation, namely the involvement of micro-cap firms that remain in the sample despite imposing the USD 5 stock price screen. The value-weighted specifications confirm this interpretation. As portfolio weights are shifted towards the largest firms, excess kurtosis decreases considerably. But along with it, portfolio performances also decrease significantly, with return figures of a high of 12.84% for the *ST_RR_FF3_VW*. The result is what has been observed in the USA portfolios. That can signal position sizing that dominates most of the tail behavior, which means small-cap stocks have a disproportionate influence on outcomes. The other reason implicated, to be explored in greater depth in further sections of the research, is the possibility of sub-sample extreme returns from specific economic and macroeconomic trends.

For long-term annualized returns, the European conventional approach returns approximately 9.84% per annum, equally weighted, and produces a Sharpe ratio of 0.55. After applying residual reversal, the yearly mean falls to around 0 percent, and the risk-adjusted performance is statistically less strong. The value-weighted version performs even worse: portfolios yield negative returns (except the *LT_CR_VW*), and observations are not statistically significant. These statistics record the findings in the United States, showing that the long-run reversal premium is economically modest and drops off almost entirely once factor exposures are accounted for, which suggests that any systematic gains are generated largely by systematic risks rather than by a persistent independent anomaly.

4.3. Main Results: Asia

Finally, the reversal portfolios are implemented on the Asian region dataset, concluding the overview of those strategies among different countries. The results in Table 5 confirm patterns found in the USA and partially in the European datasets; the short-term reversals appear strong, yielding significant returns. While a long-term horizon is not significant and with has lower performance. It will be key to further analyse data from a more specific perspective to come to conclusions on the robustness and reliability of such strategies.

Table 5: Summary Statistics Reversal Strategies Asia

Table 5 summarizes the monthly performance characteristics of all reversal strategies in the Asian sample after implementation exactly as defined in the data section. Similar to Tables 3 and 4, the page distinguishes short-term portfolios from long-term portfolios. It splits results for equal-weighted (Panel A) and value-weighted (Panel B) implementations, so that the influence of firm size on the anomaly can be inspected. Within each block, the first column reports the benchmark conventional reversal strategy (*CR*), while the next three columns show the residual reversals that remove successively richer sets of factor exposures (*CAPM*, *FF-3*, *FF-5*). For every specification, the table lists the key distributional statistics of monthly returns: mean (annualised), t-statistic, p-value, Volatility (annual), Sharpe ratio, skewness, excess kurtosis, the smallest and largest single-month outcomes, and several percentiles that capture the shape of the return distribution. *,**,*** represent respectively significance levels of 10%, 5% and 1%.

	Short-Term				Long-Term			
Panel A: Equal Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	22.13%***	23.21%***	23.15%***	22.98%***	10.13%***	2.56%	2.56%	2.60%*
t-stat	8.61	8.38	10.09	10.46	4.99	1.54	1.54	1.92
p-value	0.00	0.00	0.00	0.00	0.00	0.12	0.12	0.05
Std. Dev. (%)	18.51%	15.53%	12.86%	12.31%	14.20%	8.87%	8.87%	7.23%
Sharpe ratio	1.20***	1.50***	1.80***	1.87***	0.71***	0.29***	0.29***	0.36***
t-stat	22.77	19.95	21.60	21.89	15.43	5.23	5.23	6.45
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	2.08	2.58	1.83	1.89	0.34	0.65	0.65	0.08
Excess kurtosis	12.30	17.33	10.42	9.38	1.95	2.45	2.45	0.96
Minimum (%)	-9.39%	-9.08%	-7.27%	-5.92%	-15.25%	-6.70%	-6.70%	-7.86%
Percentile 25 (%)	-1.38%	-0.62%	-0.29%	-0.18%	-1.38%	-1.31%	-1.31%	-1.02%
Median (%)	15.82%	15.97%	18.41%	18.69%	6.23%	2.42%	2.42%	1.75%
Percentile 75 (%)	4.14%	3.77%	3.48%	3.27%	2.95%	1.42%	1.42%	1.39%
Maximum (%)	48.40%	41.17%	31.09%	28.69%	17.14%	11.64%	11.64%	7.51%

	Short-Term				Long-Term			
Panel B: Value Weighted	CR	RR_CAPM	RR_FF3	RR_FF5	CR	RR_CAPM	RR_FF3	RR_FF5
Mean (%)	12.91%***	13.08%***	11.10%***	12.57%***	6.67%	-0.55%	0.80%	-0.22%
t-stat	3.84	3.36	3.37	4.10	2.26	-0.18	0.27	-0.07
p-value	0.00	0.00	0.00	0.00	0.02	1.14	0.79	1.06
Std. Dev. (%)	24.17%	21.86%	18.48%	17.20%	20.66%	16.73%	15.83%	16.78%
Sharpe ratio	0.53***	0.59***	0.60***	0.73***	0.32***	-0.03	0.05	-0.01
t-stat	12.46	10.70	10.73	12.61	7.62	-0.61	0.93	-0.25
p-value	0.00	0.00	0.00	0.00	0.00	1.46	0.35	1.20
Skewness	0.70	0.21	-0.18	-0.35	0.09	0.02	0.28	-0.92
Excess kurtosis	4.58	4.57	1.82	2.13	2.75	2.99	1.51	7.95
Minimum (%)	-26.22%	-32.21%	-19.82%	-19.66%	-22.70%	-22.31%	-16.34%	-29.65%
Percentile 25 (%)	-2.70%	-2.14%	-1.83%	-1.34%	-2.72%	-2.31%	-2.56%	-2.25%
Median (%)	7.53%	12.59%	10.88%	12.02%	3.45%	-4.85%	-2.92%	-0.71%
Percentile 75 (%)	4.60%	3.96%	3.89%	3.69%	3.47%	2.12%	2.46%	2.56%
Maximum (%)	41.22%	31.32%	18.87%	19.22%	32.00%	17.95%	17.60%	19.94%

Looking at Table 5, it is relevant to notice the short-term reversals earning the best performances in terms of returns and risk (Sharpe ratios). Indeed, the *ST_CR_EW* scores around 22% return per annum, almost double the USA figure. Controlling for systematic exposures, it boosts the mean still further: the FF5 residual strategy scores a 22.98% return with a Sharpe ratio of 1.88, and the improvement is achieved with materially lower volatility (12.31% versus 18.51% for the CR). Skewness is positive, and excess kurtosis still presents considerably high positive levels, indicating fat tails on the return distribution. Even on the Asian dataset, the high-tail dominance is pronounced, and the maximum monthly return exceeds, on absolute magnitude, the minimum return. Switching to Panel B, Value-Weighting tempers the headline numbers but leaves the hierarchy unchanged: the residual variants outperform the conventional benchmark and their U.S. and European counterparts alike. The *ST_RR_FF5_VW* portfolio, for example, compounds at 12.6% a year with a Sharpe ratio above 0.73. On the contrary, it is significant to signal the decrease in excess kurtosis among the portfolios compared to the equally weighted reversals. It indicates the effect of distributing higher weights to high-capital firms and so controlling for possible extreme returns. Also, the distance between the minimum and maximum returns narrows. Finally, it is clear to state that value-weighted strategies couldn't perform better than the *EW* in terms of risk-adjusted returns, as portfolios' Sharpe ratios are significantly lower than in Panel A.

The long-term reversals follow similar patterns seen in the other regions. Equal-weighted portfolios barely break even after residualisation, and the value-weighted implementations slip negative, with t-statistics that rarely represent statistical significance of findings. The conclusion is the same as for the Western markets: irrespective of geography, long-term conventional and residual reversals fail to generate economically meaningful pay-offs once factor exposures and transaction-cost surrogates are stripped away.

4.4. Further Analysis of Reversal Strategies

To reach the conclusions regarding persistence and robustness of reversal strategies, through different models and regions, further analysis is required. In the present section, I will be analysing the obtained portfolios from several perspectives, such as cumulative returns, risk-adjusted measures, and sub-sample performance, to assess reversal reaction to macroeconomic factors and economic cycles. The focus will be solely on Short Term Reversals (Equal and Value Weighted) since the long-term horizon didn't score significant results already on the first portfolio screening (see Tables 3,4, and 5).

4.4.1. Sharpe Ratios: Assessing Reversal Performance

The first measure to investigate reversal persistence throughout time is building Sharpe Ratios based on a 10-year rolling window. It has been done for the three regions, and it analyses how the risk-adjusted attractiveness of the short-term reversal strategies has evolved through time. Figure 5 visualises six variants: the conventional reversal (*CR*) and its residual counterparts based on *CAPM, FF3* and *FF5* regressions, each reported with both equal and value-weighted portfolio construction. Panels A, B, and C refer, respectively, to the United States, Asia, and Europe.

For the United States (Panel A), the record shows that during the first part of the implementation period, from the early 1980s through the mid-1990s, equal-weighted reversal portfolios produce notable risk-adjusted performances. The Sharpe ratio for the residual strategy using FF5 is more than 2, and for the conventional reversal strategy, between 1.5 and 1.8. But the performance declines over the years. By the onset of the global financial crisis, nearly all Sharpe ratios had halved, and the 2008 shock pushed them below 1. Throughout the period, value-weighted portfolios consistently underperform their equal-weighted counterparts, reinforcing the observation that the reversal effect is more pronounced among smaller-cap stocks. The Asian sample (Figure 5, Panel B), which begins in 1983, exhibits another but complementary pattern. Sharpe ratios collapsed in the late 1990s. As in the USA case, reversal strategies in Asia never return to their former levels; by the late 2010s, all are at or below 0.5. This trend implies a gradual decline in reversal persistence, as markets become more efficient and liquid in trading, thereby potentially undermining the reversal phenomenon.

Figure 5: Sharpe ratios on 10-year rolling windows. A, B, and C, represent the USA, Asia, and Europe.

European dynamics are considerably different compared to Asia and the U.S.; different trends are found in the Sharpe Ratio evolutions (Panel C). Up until 1997, CRs portfolio score ratios around 0.5 quite stably; after that, much higher volatility is found in performance. Finally, in late-2007, value-weighted portfolio yields fall precipitously as the global financial crisis and, subsequently, the euro-area sovereign-debt turmoil unwind short-term reversal premia. The decline is not really noticeable in the equal-weighted portfolios, which seem to have a strong upwards slope throughout the whole period. This poses interesting views on what can be the robustness of those strategies to global phenomena, especially in times of lower liquidity in the market, which can boost reversal performance. This pronounced divergence between *CR* and *RR* series warrants a deeper sub-sample investigation, which the next section undertakes.

Together, the evidence in Figure 5 yields collective insights. First, the added benefit of residual construction exhibits stability in the risk-reward paradigm across periods: during the United States, Europe, and Asia Reversals, the Sharpe ratios of the residual variants systematically surpass those of the benchmark models in all considered periods. This implies that successively removing an increasingly wide array of systematic effects yields a purer stock-specific reversal signal that cushions portfolios during macro-driven drawdowns and increases average excess returns and often accompanied by lower volatility. Second, the breadth of the conditioning model matters: the incremental jump in Sharpe from *CR* to *RR* grows as the hedge migrates from the CAPM to FF3 and is largest for FF5, confirming that a more comprehensive factor net more effectively neutralises common risk swings and allows the residual leg to dominate performance. Third, the portfolio weight assignment does not result in a risk-adjusted advantage: both equally and value-weighted constructions, in both their cumulative return (*CR*) and relative return (*RR*) versions, respond with equal intensity to extreme economic events. Furthermore, value-weighted constructions, with extremely low frequency, provide higher Sharpe ratios, which implies that focusing exposure on large-capitalization stocks does not increase efficiency after risk hedging adjustment.

4.4.2. Sub-sample Evolutions

Table 6 gives a deeper view of the time series evolution of reversal performances. Monthly figures of returns and standard deviations, by splitting the sample into five decades, confirm the earlier annual Sharpe trends. Residual hedging dominates: the *ST_RR_FF3_EW* column beats the conventional *CR_ST_EW* in all the subsamples where they can be compared. The significance of those results is often verified for the level of confidence of 1% on a normal distribution assumption, but in some cases, the t-statistics fall under the threshold, especially on the last two subsets (2003-2013 and 2013-2023). Those two last periods are also peculiar in terms of returns, as the U.S. and Asia correspond in a considerable decrease in performance. It can indicate a dispersion or dissolvence of the reversal robustness compared to the past, which questions the present persistence of this strategy among global markets trends. Regarding Europe, the trends shown are differing from the first two regions with a more stable return yielding also on the last subsets, disregarding of the crisis Europe faced during those years. The scenario is opposite in the Value weighting strategy for the 2003-2013 period, with the *CR_ST_VW* and *ST_RR_FF3_VW* yielding negative returns.

Equal weight is the best return ranking weighting scheme: all areas show the *EW* application outperforming its *VW* counterpart. Value weighting rarely compensates for worse performance with lower risk: its variance is the same or higher, and returns deteriorate. Decades and regions throughout, the equally weighted residual portfolios (FF3) yield the most statistically significant findings: nearly all the cells have a t-statistic comfortably above the 5% (and often 1%) confidence level, while their traditional counterparts sometimes fall into less significant results. Upon bringing in the value-weighting schemes, the evidence collapses dramatically; numerous value-weighted observations, be they residual or raw, fall below the 5% critical level, indicating that statistical reliability diminishes as the focus shifts towards larger capitalization units, and hence provides no assurance regarding the strategy employed. In summary, factor-adjusted residual integration enhances performance and significance under the equal weight approach, but no such assertion can be made under value weighting.

Table 6: Sub-Sample performances among regions

The table reports, for five consecutive decades, the monthly excess-return, volatility and associated t-statistic of four short-term reversal strategies in each region (U.S., Asia, Europe). Within every decade, the first two columns show conventional reversal portfolios using equal- and value-weighting, while the last two columns show their residual (Fama-French-3) counterparts.

Panel A: U.S.

	CR_ST_EW			CR_ST_VW			ST_RR_FF3_EW			ST_RR_FF3_VW		
Sub-Sample	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat
1973-1983	1.98%	4.28%	5.1	0.83%	5.20%	1.8						
1983-1993	1.36%	3.30%	4.5	0.20%	4.26%	0.5	1.65%	2.67%	6.8	0.50%	3.53%	1.6
1993-2003	1.26%	5.63%	2.4	1.66%	6.84%	2.7	1.60%	3.47%	5.1	1.54%	5.17%	3.3
2003-2013	0.40%	4.01%	1.1	-0.32%	5.53%	0.6	1.03%	3.21%	3.5	0.25%	4.87%	0.6
2013-2023	0.63%	4.89%	1.4	-0.11%	5.75%	0.2	0.74%	3.40%	2.4	0.48%	4.35%	1.2

Panel B: Asia

	CR_ST_EW			CR_ST_VW			ST_RR_FF3_EW			ST_RR_FF3_VW		
Sub-Sample	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat
1973-1983	1.94%	4.65%	4.6	0.89%	5.99%	1.6						
1983-1993	2.28%	6.17%	4.0	1.42%	8.58%	1.8						
1993-2003	2.97%	6.56%	5.0	1.80%	8.50%	2.3	3.51%	4.21%	9.1	1.82%	5.85%	3.4
2003-2013	1.32%	4.53%	3.2	0.85%	5.64%	1.7	1.52%	3.44%	4.8	0.72%	5.29%	1.5
2013-2023	0.61%	3.89%	1.7	0.26%	4.98%	0.6	0.89%	3.09%	3.2	0.29%	4.82%	0.7

Panel C: Europe

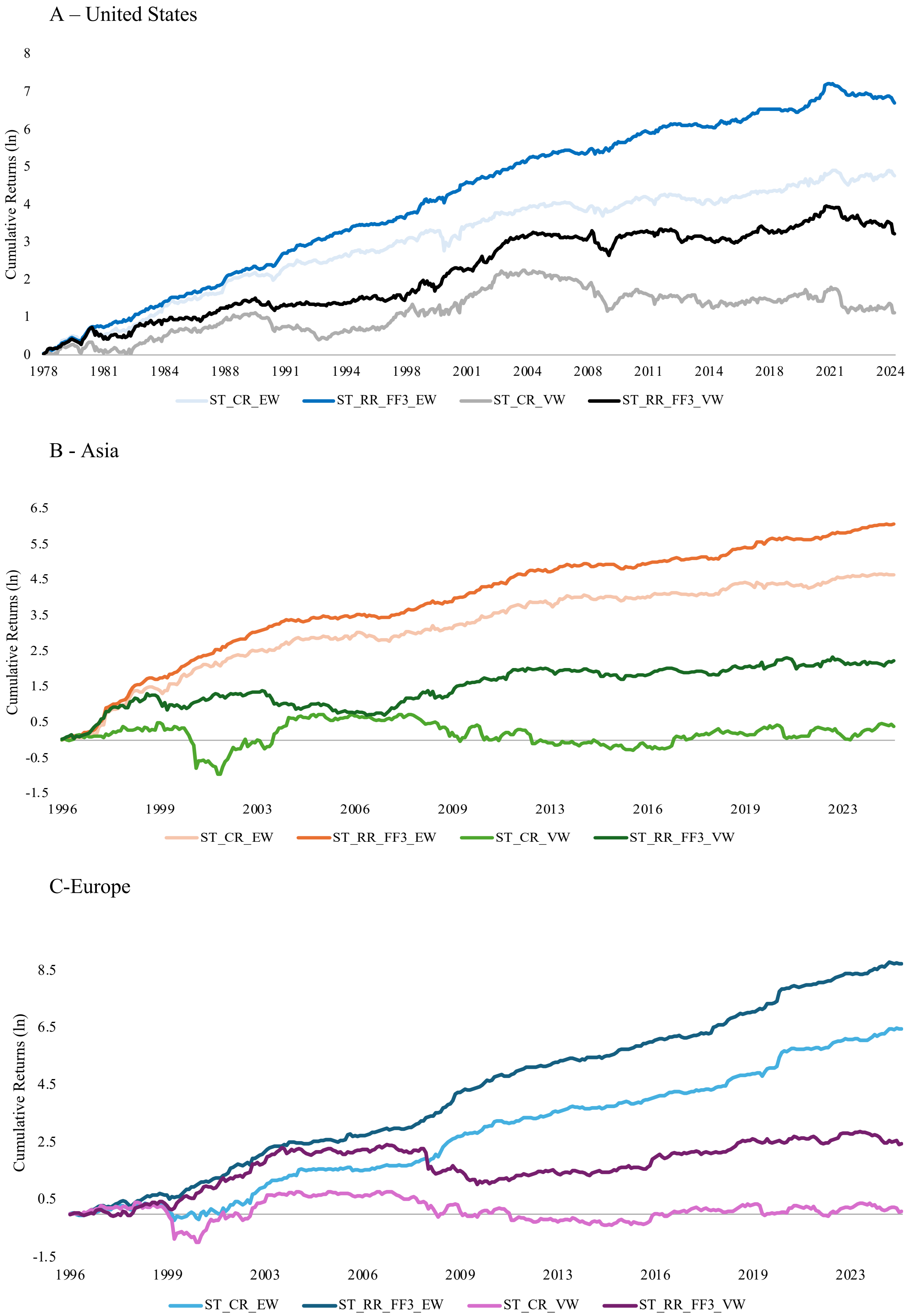
	CR_ST_EW			CR_ST_VW			ST_RR_FF3_EW			ST_RR_FF3_VW		
Sub-Sample	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat	Return	Volatility	t-stat
1973-1983	0.80%	6.05%	1.4	0.74%	7.43%	1.1						
1983-1993	1.06%	7.73%	1.5	0.91%	7.84%	1.3						
1993-2003	1.68%	6.53%	2.8	1.67%	9.70%	1.9	2.61%	4.79%	6.0	2.65%	6.99%	4.1
2003-2013	2.24%	4.63%	5.3	-0.49%	6.23%	0.9	2.66%	4.64%	6.3	-0.25%	7.09%	0.4
2013-2023	2.10%	5.24%	4.4	0.63%	5.63%	1.2	2.57%	5.16%	5.5	1.30%	5.28%	2.7

4.4.3. Cumulative Returns: Robustness of Returns

Cumulative return plotting gives a much more detailed explanation of strategy performance, timing, and extent of drawdown. Also, whether the strategy delivers persistent or episodic profits details that cannot be inferred from static statistics such as long-run means or Sharpe ratios. Figure 6 presents monthly cumulative returns for *ST_CR* and *ST_RR_FF3* strategies. The graphs have been constructed on the assumption of investing 1$ at the starting date of the portfolio. Across the three regions, several patterns are evident. Most strikingly, using the residual-based approach consistently increases the reversal premium. In all markets, the factor-neutral, equal-weighted portfolios perform better than their conventional counterparts. As previously seen and now again, value-weighting consistently shows lower levels of performance. In the United States, the value-weighted *CR* strategy earns modest returns after the late 1990s dot-com bubble and plunges during the 2008 financial crisis, forming approximately a flat line. On the contrary, the equal-weighted counterpart keeps increasing steadily. We find the same pattern in Asia, where the value-weighted portfolio stays near break-even after 2008, while equal-weighted residual and traditional strategies give steady returns. In Europe, the value-weighted strategy also shows a gradual increase, while the equal-weighted counterparts show considerably higher cumulative returns. It is only in the early years, until 2008, that the European VW residual approach (*EU_ST_RR_FF3_VW*) beats the other portfolio specifications.

Collectively, the cumulative returns findings confirm pieces of evidence presented in the previous sections of results, demonstrating that in every region, the most robust strategy is the *ST_RR_FF3_EW*, which at this point can be considered a better performing portfolio creation compared to the conventional counterpart. Factor hedging reliably enhances persistence, and regional shocks such as the Great Financial Crisis or the European debt crisis leave distinctive, interpretable fingerprints on the long-horizon wealth trajectories of reversal-based portfolios. Finally, to assert conclusions from this research, it is necessary to identify empirically the independence of the residual strategy from its conventional counterpart and whether it is typically less exposed to risk factors. The regression result section will follow for this purpose.

Figure 6: Cumulative monthly returns for reversal portfolios among different Regions. Natural Logarithms of returns are used in the Figure. Panel A, B and C show results respectively for the USA, Asia and Europe



5. Regression Results

The last part of the research aims to prove statistically two main concepts, which were broadly introduced in the sections before. The first scope is to demonstrate that the Residual Reversal portfolios implemented can be considered as standalone reversal strategies, relatively independent from the Conventional counterparts. The one mentioned is among the main points of the research question, and the demonstration of that would indicate that the Residual Reversal could be an innovative model that substitutes the *CR*. As a second objective, another regression will be utilized to investigate whether the *RRs* show less exposure (compared to the *CRs*) to risk factors. In my case, the factors considered will be the FF3 factors and the interaction variables described in the data section, inspired by the research of Blitz et al. (2013). The whole regression analysis is made only on the Short-Term Reversal portfolios, since it was demonstrated that the long-term strategy was not able to yield significant and robust returns. Also, only the Equal-weighted portfolios will be taken in examination due to similar reasons: low statistical significance of VW on results and the lower performance compared to the EW counterpart for each model.

5.1. Residual Reversal as a standalone strategy: Regression findings

Table 7 reports the regression results that explain how much each residual reversal portfolio is explained by its conventional reversal counterpart. Using the equal-weighted CR returns series as the sole explanatory variable, three iterations of the dependent portfolio are tested: *ST_RR_CAPM_EW*, *ST_RR_CAPM_EW*, and *ST_RR_CAPM_EW*. This procedure is conducted for the United States, Asian, and European regions. In every geography, the slope coefficient is below 1. In the U.S., the loading drops from 0.78 for CAPM-based RR to 0.53 for FF3 and 0.47 for FF5, also for Asia (1.03, 0.62, 0.57), and Europe (0.89, 0.82, 0.81). The sub-unit betas indicate that a portion of each residual strategy's monthly variations is linked with the respective *CR* portfolio. Notably, the portion decreases when more risk factors are controlled for in the portfolio’s implementation. That is, when returns become adjusted for more risk factors, the *RR* portfolios reveal a greater divergence from the standard reversal signal. The intercepts also affirm this assertion. Across all panels, the alphas are large, economically relevant, and highly significant (p-values < 0.01), varying between 40 and 120 bp per month. Thus, residual portfolios earn stand-alone abnormal performance not captured by the conventional strategy.

Finally, the explanatory power of the regressions recedes markedly with each layer of factor purging. The U.S. adjusted R-squared falls from 73 % in the CAPM regression to 54 % under FF3 and 47 % under FF5; similar two-digit contractions appear in Asia (from 83 % to 70 % and 65 %) and also in Europe except from the FF5 specification (from 66 % to 45% and 46 %). The declining R-squared illustrates that some of the variation of the factor models is unique to the *RR* construction and cannot be replicated by a simple position in *CR*. However, the explanatory power of the model still scores quite considerable results, which it is quite surprising and not fully expected. The key takeaway from those findings, given the decreasing betas, persistent positive alphas, and decreasing R-squared statistics, is the capacity of the reversal strategies to generate fractions of independent returns which are deeper if the factor model used is more “sophisticated[6]”.

[6] Refers on the number of factors present in the model.

Table 7: Regression Results for the Residual Reversal exposure to the Conventional Reversal

For each region block, the table summarizes how the residual-reversal portfolios co-move with their equally-weighted conventional reversal (independent variable) analogue. Monthly *RR* returns are regressed on monthly *ST_CR_EW* returns; the resulting slope, Alpha (annualized), R-squared and Adjusted R-squared are displayed. Values between parentheses report p-values that signal the statistical significance of the coefficients.

Panel A: U.S.

Dependent Variable	Beta	Alpha	R^2	Adjusted R^2
ST_RR_CAPM_EW	0.78	4.45%	72.96%	73.00%
(N= 599)	*(0.00)*	*(0.00)*		
ST_RR_FF3_EW	0.53	9.00%	53.91%	53.99%
(N= 599)	*(0.00)*	*(0.00)*		
ST_RR_FF5_EW	0.47	8.90%	47.11%	47.19%
(N= 599)	*(0.00)*	*(0.00)*		

Panel B: Asia

Dependent Variable	Beta	Alpha	R^2	Adjusted R^2
ST_RR_CAPM_EW	1.03	-5.01%	82.53%	82.56%
(N= 377)	*(0.00)*	*(0.00)*		
ST_RR_FF3_EW	0.61	11.58%	70.48%	70.53%
(N= 377)	*(0.00)*	*(0.00)*		
ST_RR_FF5_EW	0.57	12.33%	65.08%	65.14%
(N= 377)	*(0.00)*	*(0.00)*		

Panel C: Europe

Dependent Variable	Beta	Alpha	R^2	Adjusted R^2
ST_RR_CAPM_EW	0.69	11.34%	66.17%	66.23%
(N= 377)	*(0.00)*	*(0.00)*		
ST_RR_FF3_EW	0.56	17.86%	44.70%	44.79%
(N= 377)	*(0.00)*	*(0.00)*		
ST_RR_FF5_EW	0.56	15.62%	45.94%	46.03%
(N= 377)	*(0.00)*	*(0.00)*		

5.2. Reversal strategies and their exposure to factors: Regression findings

The scope of the research is also to find a Reversal strategy that shows less exposure and co-movements to factor performances. Tables 8 and 9 show the interaction of conventional and residual reversal (Using FF3 as a factor model to obtain residuals) with factor performances. The results found can assist my conclusions on alternative models implied from the reversal principle, which differ from the conventional method. The Asian dataset is not taken into account in the regression analysis since different factors were applied to stocks belonging to different countries (China and Japan, check the Data section for details), the analysis would not be consistent compared to Europe and the United States.

Table 8: Regression Results for factor exposure on Reversal returns among U.S. equities

For the United States dataset, the table summarizes the reversal portfolios' monthly average returns, Standard deviation, and Sharpe Ratio. Also, regression results, defined as in Eq. (18 and 19), show factor exposure of returns for the dependent variable *ST_CR_EW*, in Panel A, and *ST_RR_FF3_EW*, in Panel B. Values between parentheses report p-values that signal the statistical significance of the coefficients.

Panel A: Short-Term Conventional Reversal

Return	Stdev	Sharpe						
1.01%	4.46%	0.78						
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	R^2	Adjusted R^2
0.76%	0.306	-0.042	0.140				8.89%	8.27%
(0.00)	*(0.00)*	*(0.49)*	*(0.02)*					
1.08%	0.356	0.255	0.729	-0.197	-0.544	-1.169	30.95%	30.13%
(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*		

Panel B: Short-Term Residual Reversal

Return	Stdev	Sharpe						
1.28%	3.21%	1.38						
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	R^2	Adjusted R^2
1.13%	0.188	0.029	0.047				7.07%	6.45%
(0.00)	*(0.00)*	*(0.51)*	*(0.26)*					
1.15%	0.112	0.091	0.185	0.166	-0.096	-0.251	9.76%	8.70%
(0.00)	*(0.00)*	*(0.17)*	*(0.00)*	*(0.00)*	*(0.27)*	*(0.00)*		

For the USA sample, Table 8 provides evidence that the residual-reversal specification shows less exposure and dependency on factors, resulting in generating higher significant alphas. For both the simple and the interaction variable specifications, the alphas generated by the strategies appear to be higher when the dependent variable is the *ST_RR_FF3_EW*. In the unspecified regression, both strategies exhibit positive and highly significant intercepts, though their characteristics differ markedly. The Conventional Reversal (CR) strategy delivers a monthly alpha of 0.76%, accompanied by a substantial market beta (0.306) and a notable tilt toward value (Beta HML = 0.140). In contrast, the Residual Reversal (RR) strategy not only maintains but increases its alpha to 1.13% per month, while substantially reducing market exposure with a coefficient of 0.188 and rendering the style factor loadings statistically less significant. This suggests that by removing FF3-related return components at the formation stage, the RR strategy achieves similar or improved profitability with considerably lower exposure to systematic risk. The decline in explanatory power from 8.27% to 6.45% further underscores the diminished influence of the Fama–French factors, highlighting how factor adjustment shapes the characteristics of reversal strategies. Moreover, interaction variable coefficients are less significant and don't show a clear pattern in the reversal portfolio for the residual reversal strategy. Indeed, when the additional terms are added, the divergence widens. The Conventional Reversal strategy exhibits a pronounced negative correlation with the performance of positive style factors, as evidenced by significant negative coefficients (e.g., RMRF_UP = −0.197, SMB_UP = −0.544, HML_UP = −1.169). These interaction terms are all highly statistically significant, suggesting that a substantial portion of the strategy's returns is mechanically driven by contrarian exposure to factors that performed well in the recent past. In contrast, the residual version of the strategy does not display the same systematic pattern; its factor sensitivities are both weaker and insignificant (e.g., SMB_UP = −0.096, not significant), and the explanatory power remains modest (Adjusted R-squared < 10%). Notably, the alpha of the residual reversal strategy remains quite stable around 1.15% in both specifications. It indicates that the majority of its performance is orthogonal to both contemporaneous and lagged exposures to the Fama-French three-factor model.

Table 9: Regression Results for factor exposure on Reversal returns among European equities

For the European dataset, the table summarizes the reversal portfolios' monthly average returns, Standard deviation, and Sharpe Ratio. Also, regression results, defined as in Eq. (18 and 19), show factor exposure of returns for the *ST_CR_EW*, in Panel A, and the ST_RR_FF3_EW, in Panel B. Values between parentheses report p-values that signal the statistical significance of the coefficients.

Panel A: Short-Term Conventional Reversal

Return	Stdev	Sharpe						
2.03%	5.82%	1.21						
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	*R^2*	Adjusted R^2
1.83%	0.227	0.251	0.208				5.89%	4.88%
(0.00)	*(0.11)*	*(0.06)*	*(0.03)*					
2.07%	0.268	0.705	0.664	-0.173	-0.894	-0.820	13.37%	11.73%
(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.14)*	*(0.00)*	*(0.00)*		

Panel B: Short-Term Residual Reversal

Return	Stdev	Sharpe						
2.62%	4.85%	1.87						
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	*R^2*	Adjusted R^2
2.50%	0.081	0.221	0.200				3.00%	1.96%
(0.00)	*(0.11)*	*(0.06)*	*(0.03)*					
2.46%	0.020	0.491	0.143	0.162	-0.523	0.120	4.94%	3.14%
(0.00)	*(0.76)*	*(0.00)*	*(0.31)*	*(0.12)*	*(0.03)*	*(0.53)*		

The European results in Table 9 reinforce the key trends observed in the U.S. sample. The Residual Reversal (RR) strategy continues to deliver a higher alpha (2.50%–2.46%) with lower standard deviation and a stronger Sharpe ratio (1.87), while exhibiting considerably weaker and often not significant exposure to Fama–French factors, both in unspecified and interaction regressions. In contrast, the Conventional Reversal (CR) strategy maintains notable factor loadings, particularly strong and significant tilts toward market, size, and value, and its interaction terms (e.g., SMB_UP = −0.894, HML_UP = −0.820) again reflect mechanical contrarian positioning relative to recent factor winners. Importantly, RR's alpha remains stable despite the introduction of interaction terms, while CR's explanatory power (Adjusted R-squared) increases substantially with them, confirming that a sizable portion of its performance stems from dynamic factor timing. These findings confirm the robustness of the earlier conclusion: RR isolates reversal profits with far less systematic risk.

6. Conclusions

This paper tested stock-return reversals over 1973-2023 in the US, Europe, and Asia. The findings show that short-term conventional reversal, buying last month's losers and selling last month's winners, remains a statistically and economically viable strategy in all three markets. Conversely, long-term reversal strategies that rely on multi-year formations and intervals of inactivity do not appear to produce consistent excess returns when standard risk factors are taken into consideration. Consequently, the reversal phenomenon seems to be limited to short-term periods, during which liquidity provision, order imbalances, and cognitive biases are particularly evident. Furthermore, the creation of reversal portfolios using residual returns improves overall performance. The residual strategies maintain or improve average returns while, at the same time, they reduce volatility, thereby improving Sharpe ratios in all regions. Conditional regression analyses confirm that residual-based portfolios earn significant, statistically reliable alphas with lower factor exposure compared to conventional strategies. The correlations of their returns with conventional reversals tend to decline proportionally to the quantity of factors included within the regression window. This suggests that residual reversal could be a separate source of return, one that is less correlated with factor drivers. However, overall performance is unstable in the long term. The rolling ten-year Sharpe ratios indicate that in the first decades of the strategy, performance highs are scored. Thereafter, it has subsequently declined, a trend consistent with a continuing increase in market liquidity as a result of decimalization, algorithmic trading, and declining transaction costs. These findings highlight the procyclical character of reversal returns. Finally, the weighting schemes on portfolio formation impact outcomes. Equal-weighted portfolios perform better than value-weighted counterparts in most regions and time periods.

As a whole, results confirm the presence of a short-horizon, residual reversal premium, indicating its responsiveness to market-wide liquidity conditions, and demonstrate that long-horizon reversal strategies have largely become economically irrelevant. The research conclusions suggest several clear avenues for further inquiry. First, embedding detailed trading-cost estimates such as commissions, bid–ask spreads, and market-impact metrics. It would convert gross alphas into net, capacity-adjusted figures and indicate whether residual reversal remains viable at the institutional scale. Second, applying the same framework to emerging and frontier markets would test whether thin liquidity and higher information frictions magnify residual reversal or whether elevated costs neutralise the raw premium. Third, conditioning pay-offs on macro variables such as monetary-policy stance, global liquidity cycles, or controlling for recession periods could explain the timing and size of results observed in the historical record. Finally, it would be valuable to investigate if an aggregated global dataset could outperform the regional results and if investors should place bets on the global persistence of reversals. Pursuing these extensions would sharpen our understanding of the drivers, limits, and potential adaptations of reversal strategies.

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