NIMBUS FINANCIAL LAB

Momentum Under Pressure:

What Drove S&P 500 Stock Returns During the 2025 Market Dislocation?

WHITE PAPER

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Nimbus Financial Lab is a quantitative investment research and strategy firm that focuses on the systematic analysis of financial data in all its forms. We extract deep insights from both company filings and the time-series behavior of financial assets to develop data-driven trading strategies. Our mission is to deliver investment strategies that generate sustainable returns and also consistently outperform both market-wide and industry-specific indices.

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Foreword

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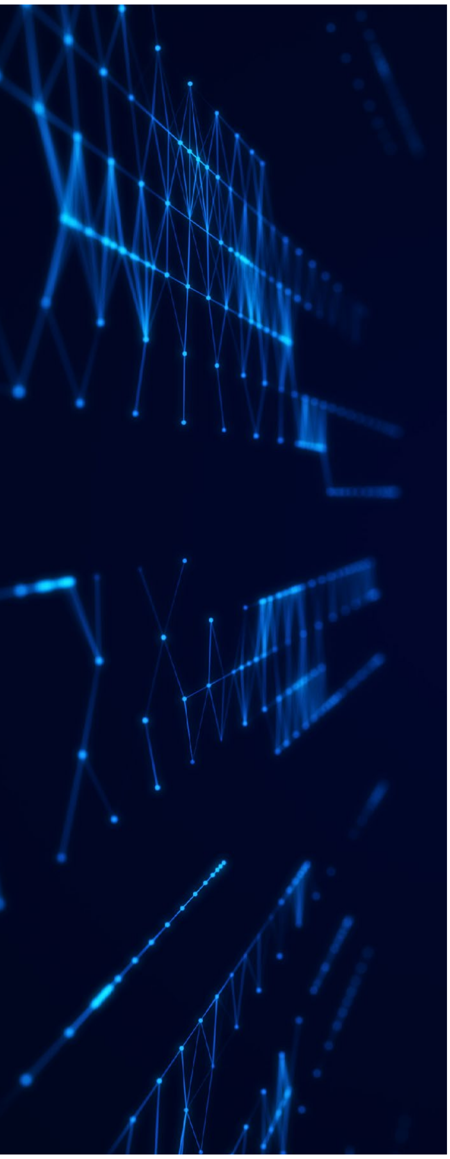

At Nimbus Financial Lab, we have been actively testing algorithms based on momentum strategies for some time. During this testing phase, following the election of Donald Trump as U.S. President, a series of domestic and international developments—most notably the announcement of new tariff policies—introduced considerable uncertainty into the market. These events, along with other global shifts, triggered heightened volatility starting in mid-February.

In this environment, we observed notable deviations in the performance of our momentum-based algorithms compared to more stable periods. While academic literature has extensively documented the predictive power of past performance in explaining stock returns, there remains a relative scarcity of research that focuses specifically on return behavior during turbulent or transitional market conditions—particularly in the immediate aftermath of political and macroeconomic shocks.

Motivated by this gap, we decided to conduct a focused analysis of the February 19 to June 12, 2025 period. While our findings broadly align with recent studies on momentum crashes and mean reversion dynamics, they also suggest the need for a more nuanced approach that integrates firm fundamentals and market context.

This report marks the first step in a broader effort. In the coming months, we intend to expand this analysis to cover additional historical downturns and to incorporate a deeper balance sheet–based perspective. By doing so, we aim to better understand how stock performance differentiates during periods of market stress, and how predictive models can be improved for greater resilience across economic regimes.

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Introduction

Momentum investing, the strategy of buying stocks that have performed well in the recent past and selling those that have performed poorly, has become one of the most widely examined anomalies in asset pricing. Though the practice long predates formal academic recognition, it was popularized and institutionalized by investors like Richard Driehaus, who famously advocated a philosophy of “buying high and selling higher.” Rather than seeking undervalued stocks, Driehaus emphasized price action and growth, capturing investor herding and short-term price trends.

Academic research later lent rigorous empirical support to momentum strategies. Seminal work by Narasimhan Jegadeesh (1990) demonstrated that past stock returns exhibit systematic patterns, with significant negative serial correlation at short horizons and strong positive autocorrelation over longer horizons, especially at the twelve-month mark. In his study spanning 1934–1987, the author showed that stocks sorted into decile portfolios based on predicted returns produced a striking 2.49% per month spread between the highest and lowest deciles, revealing that stock returns are, to a degree, predictable.

At the core of this discussion lies the broader concept of volatility clustering, a well-documented phenomenon in financial markets. Volatility tends to arrive in bursts, with periods of high volatility followed by more of the same, and low volatile periods follow low volatile periods (Brooks, 2019). This phenomenon, also known as volatility pooling, implies that large returns are often followed by more large returns, regardless of sign, and has implications for risk management, trading strategies, and the autocorrelation structures of returns. It also means that momentum strategies implemented in high-volatility regimes may experience both amplified gains and losses, depending on timing.

Building on this, scholars such as Cooper, Gutierrez, and Hameed (2004) tested overreaction theories and documented how momentum profits vary with market conditions. Their findings shows that momentum strategies are profitable after positive market states (mean return: +0.93%), but fail or reverse after down markets (mean return: –0.37%). This asymmetry indicates that momentum strategies do not operate uniformly across market states, but rather depend on macro sentiment and regime shifts. Moreover, they found that macroeconomic variables do not fully explain these effects, suggesting behavioral and structural forces are at play.

The temporal dimension of momentum is another important consideration. While short-term momentum strategies (e.g., 1–3 month holding periods) have often been found profitable, longer-term reversals are frequently observed, especially after extreme market conditions. This paradox lies at the heart of models like the Fama-French three-factor framework, which initially struggled to reconcile momentum returns with its value-oriented view (1996). Later refinements, including Carhart’s four-factor model with the UMD (Up Minus Down) factor, were developed to accommodate the momentum anomaly (Arnott, R.D. et. al., 2019).

Further evidence from Cheng et.al., (2017) links the magnitude of momentum reversals to liquidity provision and institutional investor behavior. Their research shows that stocks with poor past returns tend to experience stronger reversals in subsequent months, in part because active institutions participate less in those names, reducing liquidity and exacerbating price overshooting. This liquidity channel adds a microstructure dimension to the momentum-reversal story, reinforcing the idea that return dynamics are not purely driven by fundamentals or macro factors, but also by market participant behavior and flow constraints.

Even with robust academic support for momentum strategies, one key concern for practitioners remains: how stocks, and momentum stocks in particular, behave under different market states, especially during episodes of systemic market stress. For a portfolio manager, knowing which stocks are likely to persist, reverse, or collapse during market crashes and rebounds is far more actionable than knowing average momentum returns in a neutral setting. Researchers such as Daniel and Moskowitz (2016) have highlighted that momentum underperforms in recovery periods due to negatively skewed returns, suggesting crashes are often followed by sharp, unpredictable reversals, which can be damaging for trend-based strategies.

While existing literature has provided substantial evidence on momentum and mean-reversion dynamics, short-term market collapses and subsequent rebounds remain comparatively underexplored, largely due to their episodic, rapid, and unpredictable nature. Nevertheless, such periods offer a unique opportunity to examine how individual stocks respond to sharp and systemic shifts in market sentiment, thereby illuminating whether recent winners sustain their outperformance or whether reversals dominate under distressed conditions. This distinction holds significant implications for risk budgeting, dynamic portfolio allocation, and scenario-based stress testing.

At Nimbus Financial Lab, we contribute to this body of work by analyzing the cross-sectional behavior of S&P 500 stocks during a recent two-phase market event: the sharp market downturn from February 19 to April 8, 2025, followed by a rapid rebound through June 12, 2025. Our objective is to move beyond traditional momentum portfolios and instead examine how different types of stocks behave in clearly segmented market states, defined by structural breaks in index-level returns.

By constructing firm-level regressions and quadrant-based performance maps, we evaluate whether characteristics such as beta, size, leverage, volume, asset efficiency, and prior momentum help explain which stocks collapse and which rebound. Importantly, our approach allows us to identify patterns that are conditional on market regime, rather than assuming a homogeneous return-generating process across time. The findings, detailed in the next sections, provide both theoretical relevance and practical implications for asset managers navigating volatile markets.

Chapter One

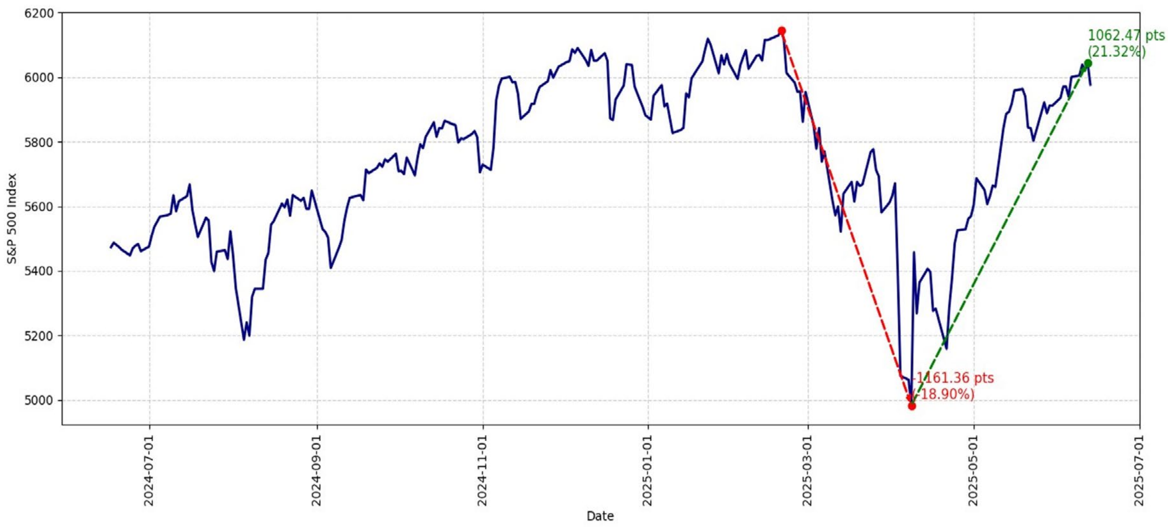
Market Dislocations and the Limits of Momentum Strategies — Evidence from the 2025 S&P 500 Drawdown and Recovery

The first half of 2025 marked a period of pronounced volatility for the S&P 500 Index, driven by a confluence of domestic policy shifts and evolving global dynamics. While the index is composed of large, diversified firms and is often treated as a barometer of U.S. economic health, its performance is highly responsive to both domestic policy announcements and global economic developments.

Among the key domestic influences during this period were policy announcements from the Trump administration, particularly surrounding the reactivation of tariff-oriented trade strategies. On February 13, 2025, the administration unveiled a plan for universal tariffs, a move that revived earlier trade protectionist rhetoric from Trump's first term. This was followed by a formal announcement of a global 10% tariff implementation on April 2, which coincided with growing investor anxiety, intensified media coverage, and market repricing of global supply chain risk.

It is important to note that the market's reaction to these developments cannot be attributed to any single announcement in isolation. Rather, the observed market decline should be interpreted in the context of a broader macroeconomic and geopolitical environment. The early months of 2025 were marked by rising oil prices, uncertainty around interest rate policy, and tensions in global trade relations, all of which exerted pressure on investor sentiment and risk premiums. Consequently, while the Trump administration's tariff strategy likely contributed to heightened market uncertainty, it operated alongside several international headwinds, including slower growth forecasts from China, weakening European industrial production, and volatility in emerging markets. Empirically, the S&P 500 began its descent shortly after the initial tariff strategy announcement and reached a local bottom shortly following the April 2 implementation date.

Figure 1: S&P 500 Index Movements Between Selected Dates (2025)



Source: Yahoo Finance

Figure 1 illustrates the movement of the S&P 500 Index between July 2024 and July 2025, highlighting two distinct phases of market behavior in early 2025. Empirically, The S&P 500 reached its local high on February 19. From that date until April 8, when it hit a local bottom, the index declined sharply. The index shed 1,161 points, or approximately 18.9%, over a period of less than five weeks—one of the sharpest non-recessionary drawdowns in recent history. However, the rapid recovery that followed, with the index rebounding by 21.3% over the next two months (April 8-June 12), suggests that the market did not fully price in a long-term macro deterioration. Instead, the correction appears to have been a response to short-term uncertainty. The sharp contrast between the decline and recovery phases underscores the volatility characterizing this period.

As Nimbus Financial Lab, we entered this period positioned according to the recommendations of our momentum-based algorithmic strategy, which identifies recent outperformers based on price trends and allocates accordingly. This approach, built on the strong empirical foundation of prior academic work, had historically yielded robust returns in neutral or upward-trending environments. However, over the course of the past three months, we observed that the algorithm underperformed significantly during the crash-rebound cycle, prompting a deeper investigation into why momentum failed in this particular market regime.

Beginning our deeper investigation with academic literature, our experience aligns closely with the findings of Daniel and Moskowitz (2016), who demonstrate that momentum strategies are highly vulnerable in so-called “panic” states—periods characterized by recent market declines, elevated volatility, and abrupt rebounds. Momentum returns are typically negatively skewed, meaning they often generate small, consistent gains but are periodically interrupted by severe losses. These momentum crashes tend not to occur during protracted downturns but rather during sharp market reversals, when past losers rebound and short positions are forcefully unwound. In such regimes, momentum strategies struggle not due to poor design, but because the underlying return dynamics shift from trend-following to mean-reversion.

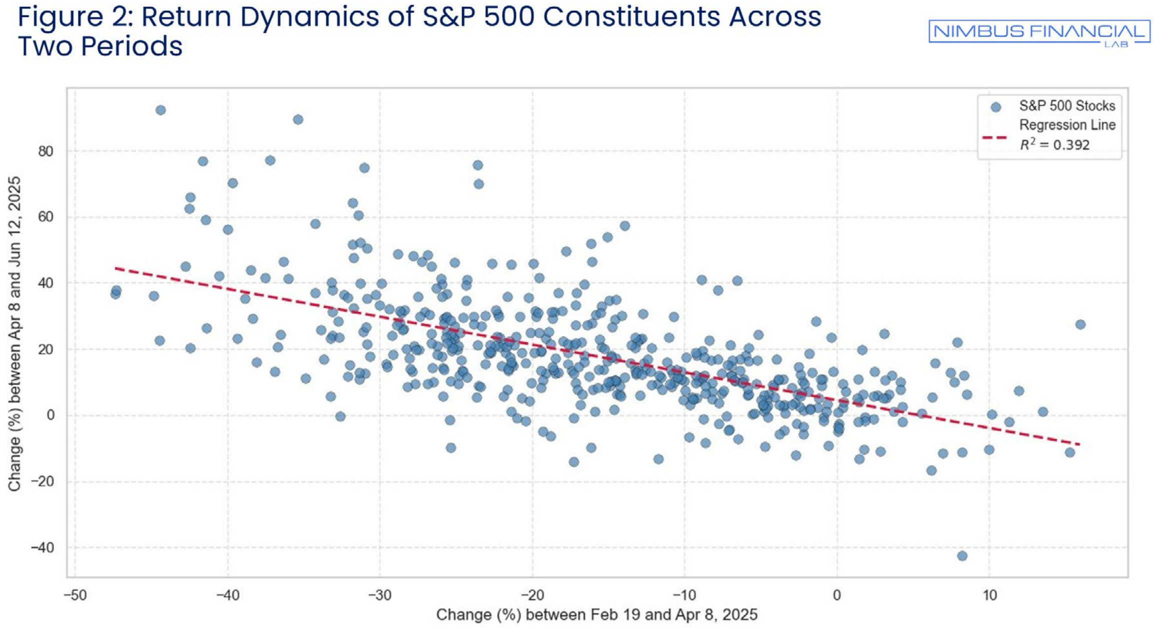
The broader academic literature further supports the view that stocks do not respond uniformly during crises, challenging the notion that momentum works equally well across all environments. For instance, Wang et al. (2009), in a study of eight historical U.S. market crashes, show that individual stock reactions to crashes depend on firm-level fundamentals such as leverage, sector affiliation, and liquidity. Their event study methodology reveals a clear heterogeneity in crash vulnerability, implying that portfolio strategies must condition on financial traits to navigate extreme environments effectively.

In line with this, Ang, Chen, and Xing (2005) document a downside risk premium in the cross-section of returns: stocks that exhibit strong co-movement with the market during downturns earn higher average returns in the long run as compensation for that risk. Conversely, stocks that are more insulated from downside beta tend to underperform in post-crisis recoveries. This insight introduces an important second axis—sensitivity to downside market movements—along which firms may diverge significantly in recovery trajectories.

Other researchers have focused on quality as a measure of resilience during market disruptions. As highlighted by Asness, Frazzini, and Pedersen (2017), high-quality firms—those characterized by profitability, low leverage, stable earnings, and sound management—tend to decline less in downturns and recover more quickly. Their Quality Minus Junk (QMJ) factor, which goes long quality stocks and shorts low-quality stocks, produces strong risk-adjusted returns and serves as a potential complement—or even a hedge—against momentum strategies in volatile environments.

To locate the root of the problem our strategy encountered, we began by examining how the individual stocks listed in the S&P 500 behaved over the period in question. Figure 2 explores how individual S&P 500 stocks responded across two consecutive periods of market stress and recovery in early 2025.

Figure 2: Return Dynamics of S&P 500 Constituents Across Two Periods



Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

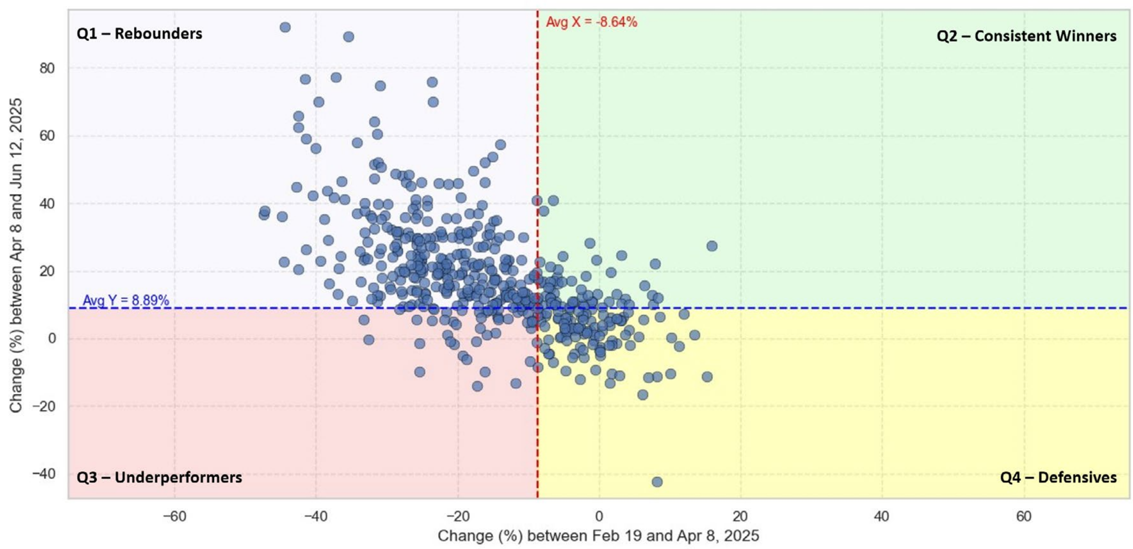
Each dot represents a single stock, with the x-axis measuring its percentage return during the collapse pahse (Feb 19-Apr 8, 2025), and the y-axis capturing its percentage return during the rebound phase (Apr 8–Jun 12, 2025).

The most striking pattern is the negative slope of the regression line, which quantifies the relationship between returns in the two periods. The R^2 value of 0.392 indicates that approximately 39% of the variation in rebound-period returns can be explained by how stocks performed during the collapse. The downward slope suggests a partial momentum reversal effect: stocks that fell more sharply during the downturn tended to recover more robustly but not uniformly or completely. However, the scatter of data points shows considerable variation around the trend, implying that not all severely impacted stocks rebounded to the same degree, and some continued to lag.

This discrepancy has led us to recalibrate our analytical lens. Rather than asking only whether momentum exists, we now ask how momentum interacts with market states, and whether other factors, such as quality, volatility, and downside beta, should be used to condition or hedge momentum exposures.

In this context, before subjecting all of the aforementioned factors to formal analysis, we extended our descriptive analysis in greater detail. Specifically, we examined the average returns of individual stocks over the relevant period to assess how they were priced during this market phase. Figure 3 offers a quadrant-based visualization that categorizes S&P 500 stocks based on their returns across two consecutive periods: the collapse phase and the rebound phase.

Figure 3: Above and Below-Average Return Mapping of S&P 500 Constituents Across Two Periods

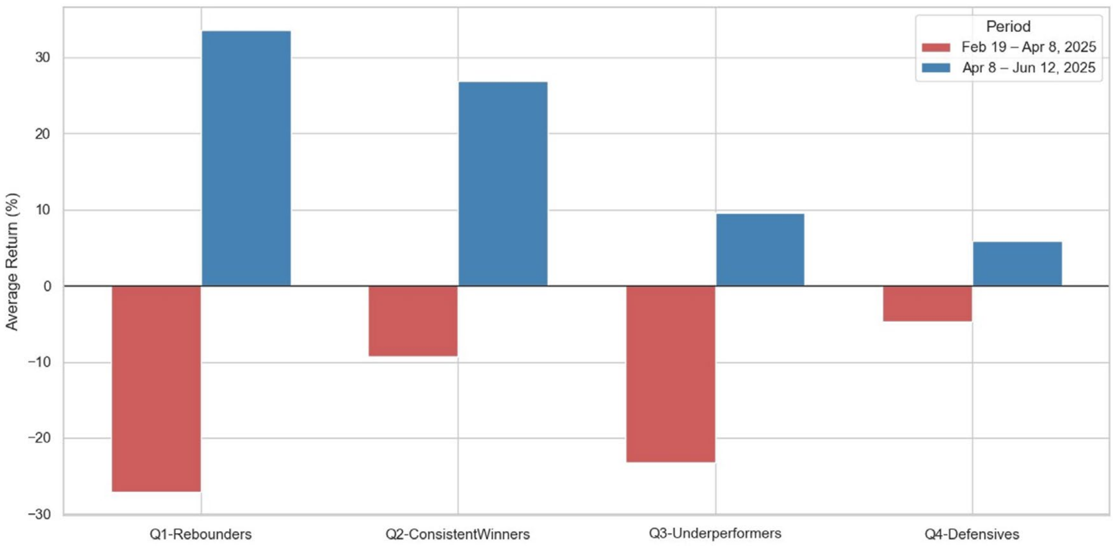


Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

The x-axis shows percentage change during the collapse, while the y-axis reflects performance during the rebound. The red vertical line (Avg X = –8.64%) and the blue horizontal line (Avg Y = 8.89%) represent the average return in each respective period, dividing the plot into four distinct performance quadrants.

Building on the quadrant framework introduced in Figure 3, which categorizes S&P 500 stocks based on their relative performance before and after the February–April 2025 market collapse, Figure 4 provides a deeper examination of how these groups performed on average across the two periods. This bar chart clearly quantifies the cross-period return dynamics for each quadrant, allowing us to move from a scatter-based conceptual view to an aggregated performance perspective.

Figure 4: Cross-Period Return Dynamics by Quadrant Classification of S&P 500 Constituents



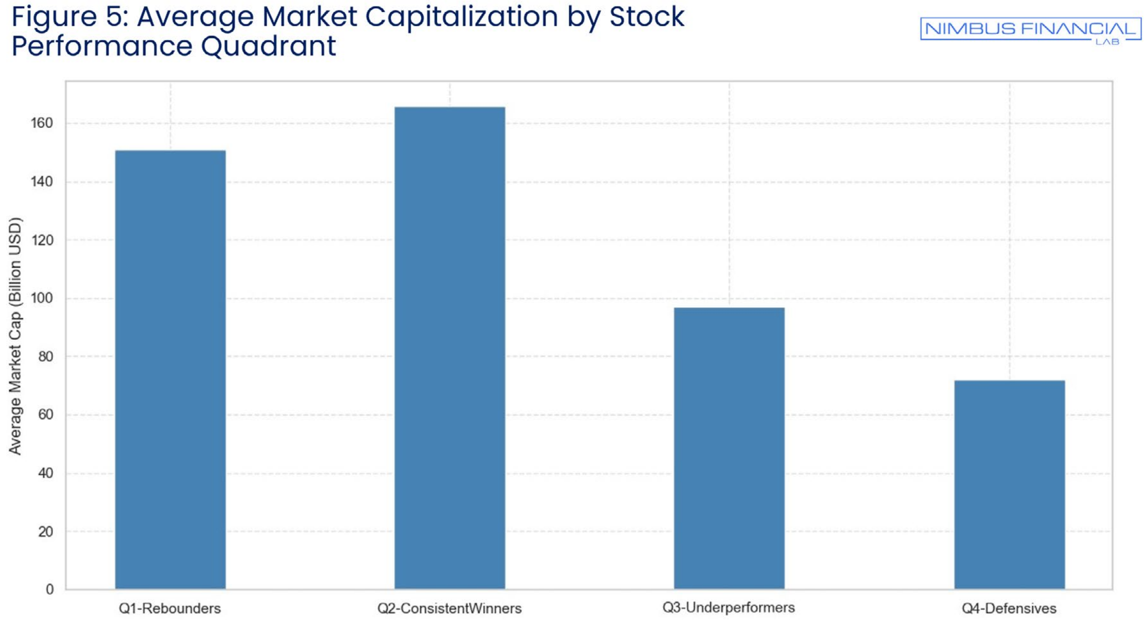
Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

The most notable insight comes from the Q1 – Rebounders group: firms that underperformed during the collapse (below-average returns) but delivered strong outperformance during the recovery. On average, these stocks suffered a steep decline of around –28% in the first phase, but then bounced back sharply with an average return exceeding +30%. This dramatic reversal underscores the market's tendency to reprice oversold assets when sentiment shifts. In contrast, Q2 – Consistent Winners, which includes stocks that performed well in both periods, experienced modest losses during the collapse but posted a strong average rebound, though slightly weaker than Q1.

The Q3 – Underperformers group fared poorly in both periods, with average losses exceeding –20% in the collapse and only weak recovery gains afterward. This persistent underperformance suggests structural weakness, sector-specific distress, or investor aversion that carried through both phases. Meanwhile, Q4 – Defensives performed relatively better during the initial downturn (limited drawdowns), but lagged in the recovery, suggesting that the market rotated out of safe-haven names once risk appetite returned.

In addition, since firm size and beta have been extensively studied in the literatüre, particularly in relation to how they shape stock behavior during periods of market stress, we extended our descriptive analysis to examine these dimensions as well.

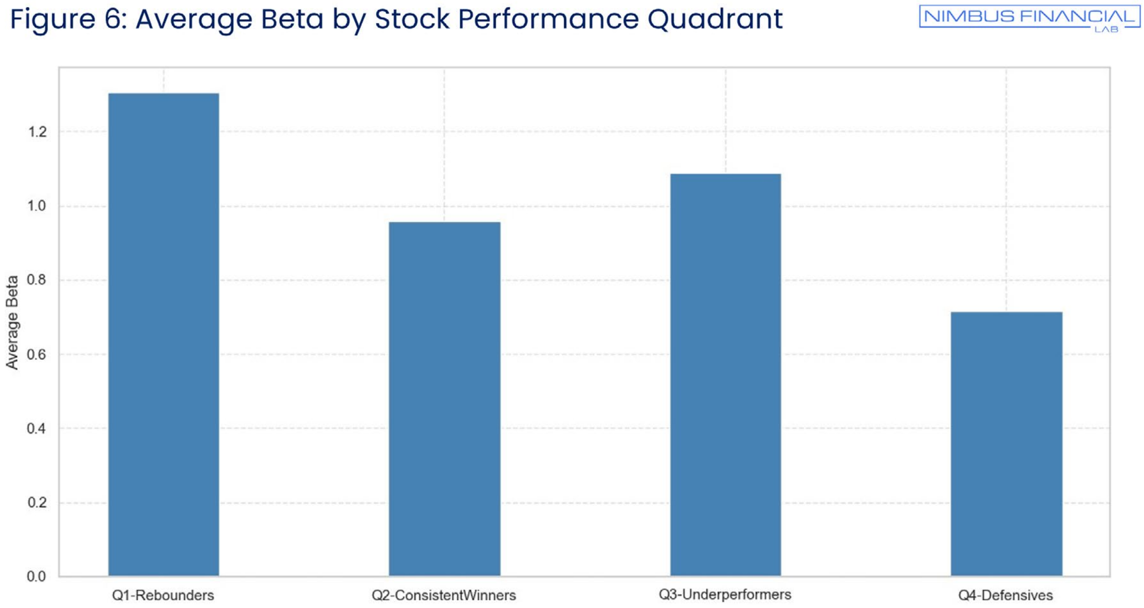
Figure 5: Average Market Capitalization by Stock Performance Quadrant



Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

Figure 5 illustrates the average market capitalization of stocks within each performance quadrant. The data reveal a clear gradient: Q2–Consistent Winners and Q1–Rebounders are, on average, significantly larger firms than those in Q3–Underperformers and Q4–Defensives. This suggests that firm size may be a relevant factor in how stocks respond to extreme market movements. Larger firms, with stronger balance sheets and more diversified operations, may be better positioned to withstand volatility, either by maintaining relative strength (Q2) or by attracting capital during rebounds (Q1). Conversely, smaller firms appear more frequently in quadrants characterized by underperformance or defensive stability, pointing to a potential size-related vulnerability or muted upside during recoveries.

Figure 6: Average Beta by Stock Performance Quadrant



Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

Figure 6 presents the average beta values across the same four quadrants, offering insight into the systematic risk exposures of each group. As expected, Q1–Rebounders exhibit the highest average beta, indicating stronger sensitivity to market-wide movements which is consistent with the notion that high-beta stocks suffer sharper losses in downturns but also benefit more during rebounds. Q4–Defensives, by contrast, display the lowest average beta, confirming their limited co-movement with broader market swings and their relative insulation during the collapse period. Meanwhile, Q2–Consistent Winners show lower beta exposure than Q1 or Q3, suggesting that their strong performance was not primarily driven by market beta but likely by other firm-specific characteristics such as quality, profitability, or investor sentiment resilience.

Chapter Two

Econometric Analysis of Cross–Sectional Return Drivers in Market Dislocation

In this section, we identify a set of explanatory variables based on the academic literature on momentum strategies and stock performance under varying market conditions. Guided by these insights, we construct two separate econometric models to explain cross-sectional return variation during distinct phases: the collapse period (February 19 – April 8, 2025) and the rebound period (April 8 – June 12, 2025).

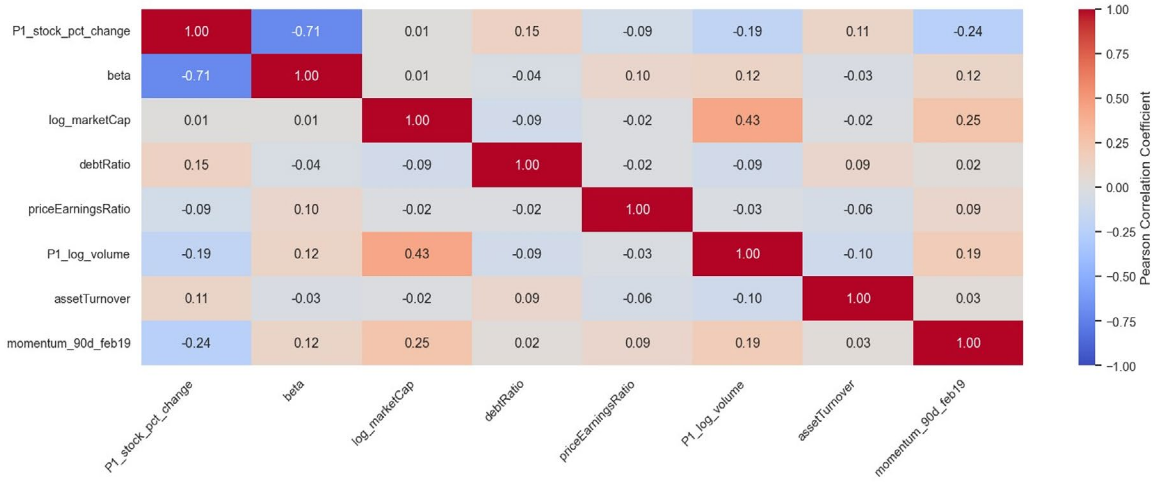
For the collapse period model, the following variables were selected: Stock return during the collapse period (P1_stock_pct_change): This serves as the dependent variable and represents the percentage change in stock prices from the beginning to the end of the market downturn. Beta coefficient (beta): A measure of systematic risk, capturing a stock's sensitivity to broader market movements. Logarithm of market capitalization (log_marketCap): A size proxy, included to test whether larger firms behaved differently under stress. Debt ratio (debtRatio): Captures financial leverage and the extent of a firm's balance sheet risk. Price-to-earnings ratio (priceEarningsRatio): A valuation metric, used to explore whether relatively expensive or cheap stocks performed differently during the collapse. Logarithm of average 30 trading days volume before collapse (P1_log_volume): Serves as a proxy for liquidity and investor interest prior to the downturn. Asset turnover ratio (assetTurnover): An operational efficiency metric reflecting how effectively a firm utilizes its assets to generate revenue. Prior momentum over the 90 days leading up to February 19, 2025 (momentum_90d_feb19): Included to assess how pre-crisis price trends influenced performance during the collapse.

$$Eq.1.\quad P1\_stock\_pct\_change_i = \alpha + \beta_1 \cdot beta_i + \beta_2 \cdot log(MarketCap_i) + \beta_3 \cdot debtRatio_i + \beta_4 \cdot priceEarningsRatio_i + \beta_5 \cdot log(Volume_i) + \beta_6 \cdot assetTurnover_i + \beta_7 \cdot momentum\_90d\_feb19_i + \varepsilon_i$$

All variables were obtained via API calls using the Financial Modeling Prep (FMP) platform, with a custom-built data retrieval system developed in Python. Once retrieved, relevant variables such as market capitalization and volume were log-transformed to correct for skewness and to facilitate linear modeling.

Before estimating the model, we conducted a Pearson correlation test to examine pairwise relationships among the independent variables. This step ensured that multicollinearity issues were minimized, thereby improving the reliability of coefficient estimates in the subsequent regression analysis. Figure 7 shows the result of Pearson correlation test results.

Figure 7: Correlation Matrix of Collapse Period (Feb 19 – Apr 8, 2025) Variables



Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

As shown in Figure 7, no evidence of multicollinearity that would violate econometric assumptions is observed in the correlation matrix. The pairwise Pearson correlation coefficients between the independent variables remain well below critical thresholds, indicating that the variables do not exhibit problematic linear dependencies. Therefore, in the second stage, we proceeded with the estimation of the econometric model constructed using the selected variables. The output of this model is presented below in Table 1 in tabular form, summarizing the regression estimates for the collapse period.

Table 1: Regression Coefficients Explaining Stock Returns During the Collapse Period (Feb 19 – Apr 8, 2025)

Variable	Coefficient	Std. Error	t-Stat	p-Value	95% CI
Intercept (const)	-14.118	8.608	-1.64	0.102	[-31.030, 2.794]
Beta	-19.798	0.903	-21.936	0	[-21.572, -18.025]
log_marketCap	1.366	0.369	3.702	0	[0.641, 2.092]
debtRatio	5.852	1.517	3.858	0	[2.872, 8.833]
priceEarningsRatio	0.0001	0.004	0.031	0.975	[-0.007, 0.008]
P1_log_volume	-1.233	0.363	-3.399	0.001	[-1.945, -0.520]
assetTurnover	1.474	0.613	2.404	0.017	[0.269, 2.678]
momentum_90d_feb19	-0.171	0.03	-5.69	0	[-0.230, -0.112]

Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

The results of the collapse period regression reveal several significant relationships between firm characteristics and stock performance during the sharp market downturn between February 19 and April 8, 2025. First and most prominently, market beta emerges as the strongest explanatory variable with a large negative coefficient (–19.80, $p < 0.001$). This indicates that stocks with higher systematic risk—i.e., higher sensitivity to the overall market—suffered significantly worse returns during the collapse period. Economically, a one-unit increase in beta is associated with a decline of nearly 20 percentage points in stock return, reaffirming the classical view that high-beta stocks underperform in bear markets due to their greater exposure to aggregate shocks.

Firm size, proxied by the natural logarithm of market capitalization, is positively and significantly associated with collapse-period performance. The coefficient estimate of +1.37 ($p < 0.001$) suggests that larger firms fared better during the downturn, consistent with the “flight to quality” hypothesis. Investors may have reallocated capital toward larger, more stable firms amid rising uncertainty and liquidity stress, leading to relative outperformance of large-cap stocks.

Interestingly, leverage, measured by the debt ratio, also exhibits a positive and statistically significant coefficient (+5.85, $p < 0.001$). While this might appear counterintuitive—since high leverage typically exacerbates risk in downturns—it may reflect the sectoral composition of debt-heavy firms or a partial rebound effect where initially distressed stocks attracted contrarian investors. This result suggests the importance of interacting financial indicators with sector controls or examining subsample dynamics in future extensions.

In contrast, valuation, as captured by the price-to-earnings (P/E) ratio, does not significantly influence returns during the collapse period. The near-zero and statistically insignificant coefficient indicates that stocks' relative valuation levels were not predictive of their performance under sharp market stress, which is consistent with prior findings that valuation-based anomalies often weaken during extreme periods when fundamentals are temporarily disregarded.

The coefficient for P1_log_volume is –1.23 and is statistically significant ($p = 0.001$), indicating a strong and negative relationship between a stock's average trading volume before the collapse and its subsequent return during the collapse period. Interpreted economically, this suggests that stocks with higher pre-collapse trading activity experienced larger losses during the downturn. This could reflect several mechanisms: (1) higher-volume stocks may have been more widely held or crowded, making them more vulnerable to sharp selling when sentiment reversed; (2) elevated pre-collapse volume may have indicated speculative interest or overexposure, which was unwound rapidly during the crash; or (3) these stocks may have been perceived as more liquid, making them easier to offload under stress, thus bearing more of the selling pressure. In short, the market appears to have punished the stocks that were more actively traded just prior to the collapse, possibly due to a mix of liquidity-driven selling and the unwinding of crowded positions.

Moreover, firms with greater asset turnover, a proxy for operational efficiency, exhibited stronger relative performance, with a positive and significant coefficient of +1.47 ($p = 0.017$). This suggests that firms with more efficient asset utilization were perceived as better positioned to weather the downturn, or were less exposed to operational fragility.

Finally, the model identifies a notable momentum reversal pattern: the coefficient on momentum over the 90 days prior to February 19 is negative and highly significant (–0.17, $p < 0.001$). This indicates that stocks with strong pre-collapse momentum tended to underperform more severely during the market decline, consistent with patterns observed in crash periods where prior winners become targets of profit-taking and deleveraging.

As presented in Table 2, the model achieves an R-squared of 0.561 and an adjusted R-squared of 0.555, indicating that approximately 56% of the variation in collapse-period stock returns is explained by the included predictors. This represents a strong explanatory power for cross-sectional stock return models, especially during a high-volatility market downturn.

The overall model is statistically significant (F-statistic = 90.31, $p < 0.001$), confirming that the joint set of explanatory variables contributes meaningfully to explaining return variability.

Table 2: Model Fit Statistics for Collapse Period (Feb 19 – Apr 8, 2025) Regression

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Metric	Value
Dependent Variable	P1_stock_pct_change
Observations	503
R-squared	0.561
Adjusted R-squared	0.555
F-statistic	90.31
Prob (F-statistic)	< 0.001
Log-Likelihood	-1772
AIC	3560
BIC	3594
Durbin-Watson	1.346
Omnibus Test (Normality)	p = 0.129
Jarque-Bera Test	p = 0.084
Condition Number	2500

Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

Following the analysis of the collapse period, an important next step is to investigate the factors that explain the performance of the same stocks during the subsequent rebound period. To test this, we constructed a second cross-sectional regression model using a new set of variables corresponding to the rebound period *(April 8 – June 12, 2025)*.

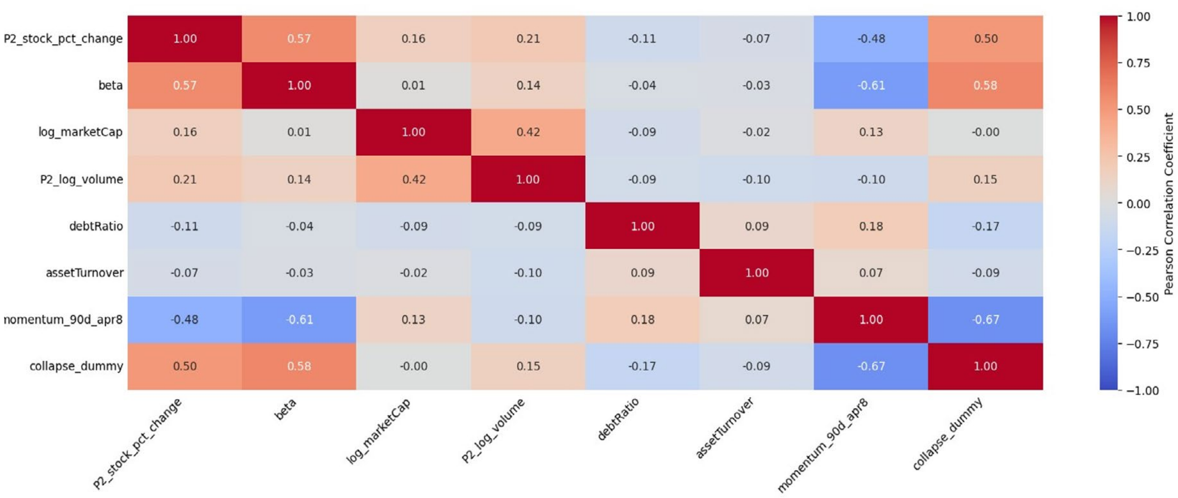
For the rebound period model, the following variables were selected: Stock return during the rebound period (*P2_stock_pct_change*): This is the dependent variable, representing the percentage change in each stock's price from the start to the end of the rebound phase. Beta coefficient (*beta*): A measure of systematic market risk, indicating how sensitive a stock is to overall market movements. Logarithm of market capitalization (*log_marketCap*): A size-related control variable, reflecting the scale and perceived stability of the firm. Logarithm of average volume prior to 30 days to the rebound (*P2_log_volume*): A liquidity proxy capturing trading activity just before the rebound began. Debt ratio (*debtRatio*): A measure of financial leverage, relevant for understanding how balance sheet risk may influence rebound performance. Asset turnover (*assetTurnover*): This operational efficiency ratio reflects how effectively a company utilizes its assets to generate revenue. Prior momentum before April 8, 2025 (*momentum_90d_apr8*): This variable captures the trailing 90-day price trend leading into the rebound, included to test whether momentum effects persisted in recovery conditions. Collapse-period loss indicator (*collapse_dummy*): Collapse_dummy: A binary variable equal to 1 for stocks that experienced larger-than-average losses during the collapse period (i.e., Q1–Q3 stocks), and 0 otherwise, used to capture non-linear effects of extreme collapse exposure.

$$Eq.2. \quad P2\_stock\_pct\_change_i = \alpha + \beta_1 \cdot beta_i + \beta_2 \cdot log(MarketCap_i) + \beta_3 \cdot P2\_\log\_volume_i + \beta_4 \cdot debtRatio_i + \beta_5 \cdot assetTurnover_i + \beta_6 \cdot momentum\_90d\_apr8_i + \beta_7 \cdot collapse\_return_i + \varepsilon_i$$

As in the previous model, the full dataset was obtained using API calls through a Financial Modeling Prep account, with data acquisition handled via Python programming scripts. To normalize the distribution of skewed variables, both *market capitalization* and *volume* were log-transformed prior to model estimation.

Before proceeding to the regression analysis, we conducted a Pearson correlation test to examine the potential presence of multicollinearity among the selected explanatory variables. As visualized in Figure 10, most variables exhibit low to moderate pairwise correlations, remaining within acceptable econometric bounds.

Figure 10: Correlation Matrix of Rebound Period (April 8 – June 12, 2025) Variables



ce: Financial Modeling Prep, Nimbus Fin Lab Calculations

However, there is a notable negative correlation between momentum_90d_apr8 and collapse_dummy (ρ = −0.67), indicating that stocks with strong pre-rebound momentum tended to avoid collapse classification. Still, given their distinct economic interpretations, both were retained in the model. Overall, the correlation structure does not appear to violate core econometric assumptions, and thus the model was estimated using the full set of predictors. The output of the second model presented in Table 3.

Table 3: Regression Coefficients Explaining Stock Returns During the Rebound Period (April 8 – June 12, 2025)

Variable	Coefficient	Std. Error	z-Stat	p-Value	95% CI
Intercept (const)	-65.9449	13.919	-4.738	0	[-93.225, -38.665]
beta	14.5638	2.029	7.179	0	[10.588, 18.540]
log_marketCap	2.1304	0.614	3.468	0.001	[0.926, 3.335]
log_volume	0.8395	0.507	1.657	0.098	[-0.154, 1.833]
debtRatio	-1.072	2.232	-0.48	0.631	[-5.446, 3.302]
assetTurnover	-0.5091	0.973	-0.523	0.601	[-2.417, 1.399]
momentum_90d_apr8	-0.1752	0.073	-2.408	0.016	[-0.318, -0.033]
collapse_dummy	5.8474	1.571	3.722	0	[2.768, 8.927]

Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

The coefficient for market beta shifts dramatically in this model. With a value of +14.5 and strong statistical significance ($p < 0.001$), the interpretation contrasts starkly with the collapse-period regression. Here, higher-beta stocks—those more sensitive to overall market movements—outperformed during the rebound. This finding reflects a classical risk-on recovery dynamic, where investors reallocated capital to riskier assets in anticipation of improving conditions. A one-unit increase in beta is associated with a 14.6 percentage point increase in stock returns during the rebound, confirming that systematic risk was rewarded as sentiment shifted positively.

Firm size, proxied by the natural logarithm of market capitalization, maintains its significance with a positive coefficient of +2.13 ($p = 0.001$). This implies that larger firms continued to outperform in the rebound period. While this might at first appear surprising—given that smaller stocks often lead recoveries—it reinforces the idea that investors maintained a preference for stability and liquidity even amid market recovery, possibly due to lingering macroeconomic uncertainty or skepticism regarding the breadth of the rebound.

In contrast to its importance during the collapse, pre-rebound average trading volume (P2_log_volume) shows a positive but only marginally significant coefficient (+0.84, $p = 0.098$). This suggests that liquidity or crowding effects were no longer central in determining performance as the market rebounded. Stocks that had been heavily traded in the lead-up to the rebound did not perform significantly differently than those with lighter pre-rebound volume, indicating a reduction in panic-driven or flow-driven trading behavior.

Leverage, measured by the debt ratio, also loses its significance in this model (coefficient = –1.07 (p = 0.631). While leverage was positively associated with returns during the collapse—perhaps due to contrarian or sector-specific behavior—it does not appear to have helped or hurt stocks in the recovery. This might suggest that investors were no longer penalizing balance sheet risk, or that any such effects were offset by other firm characteristics.

Likewise, asset turnover, a proxy for operational efficiency, shows a small and statistically insignificant effect on returns (coefficient –0.51, p = 0.601). This reflects a broader shift in market dynamics: whereas efficiency helped explain resilience during the crash, it offered no clear advantage during the rebound. Investors may have become less focused on fundamentals and more driven by macro signals or sentiment-driven trading.

The coefficient on momentum over the 90 days prior to April 8 is -0.17, and this relationship is statistically significant (p = 0.016). This implies stocks with stronger pre-rebound momentum actually underperformed during the recovery. This finding runs counter to typical continuation patterns and suggests a degree of mean reversion or sentiment rotation, with investors favoring previously beaten-down stocks.

Collapse_dummy is a binary indicator designed to capture whether a stock experienced a larger-than-average decline during the collapse period (February 19 – April 8, 2025). Specifically, it takes the value 1 for stocks positioned to the left of the vertical red line in Figure 3, i.e., those that fell more than the average drawdown (Q1–Q3), and 0 for stocks that performed at or above average (Q2–Q4). The regression results show that this variable is positive and highly statistically significant (coefficient = +5.85, p < 0.001). This finding implies that stocks that were hit harder during the collapse phase went on to outperform during the rebound period, consistent with partial return reversals and investor reallocation toward oversold assets.

Table 4: Model Fit Statistics for Rebound Period (April 8–June 12, 2025) Regression

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Metric	Value
Dependent Variable	change_2_pct_change
Observations	503
R-squared	0.406
Adjusted R-squared	0.398
F-statistic	44.12
Prob (F-statistic)	2.12e-48
Log-Likelihood	-1996.6
AIC	4009
BIC	4043
Durbin-Watson	1.401
Omnibus Test (Normality)	p = 0.000
Jarque-Bera Test	p ≈ 1.67e-66
Condition Number	729

Source: Financial Modeling Prep, Nimbus Fin Lab Calculations

As visualized in Table 4, the rebound model explains approximately 40.6% of the cross-sectional variation in stock returns from April 8 to June 12, 2025. Compared to the collapse-period model ($R^2 \approx 56\%$), this explanatory power is somewhat lower but still meaningful, particularly given the noisier and more sentiment-driven dynamics that tend to dominate recovery phases. The strongest drivers of rebound performance were market beta and the collapse_dummy variable, indicating that stocks with greater market sensitivity and those that had suffered deeper-than-average losses during the collapse phase went on to generate stronger returns during the rebound. In contrast, traditional firm fundamentals such as leverage and operational efficiency played a more limited role. These findings reinforce the narrative of a risk-on regime shift, where investors rotated into high-beta, previously oversold stocks, betting on their upside potential as sentiment improved and macro conditions began to stabilize.

Conclusion

Momentum strategies—those that systematically invest in recent winners and avoid laggards—have long been regarded as among the most persistent and profitable anomalies in empirical finance. At Nimbus Financial Lab, our proprietary momentum algorithm has historically generated strong relative performance in stable or trending markets by identifying stocks with favorable short- to medium-term price dynamics. However, the sharp decline and subsequent rebound of the market in early 2025 offered an empirical stress test to this approach and revealed notable weaknesses in its behavior during periods of heightened volatility and regime transition.

While the early 2025 market downturn does not constitute a formal recession or systemic crisis, it nonetheless triggered significant cross-sectional dispersion in equity returns, presenting a relevant and analytically rich environment to evaluate the robustness of momentum-based strategies. In this particular episode, our algorithm—designed to rotate into high-performing stocks—underperformed significantly as many prior winners rapidly became underperformers and previously neglected stocks staged sharp rebounds. This momentum disruption prompted a broader reassessment of the model's behavior under non-trending and high-volatility market regimes.

The academic literature has long acknowledged that momentum strategies are prone to "crash risk" and negative skewness, particularly during rebounds from sharp downturns. Notably, Daniel and Moskowitz (2016) highlight how momentum strategies tend to fail in "panic states," characterized by elevated volatility and abrupt market reversals. Moreover, studies such as Wang et al. (2009) and Ang et al. (2006) emphasize that stock responses during downturns are far from uniform, and that firm-specific characteristics—such as size, leverage, liquidity, and downside beta—shape outcomes in ways momentum alone cannot capture. These insights informed the design of our study and our selection of variables in modeling cross-sectional returns during the collapse and rebound periods.

To empirically investigate these dynamics, we constructed two separate cross-sectional econometric models, one for the collapse period *(Feb 19 – Apr 8, 2025)* and one for the rebound period *(Apr 8 – Jun 12, 2025)*. Each model utilized a set of explanatory variables inspired by both momentum literature and practical implementation constraints, including beta, size (log market cap), liquidity (log volume), debt ratio, asset turnover, and pre-period momentum. Data was obtained using the Financial Modeling Prep API and processed via Python, with transformations applied to control for skewness and ensure comparability.

Our results show that momentum effects were strong and statistically significant during the collapse period—prior momentum negatively predicted performance, confirming a momentum crash dynamic. Other important predictors during the collapse included beta and volume, suggesting that high-beta and highly traded stocks were hit hardest. During the rebound, beta and collapse_dummy emerged as the most significant predictors, with high-beta stocks and those that suffered larger losses during the collapse experiencing stronger recoveries. Prior momentum showed a statistically significant negative effect, suggesting reversal behavior, while traditional firm fundamentals such as leverage and asset efficiency lost explanatory power. These results point to a short-term mean reversion dynamic and a shift toward risk-seeking behavior during the recovery phase.

It is important to emphasize that this analysis focuses on a single market disruption. While the findings offer meaningful insight into how momentum breaks down under stress, they are inherently episode-specific. To evaluate the robustness and generalizability of the patterns observed here, the same methodology should be replicated across other historical downtrend and rebound periods. Doing so will allow for a more comprehensive understanding of when, how, and why momentum strategies become vulnerable, and whether certain predictive signals consistently hold across regimes.

While the current study captures key dimensions of stock performance during this turbulent period, it also leaves several important areas open for further development. In particular, future work should extend the analysis to include balance sheet fundamentals, such as profitability, liquidity ratios, and investment intensity—variables that may offer more stable explanatory power across market regimes. The quadrant analysis employed in this report provides a useful first step in categorizing stocks by performance patterns, but we intend to deepen this framework by linking quadrant behavior to firm-level accounting data sourced from company filings. This will enable us to test hypotheses around balance-sheet-driven resilience or vulnerability in greater detail.

In conclusion, while this was not a formal recession or financial crisis, the period presented a natural laboratory for examining the fragility of momentum strategies and underscored the importance of regime-aware modeling. At Nimbus Financial Lab, we view this disruption not as a failure of the model, but as an opportunity to evolve our approach by integrating firm fundamentals with price-based signals. In the coming weeks, our team will focus on enhancing the model through more granular financial data and exploring whether certain balance sheet traits can systematically explain divergences in stock performance during transitional market phases.

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