MOMENTUM IN SWEDEN: STOCK-LEVEL OR INDUSTRY-LEVEL?

UNDERSTANDING THE SOURCE OF MOMENTUM

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Bachelor Thesis

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Abstract:

This paper shows that momentum in Sweden arises from individual firms rather than industries. We find that individual stocks display strong and persistent momentum at intermediate horizons, and this pattern remains after controlling for industry returns, firm characteristics, short- and long-horizon return effects, and alternative formation and holding periods. By contrast, we find no consistent evidence of industry momentum in either portfolio tests or cross-sectional regressions. When both sources are examined together, only stock-level momentum is statistically significant. These findings suggest that momentum profitability in Sweden is not compensation for nondiversifiable industry risk, but instead stems from behavioral or other risk-based explanations.

Keywords:

Individual stock momentum, Industry momentum, Return continuation, Behavioral drivers, Risk-based drivers

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I. Introduction

Momentum is a persistent return pattern in financial markets: stocks with high recent returns tend to continue outperforming. Jegadeesh (1990) show statistically significant profits from buying recent winners and selling recent losers, establishing momentum as an empirical challenge to standard asset-pricing models. Subsequent research shows that momentum is not unique to the U.S. market. Rouwenhorst (1998) finds similar return continuation across twelve European markets, confirming that momentum is a global phenomenon.

However, the source of momentum remains debated. Jegadeesh and Titman (1993) attribute momentum to firm-specific return continuation. Their evidence rejects risk-based explanations and indicates that investors underreact to firm-specific news, generating temporary mispricings that produce momentum. In contrast, Moskowitz and Grinblatt (1999) show that industries account for much of U.S. stock momentum. Their results imply that shared industry shocks, rather than firm-specific behavior, drive return continuation. They conclude that because industry shocks are nondiversifiable, industry momentum provides a risk-based rationale, which explains why momentum persists and is not an arbitrage opportunity.

The extent to which industries contribute to momentum in a smaller and more concentrated market such as Sweden is not well established. Rouwenhorst (1998) finds that Sweden is the only European market in his sample without statistically significant momentum profits, suggesting that momentum patterns in Sweden may differ from those in larger markets. These findings motivate a more recent examination of whether momentum exists in Sweden and, if so, whether it arises from individual firms, industries, or both. Specifically, we investigate the following three research questions:

1. Does individual stock momentum exist in the Swedish market?

2. Does industry momentum exist in the Swedish market?

3. Does individual stock momentum persist after controlling for industry momentum in the Swedish market?

By addressing these questions, we assess whether momentum profits in the Swedish market could be partly explained by industry-level risk.

We apply Moskowitz and Grinblatt (1999) methodology to all firms listed on the OM Exchange from 2000 to 2025, extending their analysis both temporally and geographically. Following Jegadeesh and Titman (1993) momentum strategy, we construct momentum portfolios at both stock and industry level. For stock-level portfolios, we rank stocks each month based on their past six-month return, form winner and loser portfolios, hold them for six months, and compute average momentum profits. For industry-level portfolios, we follow the same procedure after sorting all firms into five SIC-based industries. We then control for industry effects to test whether stock-level momentum persists.

To assess the robustness of our industry momentum results, we examine alternative formation and holding periods, validate our industry classifications using rank and autocorrelation diagnostics, and decompose short-term industry momentum by firm size and trading value. Finally, we estimate monthly Fama–MacBeth cross-sectional regressions to evaluate how individual stock and industry momentum variables explain the cross-section of adjusted stock returns. The Fama–MacBeth regressions complement the portfolio-sort approach by using every stock each month, reducing sensitivity to sorting rules and portfolio-weighting choices.

Our main finding is that momentum in Sweden exists and originates from individual stocks rather than industries. We show that stocks with strong returns over the past six to twelve months continue to outperform stocks with weak past performance. This stock momentum is robust: it persists after controlling for industry returns and firm characteristics, applying alternative formation and holding periods, and accounting for short- and long-horizon return patterns. By contrast, industries themselves do not display momentum: industries with strong recent performance do not earn higher future returns under any formation or holding period, and this result does not change when we vary the timing of the strategy or adjust industry returns for firm characteristics. Although industries exhibit stable relative rankings, indicating that our industry classifications represent economically coherent sectors, these stable positions do not translate into return persistence. This lack of persistence in returns is consistent with the structure of the Swedish market: value-weighted industry returns primarily reflect the performance of a few large, liquid firms rather than sector-wide movements. Together, our findings show that momentum in Sweden is a stock-level phenomenon, not an industry-driven one.

Our results contribute to the momentum literature by showing how momentum operates in a small and concentrated European market and demonstrate that the industry-driven momentum documented by Moskowitz and Grinblatt (1999) does not extend to Sweden. If momentum were driven by industry risks, part of its profitability would reflect compensation for exposure to nondiversifiable sector shocks, as suggested by Moskowitz and Grinblatt (1999). Instead, we find no consistent evidence of industry momentum. This finding indicates that momentum profitability in Sweden does not reflect industry risk and indicates that the source of momentum lies elsewhere, whether in behavioral explanations, such as investor underreaction to firm-specific information (Jegadeesh and Titman, 1993), or in other risk-based explanations that do not arise from nondiversifiable industry shocks. Taken together, our findings provide new evidence on return predictability outside the U.S. market and deepen understanding of how market structure shapes return persistence, valuable for portfolio construction and investment theory.

The rest of the paper proceeds as follows. Section II reviews earlier research, and outlines our contribution to the momentum literature. Section III describes our data and variable construction. Section IV presents our empirical methodology and main results. Section V examines the robustness of industry momentum. Section VI analyzes stock- and industry-level momentum using cross-sectional Fama–MacBeth regressions. Section VII concludes with a summary of the results and their implications.

II. Literature Review

A large body of research agrees that momentum is a robust and persistent return pattern. Early empirical evidence from Jegadeesh (1990) and Chan, Jegadeesh, and Lakonishok (1996) show significant positive returns from momentum trading strategies. Jegadeesh and Titman (1993) confirm that this return continuation reflects positive serial correlation and argue that if past returns predict future returns, then some component of returns must be correlated with itself over time. To understand which part of a stock's return drives this persistence Moskowitz and Grinblatt (1999) explain that a stock's return can be conceptually decomposed into three parts: firm-specific movements, industry-wide movements, and exposure to common risk factors. Each component may exhibit serial correlation and can, in principle, generate momentum. Existing research provides conflicting evidence on which component is the primary driver of momentum.

Jegadeesh and Titman (1993) document strong serial correlation in individual stock returns over 3- to 12-month formation periods. They show that the strategy of buying past winners and selling past losers, using a six-month formation and holding period, generates statistically significant abnormal profits, often close to 1% per month. These profits persist after adjusting for systematic risk, delayed reaction to common factors, and microstructure noise, and are consistent with investors underreaction to firm-specific information. Barberis, Shleifer, and Vishny (1998) support this explanation by showing how investor conservatism can cause prices to underreact to new information, leading to short-term return continuation. Jegadeesh and Titman (1993) winner–loser strategy established the standard approach to measuring momentum profits and provided evidence that momentum challenges market efficiency. Fama and French (1996) further confirm that stock-level momentum is real and robust, showing that it is an anomaly that remains after controlling for market, size, and value factors.

Griffin, Ji, and Martin (2003) examine momentum profits across 40 countries, both developed and emerging, and find economically large and statistically significant profits showing that momentum is not a U.S.-specific anomaly but a global phenomenon. Rouwenhorst (1998) further extends momentum research to smaller markets by testing stock momentum in twelve European equity markets. He finds that internationally diversified momentum portfolios yield statistically significant profits that cannot be explained by conventional risk factors. At the country level, however, Sweden stands out as the only market out of the twelve where winner–loser returns are positive but not statistically significant, raising the question of whether momentum exists in Sweden in a more recent period and, if so, whether return continuation arises from individual firms, industries, or both.

Revisiting the evidence, Jegadeesh and Titman (2001) confirm that return continuation is driven primarily by firm-specific components rather than by risk. Taken together, this evidence establishes that momentum is global and persistent, and consistent with behavioral explanations.

Further research examines whether industry-wide movements also display serial correlation and contribute to momentum, offering a risk-based explanation. Moskowitz and Grinblatt (1999) show that momentum profits are largely driven by industry-wide movements, rather than by firm-specific movements or exposure to common risk factors. They find that once industry effects are removed, stock momentum becomes weak and mostly statistically insignificant, which suggests that part of its profitability reflects compensation for industry-level risk. In contrast, Grundy and Martin (2001) argue that, once they control for industry and factor effects, momentum profits remain largely driven by stock-specific return patterns. They conclude that industry momentum exists but cannot by itself explain the profitability of momentum trading strategies. Complementing this evidence, Yan and Yu (2023) find that industry momentum contains predictive power beyond factor momentum. Taken together, existing literature shows that industry momentum is real, but researchers disagree on how much of stock momentum it explains.

The third source of serial correlation in stock returns arises from exposure to common risk factors such as market, size, value, profitability, and investment (Fama and French, 2015). If factor returns exhibit serial correlation, momentum may reflect persistence in systematic risk, not firm-level idiosyncratic risk. Lewellen (2002) challenges behavioral explanations and shows that size, value, and industry portfolios, where firm-specific noise is diversified away, display momentum as strong as individual stocks. He argues that excess covariance, not underreaction, explains much of momentum. Arnott, Kalesnik, and Linnainmaa (2023) provide further support to this view and show that factor momentum explains stock and industry momentum, suggesting that systematic components play a central role. In contrast, Asness, Moskowitz, and Pedersen (2013) extend this perspective to a global setting and find strong and persistent momentum in eight diverse markets and across asset classes. Their findings challenge both behavioral and traditional risk-based explanations, suggesting that momentum reflects broader global factors rather than firm-specific drivers.

Although prior research examines the different sources of momentum, evidence remains mixed and is largely drawn from the U.S. market. We address this gap by studying the Swedish market, the only European country where Rouwenhorst (1998) finds no statistically significant momentum. By applying Moskowitz and Grinblatt (1999) methodology, we test whether momentum exists in Sweden and, if so, whether it arises from individual firms, industries, or both.

III. Data

We use a sample of listed and delisted firms on the OM Exchange. We retrieve firm-level monthly total returns, trading value, shares outstanding, share prices, accounting data, and SIC codes from Capital IQ Pro. We obtain the risk-free rate from Sveriges Riksbank and use the three-month Swedish Treasury bill, (Sveriges Riksbank, 2025) which represents the Swedish equivalent of the three-month U.S. Treasury bill used in Moskowitz and Grinblatt (1999). The monthly sample spans September 2000 to September 2025, and accounting data range from fiscal year 2000 to the most recent reports available as of September 2025. Earlier years contain too few listed firms to form diversified industry portfolios. Moskowitz and Grinblatt (1999) study a 32-year period from 1963–1995, but comparable coverage is not available for Sweden in the earlier years.

Following Moskowitz and Grinblatt (1999), we define market capitalization ($SIZE$) as share price times shares outstanding, lagged one month, and book-to-market equity (BE/ME) as the most recently available book equity divided by lagged market capitalization. We measure operating profitability (OP) following Fama and French (2015) as operating profit over book equity and use EBIT as the operating profit measure. We define investment (INV) in accordance with Fama and French (2015) as the annual asset-growth rate, calculated as the percentage change in total assets from fiscal year $t-2$ to fiscal year $t-1$.

We match accounting data to monthly stock data using a six-month reporting lag, following Fama and French (2015). We treat book equity and BE/ME as missing when book equity is zero or negative, set INV to missing when total assets in either $t-2$ or $t-1$ are zero or negative, and treat zero trading value as missing. We retain observations where returns equal zero. Zero share prices and zero shares outstanding are set to missing before computing market capitalization, so any zero-return associated with invalid price or share information is removed mechanically by the requirement for a valid lagged market capitalization.

We winsorize OP, BE/ME, INV, and raw returns at the 1^{st} and 99^{th} percentiles to limit the influence of outliers and remove firm-month observations with market capitalizations below 50 million SEK to eliminate micro-cap data errors. These filters reduce the influence of extreme observations.

Throughout our paper, we use Newey and West (1987) heteroskedasticity- and autocorrelation-consistent t-statistics. For non-overlapping monthly returns, we use zero lags. For overlapping returns, we set the number of lags equal to the overlap length (H) minus one ($H-1$).

Table I
Summary Statistics

This table reports summary statistics for raw returns, market capitalization (*SIZE*), book-to-market equity (*BE/ME*), operating profitability (*OP*), investment (*INV*), and trading value. For each variable, we present the mean, median, standard deviation (σ), minimum, maximum, and the total number of non-missing observations. The statistics are based on monthly data for all listed and delisted firms on the OM Exchange from September 2000 to September 2025. We also report the total number of unique firms included in the sample.

Variable	Mean	Median	σ	Min	Max	Observations
Raw Return (%)	0.70	0.00	13.77	-35.71	53.33	108,261
SIZE (SEK millions)	12,916.77	957.45	46,388.25	50.00	978,472.10	108,261
BE/ME	0.56	0.38	0.58	0.01	3.32	108,261
OP	-0.06	0.10	0.61	-3.70	0.81	106,186
INV	0.35	0.09	1.04	-0.56	7.58	99,096
Trading Value (SEK millions)	40.07	0.81	185.96	0.00	15,005.22	106,122
Total Unique Firms						1,104

Table I reports summary statistics for raw returns, *SIZE*, *BE/ME*, *OP*, *INV*, and trading value, as well as the number of unique firms in the sample. Raw returns are right-skewed; the mean is 0.70% and the median is 0.00%, with a standard deviation of 13.77%, indicating large month-to-month variation even after winsorizing. *SIZE* is similarly skewed. The median firm has a market capitalization of 957 million SEK, while the mean rises to 12.9 billion SEK because a few large firms dominate the sample. *BE/ME* follows the same pattern: the median is 0.38 and the mean increases to 0.56 due to a small set of high book-to-market firms. *OP* is left-skewed as some firms report large negative operating profitability, which pulls the mean below zero while the median remains positive. *INV* is right-skewed, with a median of 0.09 and a higher mean that reflects firms with rapid asset growth. Trading value is also concentrated in a few firms. The median firm trades 0.81 million SEK per month, while the mean reaches 40 million SEK. *OP* and *INV* are annual variables. The observation counts reflect monthly observations because they enter the panel after the six-month reporting lag and are then carried forward until the next fiscal year update. The sample contains 16,682 *OP* firm-years and 15,680 *INV* firm-years. Most variables have slightly above 106,000 non-missing observations, and the sample includes 1,104 unique firms.

IV. Empirical Analysis

A. Industry Portfolio Characteristics and Returns

We form value-weighted industry portfolios by assigning each firm to one of five SIC-based categories using the Kenneth R. French Data Library's five-industry classification. The groups are: (1) Consumer, including consumer durables, nondurables, wholesale and retail trade, and selected service industries; (2) High Tech, including business equipment, communication technology, computer services, and research and development laboratories; (3) Healthcare, covering pharmaceutical products, medical equipment, and healthcare services; (4) Manufacturing, covering manufacturing industries, chemicals and industrial materials, machinery and equipment, energy production, and utilities; and (5) Other, containing firms whose SIC codes fall outside the defined ranges. Each firm has one SIC code, so its industry stays the same throughout the sample, which differs from Moskowitz and Grinblatt (1999), who allow SIC codes to vary over time.

The five Swedish industry portfolios earn positive average excess returns relative to the Swedish three-month Treasury bill, and these excess returns are jointly different from zero at the 5% significance level (F-statistic = 2.51, p-value = 0.03). After controlling for *SIZE* and *BE/ME*, however, the abnormal industry returns are not jointly statistically different from zero (F-statistic = 2.02, p-value = 0.08). The industries do not differ significantly from one another in either their mean excess returns or their mean abnormal returns. Unlike Moskowitz and Grinblatt (1999), who find that abnormal industry returns are jointly different from zero, we do not find comparable evidence of abnormal performance in Swedish data.

For each industry, we compute the average and minimum monthly number of firms and the average share of total market capitalization. The industries differ in their firm-size composition. High Tech includes about 100 firms on average per month, while Consumer has 49, yet both account for roughly 18% of market capitalization. Their similar average market weight is therefore generated by many smaller firms in one industry and fewer larger firms in the other. On average, each industry contains about 78 firms per month, and the smallest monthly count is 9. This minimum matches the 9-firm minimum reported in Moskowitz and Grinblatt (1999), and it indicates that all industries except Healthcare are well diversified.

Each month, we compute industry returns by value-weighting firm returns using lagged market capitalizations. Excess returns equal these value-weighted industry returns minus the effective monthly Swedish three-month risk-free rate, which we construct by converting the annualized SE SSVX three-month yield into a monthly effective rate.

To compute abnormal returns, we sort firms each month into a 5×5 *SIZE–BE/ME* grid. For each of the 25 *SIZE–BE/ME* portfolios, we compute a value-weighted benchmark return using lagged market capitalizations. A firm's abnormal return equals its monthly return minus this benchmark return. We then aggregate abnormal returns to the industry level using lagged market capitalizations.

We use Hotelling's T^2 test, which is a multivariate F-test (Hotelling, 1931), to test whether mean industry excess returns and abnormal returns are jointly zero and whether they are equal across industries. The F-statistic for the hypothesis that all mean excess returns equal zero is statistically significant at the 5% level, so we reject the null hypothesis, indicating that industries jointly earn positive excess returns. In contrast, the corresponding F-statistic for abnormal returns is not statistically significant, which implies that once *SIZE* and *BE/ME* are accounted for, Swedish industries do not earn abnormal returns that differ statistically from zero. The F-statistics testing whether all industries earn the same mean return are not statistically significant for either excess or abnormal returns, suggesting that no industry earns a systematically different mean return than the others.

Table II

Industry Portfolio Characteristics and Returns

This table presents descriptive statistics for the five industry portfolios. We construct the portfolios each month from September 2000 to September 2025 using SIC codes. For each industry, the table reports the average monthly number of stocks, the minimum number of stocks observed (in parentheses), and the average share of total market capitalization. The table also reports value-weighted average monthly excess returns relative to the Swedish three-month Treasury bill and average abnormal returns relative to market capitalization (*SIZE*) and book-to-market equity (*BE/ME*)-matched benchmark portfolios. We report Newey and West (1987) HAC t-statistics for abnormal returns (in parentheses). Cross-sectional industry averages appear at the bottom of the table. The table also reports multivariate F-statistics testing whether industry mean excess returns and mean abnormal returns are jointly equal to zero, and whether they are equal across industries, with p-values (in parentheses). t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

No.	Industry	Avg. No. of Stocks	Avg. Market Cap (%)	Excess Returns (%)	Abnormal Returns (%)
1	Consumer	49.44 (24)	18.01	0.97	0.37 (2.59)**
2	High Tech	100.44 (58)	18.59	0.37	-0.31 (-1.60)
3	Healthcare	60.67 (9)	3.68	1.05	0.12 (0.48)
4	Manufacturing	60.30 (36)	23.26	0.91	0.13 (0.99)
5	Other	118.59 (63)	36.46	0.92	-0.02 (-0.29)
Average		77.89 (38)	20.00	0.85	0.06 (0.43)
F-statistic	(all = 0)			2.51	2.02
(p-value)				(0.03)*	(0.08)
F-statistic	(all the same)			0.89	1.85
(p-value)				(0.49)	(0.10)

**, * indicate significance at the 1% and 5% levels, respectively.

B. Momentum Returns for Individual Stocks and Industries

B.1 The 6–6 Momentum Strategy

We construct momentum portfolios using Jegadeesh and Titman (1993) 6–6 strategy to determine whether individual stock and industry momentum exist. Each month, we sort stocks (industries) based on their past six-month raw returns ($L = 6$) and form a winner-minus-loser portfolio. The weights are based on one-month lagged market capitalization and remain fixed over the holding period. We hold each position for six months ($H = 6$), creating six active portfolios each month. The monthly momentum return is the average return of the six active portfolios at that month.

Table III shows that individual stock momentum exists, industry momentum does not, and individual stock momentum persists when controlling for industry momentum.

B.2 Individual Stock Momentum

Panel A shows that individual stock momentum is strong and statistically significant in Sweden, even after controlling for industry components. We implement the 6–6 strategy for individual stocks. Following Moskowitz and Grinblatt (1999), we hold the top 30% (winners) and short the bottom 30% (losers) and report the average monthly momentum return under six return specifications. The sorting step is based on raw past returns, while we apply adjustments when computing the monthly return of each active portfolio.

First, we report the baseline momentum profit using raw returns, which are positive (0.63%) and statistically significant at the 5% level. This result confirms the presence of individual stock momentum, consistent with the findings of Moskowitz and Grinblatt (1999).

Second, we compute momentum profits using DGTW-adjusted returns. The original DGTW benchmark portfolios used by Moskowitz and Grinblatt (1999) are constructed from U.S. CRSP–Compustat data and are unavailable for Sweden. We therefore construct our own characteristic benchmarks. Each month, we independently sort stocks into quintiles based on *SIZE*, *BE/ME*, and past 12-month momentum, forming $5 \times 5 \times 5$ (125) value-weighted benchmark portfolios. Each month, every stock is matched to one of these portfolios, and its DGTW-adjusted return equals its raw return minus the return of that portfolio. The DGTW-adjusted return shrinks the momentum profit to 0.06%, and the momentum profit becomes statistically insignificant, suggesting that part of the raw momentum return can be explained by *SIZE*, *BE/ME*, and 12-month past returns.

Third, we report individual stock momentum profits for *SIZE* & *BE/ME*–adjusted returns, computed using the 5×5 (25) *SIZE–BE/ME* benchmark portfolios constructed in Table II. Each month, every stock is assigned to one of these 25 value-weighted portfolios, and its *SIZE* & *BE/ME*-adjusted return equals its raw return minus the return of that portfolio. The *SIZE* & *BE/ME*–adjusted return is positive (0.63%) and statistically significant at the 1% level. This result appears identical to raw returns when rounded; however, the adjusted returns are in fact 0.0013% lower than raw returns. The neglible difference in returns between the two specifications implies that *SIZE* & *BE/ME* characterstics do not drive individual stock momentum.

Fourth, we compute individual stock momentum profits after removing each stock's industry component. Our results show that individual stock momentum remains statistically significant after accounting for industry components. Each month, we calculate each industry's value-weighted return and subtract this return from every stock belonging to that industry. We report two versions of this specification: Raw minus Industry, which subtracts the industry's raw return from the stock's raw return, and *SIZE* & *BE/ME* minus Industry, which subtracts the industry's abnormal return from the stock's *SIZE* & *BE/ME*-adjusted return. When we remove the industry component from stock returns, the average monthly momentum profit declines, but remains positive and statistically significant in both specifications. Raw minus Industry has a 0.51% average monthly return at the 5% significance level, while *SIZE* & *BE/ME* minus Industry has a 0.49% average monthly return at the 1% level. This result differs from Moskowitz and Grinblatt (1999), who find that momentum in the U.S. market becomes small and statistically insignificant once industry, size, and value effects are removed.

Lastly, we compute momentum profits after removing a "random" industry component. We construct random industries by replacing each stock's raw return with the average return of its two nearest neighbors in the ranking step. For endpoint stocks, which have only one neighbor, we use that single neighbor. We compute the random industry's value-weighted return using these artificial returns and subtract this return from each stock's *SIZE* & *BE/ME*-adjusted return. The momentum profit is statistically insignificant but remains positive at 0.41%, which is smaller than the return under the true *SIZE* & *BE/ME* minus Industry adjustment (0.49%). Moskowitz and Grinblatt (1999) find the opposite pattern, and momentum becomes small and statistically insignificant after removing the true industry return, while subtracting a random industry return increases the momentum profit and significance. Thus, true industry effects play a smaller role in driving momentum in Sweden than in the U.S. data examined by Moskowitz and Grinblatt (1999).

B.3 Industry Momentum

Panel B shows that industry momentum is absent in the Swedish market. This pattern contrasts with the U.S. evidence in Moskowitz and Grinblatt (1999), in which industry momentum is strong and statistically significant.

We implement the same 6–6 momentum strategy at the industry level. Each month, we sort industries based on their six-month past returns. Due to our smaller sample size, we form a momentum portfolio by holding the top one industry (winner) and shorting the bottom one industry (loser), unlike Moskowitz and Grinblatt (1999), who use top three and bottom three industries. In proportional terms, Moskowitz and Grinblatt (1999) selection represents about 15% of industries on each side, while our choice represents roughly 20%, making the sorting comparable. We report the average monthly momentum return under three return specifications.

First, we report industry momentum using raw industry returns, which serve as the baseline measure. Each month, we compute each industry's return as the value-weighted average raw return of its stocks. The momentum profit is positive at 0.08% but statistically insignificant, implying that industries in Sweden do not show momentum on their own.

Second, we report DGTW-adjusted industry returns by taking the value-weighted average of the DGTW-adjusted returns of the stocks within each industry. When we remove the influence of *SIZE*, *BE/ME* and long-term momentum, the average monthly momentum profit are -0.25% and statistically insignificant. This result suggests that there is no evidence of industry-based momentum after controlling for stock characteristics.

Third, we compute random-industry returns, in which "industries" are artificially created using the same random-grouping procedure as in Panel A. For each random industry, we compute its monthly value-weighted return and apply the 6–6 momentum strategy. The momentum profit from the placebo specification is positive at 0.28% but statistically insignificant, showing that "fake" industries do not show momentum either.

B.4 Individual Stock Momentum After Controlling for Industry Momentum

Panel C shows that individual stock momentum remains strong after controlling for industry momentum. By changing how winner and loser stocks are classified, we isolate pure stock-level momentum across three specifications.

For the Industry Neutral portfolio, we rank stocks within their own industry. The Industry Neutral portfolio is positive (0.49%) and statistically significant at the 5% level, indicating that individual stock momentum persists when we account for industry momentum. Within each industry, we form value-weighted momentum portfolios, holding the top 30% (winners) and shorting the bottom 30% (losers). Each month, we compute a winner-minus-loser return for every industry and then take the equal-weighted average across industries.

For the Excess Industry portfolio, we test whether individual stock momentum persists after removing each industry's own recent performance. The average monthly return is 0.42% and is statistically significant at the 5% level, confirming that individual stock momentum persists. Before ranking stocks, we compute each stock's six-month excess return, defined as its own six-month past return minus the industry's six-month past return. The industry return is the value-weighted average of the six-month past returns of all stocks in that industry. We then sort stocks on this excess return using 30% breakpoints to form momentum portfolios.

For the High-Industry Loser minus Low-Industry Winner portfolio, we test whether individual stock momentum persists when we combine within-industry rankings with cross-industry performance. Each month, we identify the best-performing and worst-performing industries based on their six-month past returns. Within the best industry, we hold the 30% worst-performing stocks, and within the worst industry, we short the 30% best-performing stocks. If industry momentum were present, we would expect a statistically significant negative return for this portfolio. In contrast, our estimates are statistically insignificant, indicating that industry momentum does not appear to exist in our sample.

Table III

Momentum Returns for Individual Stocks and Industries

Table III reports average monthly momentum return using the six-month formation ($L = 6$) and six-month holding ($H = 6$) strategy for individual stocks, industries, and industry-neutral portfolios over the sample period September 2000 to September 2025. We report Newey and West (1987) HAC t-statistics with 5 lags along with returns. Panel A presents momentum profits at the individual stock level under six return specifications. The panel shows results based on raw returns, DGTW-adjusted returns, market capitalization (*SIZE*) & book-to-market equity (*BE/ME*)-adjusted returns, returns adjusted for each stock's industry, returns adjusted for industry effects using *SIZE* & *BE/ME*-adjusted returns, and returns adjusted using "random industry" returns. We construct random industries by replacing each stock's raw return with the average return of its two nearest neighbors in the ranking step. We then use these synthetic returns to compute the momentum portfolio. Panel B reports momentum profits at the industry-level. We show results using raw industry returns, DGTW-adjusted industry returns, and returns based on "random industries", computed using the same random-grouping procedure as in Panel A. Panel C reports momentum profits for three portfolio constructions designed to neutralize industry effects in different ways. The panel includes results for Industry Neutral portfolios, portfolios sorted on excess industry returns and High-Industry Losers minus Low-Industry Winners portfolios. t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

Panel A: Individual Stock Momentum

	Raw	DGTW	SIZE & BE/ME	Raw – Industry	SIZE & BE/ME – Industry	SIZE & BE/ME – Random Industry
Mean (%)	0.63	0.06	0.63	0.51	0.49	0.41
(t-stat)	(1.96*)	(0.99)	(2.59**)	(2.36*)	(2.90**)	(1.84)

Panel B: Industry Momentum

	Raw Industry	DGTW Industry	Raw Random Industry
Mean (%)	0.08	-0.25	0.28
(t-stat)	(0.32)	(-1.80)	(1.53)

Panel C: Individual Stock Momentum After Controlling for Industry Momentum

	Industry Neutral	Excess Industry	High Ind. Losers – Low Ind. Winners
Mean (%)	0.49	0.42	-1.03
(t-stat)	(2.49*)	(2.31*)	(-1.66)

**, * indicate significance at the 1% and 5% levels, respectively.

V. Robustness of Industry Momentum

A. Industry Momentum Returns Across Alternative Formation and Holding Periods

This section tests whether the absence of industry momentum is robust to alternative formation (L) and holding (H) periods. Section IV shows that, under the Jegadeesh and Titman (1993) 6–6 strategy, industry momentum in Sweden is absent. Here, we test whether this finding persists under alternative formation and holding periods.

Each month, we rank the five industries by their past L-month return and assign them to three momentum portfolios: the top-ranked industry (Wi), the lowest-ranked industry (Lo), and the three remaining industries (Mid). This ranking mirrors the proportionate allocation of industries used in Moskowitz and Grinblatt (1999): they sort 20 industries into 3–14–3 groups, and with only five industries the corresponding structure becomes 1–3–1. The middle portfolio (Mid) is the equal-weighted average return of the three middle industries. Each month, we re-rank industries by their return over the past L months and compute average monthly returns for winners (Wi), losers (Lo), and the spreads of winners minus losers (Wi–Lo). We also compute winners minus the middle three industries (Wi–Mid) and the middle minus losers (Mid–Lo) to test whether any industry momentum profits arise from the long side (buying winners or middle industries) or the short side (selling losers).

After formation, each portfolio is held for H months, with new portfolios formed each month, creating overlapping positions. Table IV reports average monthly returns across all overlapping portfolios. We also compute DGTW-adjusted winners minus losers (Wi–Lo) returns for each (L, H) strategy, where individual stock returns are adjusted for *SIZE*, *BE/ME*, and stock-level momentum characteristics. We estimate returns for all combinations of L = 1, 6, 12 and H = 1, 6, 12, 24, 36. Panel B tests for lead–lag effects by skipping the most recent month between ranking and holding. Our findings in Table IV indicate that the Swedish market does not exhibit industry momentum under any of the alternative formation and holding periods, aligning with Section IV.

In Panel A, winners and losers earn similar monthly returns across all (L, H) combinations, and the resulting winners minus losers (Wi–Lo) spreads remain close to zero. Most (Wi–Lo) spreads lie between –0.5% and +0.1%, and all are statistically insignificant. The winners minus the middle three industries (Wi–Mid) and the middle minus losers (Mid–Lo) components do not display systematic differences in average monthly returns. Across all (L,H) combinations, both spreads remain statistically insignificant, with only one exception. That exception occurs at $(L = 1)$ and $(H = 1)$, where the middle minus losers (Mid–Lo) equals -0.60% with a t-statistic of -2.13, statistically significant at the 5% level. However, this result does not appear for other formation and holding periods. If industry momentum were present, winners would outperform middle industries, or middle industries would outperform losers. In Sweden, neither pattern appears. The DGTW-adjusted results show a similar pattern. Most spreads remain close to zero and insignificant. The only notable patterns appear at the longest horizon $(H = 36)$ for $(L = 6)$ and $(L = 12)$, where the negative DGTW-adjusted winners minus losers (Wi–Lo) spreads become statistically significant. These significant negative coefficients reflect long-horizon reversals, not momentum.

No shorter-horizon strategy in Panel A produces statistically significant effects. Removing firm characteristics therefore does not reveal industry momentum.

Panel B leads to the same conclusions as Panel A. Skipping the most recent month does not reveal stronger industry patterns. Two DGTW-adjusted winners minus losers (Wi–Lo) spreads become significant at the longest holding horizon ($H = 36$): one at ($L = 6$) (t-statistic = -2.06) and one at ($L = 12$) (t-statistic= -3.01). Both coefficients are negative, indicating long-horizon reversals rather than momentum. These are the same two (L, H) combinations that are significant in Panel A, underscoring that the pattern is limited to long-horizon reversals rather than momentum. These isolated results do not alter the overall conclusion: industry momentum remains absent.

Our findings differ from Moskowitz and Grinblatt (1999). In U.S. data, they find that industry momentum is strongest at short–intermediate horizons, weakens after about a year, remains profitable after DGTW adjustments, and cannot be explained by lead-lag effects. In contrast, our Swedish evidence shows no industry momentum under any formation or holding period. Instead, the only notable pattern is some long-term reversals.

Table IV

Industry Momentum Returns Across Alternative Formation and Holding Periods

This table reports average monthly returns for industry-momentum strategies from September 2000 to September 2025. Each month, we rank industries by their past L-month returns. The industry with the highest return forms the winner (Wi) portfolio, the lowest-return industry forms the loser (Lo) portfolio, and the remaining three industries form the middle (Mid) portfolio. The middle portfolio is the equal-weighted average return of these three industries. We hold each portfolio for H months using fully overlapping positions. For each (L, H) pair, the table reports average monthly returns for winners (Wi), losers (Lo), winner minus loser (Wi–Lo), buy winner minus middle (Wi–Mid), and sell middle minus loser (Mid–Lo). We report Newey and West (1987) t-statistics with H–1 lags (in parentheses) for all spread portfolios. Panel A begins the holding period immediately after the formation month. Panel B inserts a one-month skip between the end of the formation window and the first holding-period return. Both panels also report DGTW-adjusted winner minus loser (Wi–Lo) returns, which benchmark industry returns on market capitalization (*SIZE*), book-to-market equity (*BE/ME*), and individual-stock momentum characteristics. The table includes formation windows of L = 1, 6, 12 months and holding periods of H = 1, 6, 12, 24, 36 months. t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

		Panel A: No Gap					**Panel B: Month Skipped**				
L	**H=**	1	6	12	24	36	1	6	12	24	36
1	Wi	0.91	0.98	1.01	0.95	0.97	0.98	1.02	0.97	0.94	0.96
	Lo	1.42	1.03	0.97	0.97	0.95	1.18	0.93	0.95	0.94	0.94
	Wi – Lo	-0.52	-0.04	0.04	-0.02	0.02	-0.20	0.09	0.02	0.01	0.03
		(-1.49)	(-0.29)	(0.38)	(-0.26)	(0.36)	(-0.56)	(0.74)	(0.21)	(0.10)	(0.42)
	buy Wi – Mid	0.09	0.06	0.07	-0.00	0.02	0.12	0.09	0.04	-0.01	0.02
		(0.36)	(0.46)	(0.75)	(-0.00)	(0.39)	(0.44)	(0.62)	(0.40)	(-0.12)	(0.32)
	sell Mid – Lo	-0.60	-0.11	-0.04	-0.02	0.00	-0.32	0.01	-0.02	0.02	0.01
		(-2.13)*	(-0.74)	(-0.30)	(-0.27)	(0.01)	(-1.13)	(0.04)	(-0.15)	(0.21)	(0.13)
	DGTW	0.05	-0.06	-0.03	-0.00	-0.01	-0.12	-0.07	-0.06	0.00	-0.02
	[Wi – Lo]	(0.25)	(-0.88)	(-0.67)	(-0.05)	(-0.37)	(-0.59)	(-0.92)	(-1.04)	(0.00)	(-0.60)
6	Wi	0.91	0.91	0.96	0.98	0.98	0.88	0.92	0.97	0.98	0.99
	Lo	1.17	0.83	0.86	0.96	0.94	0.92	0.73	0.88	0.97	0.96
	Wi – Lo	-0.26	0.08	0.10	0.03	0.05	-0.05	0.18	0.09	0.01	0.03
		(-0.80)	(0.32)	(0.49)	(0.17)	(0.40)	(-0.14)	(0.69)	(0.49)	(0.06)	(0.32)

Continued on next page

Table IV — continued

L	**H=**	**Panel A: No Gap** 1	6	12	24	36	**Panel B: Month Skipped** 1	6	12	24	36
	buy Wi – Mid	-0.02	-0.08	-0.00	0.06	0.05	-0.13	-0.11	0.02	0.07	0.08
		(-0.10)	(-0.57)	(-0.00)	(0.56)	(0.51)	(-0.48)	(-0.73)	(0.15)	(0.61)	(0.67)
	sell Mid – Lo	-0.23	0.16	0.10	-0.03	-0.00	0.08	0.29	0.07	-0.06	-0.05
		(-0.88)	(0.79)	(0.70)	(-0.36)	(-0.03)	(0.30)	(1.34)	(0.54)	(-0.74)	(-0.65)
	DGTW	-0.12	-0.25	-0.13	-0.04	-0.09	-0.35	-0.26	-0.09	-0.04	-0.08
	[Wi – Lo]	(-0.62)	(-1.80)	(-1.16)	(-0.58)	(-2.30)*	(-1.70)	(-1.83)	(-0.86)	(-0.50)	(-2.06)*
12	Wi	1.14	1.00	0.97	0.97	0.94	0.89	0.99	0.94	0.94	0.92
	Lo	1.04	0.97	1.06	1.11	1.10	1.06	1.06	1.16	1.15	1.13
	Wi – Lo	0.10	0.04	-0.09	-0.14	-0.15	-0.17	-0.07	-0.22	-0.21	-0.21
		(0.31)	(0.14)	(-0.46)	(-0.88)	(-1.18)	(-0.54)	(-0.31)	(-1.08)	(-1.10)	(-1.32)
	buy Wi – Mid	0.13	-0.03	0.12	0.14	0.09	-0.24	-0.07	0.12	0.12	0.08
		(0.55)	(-0.16)	(0.62)	(0.79)	(0.56)	(-1.05)	(-0.45)	(0.63)	(0.72)	(0.49)
	sell Mid – Lo	-0.03	0.06	-0.20	-0.28	-0.25	0.07	0.00	-0.34	-0.33	-0.30
		(-0.13)	(0.33)	(-1.12)	(-1.26)	(-1.05)	(0.29)	(0.01)	(-1.42)	(-1.23)	(-1.06)
	DGTW	-0.36	-0.21	-0.15	-0.11	-0.15	-0.27	-0.20	-0.12	-0.12	-0.14
	[Wi – Lo]	(-1.84)	(-1.46)	(-1.32)	(-1.34)	(-3.23)**	(-1.47)	(-1.42)	(-1.14)	(-1.39)	(-3.01)**

**, * indicate significance at the 1% and 5% levels.

B. *Industry Momentum Ranking and Persistence Diagnostics*

Table V provides diagnostic tests to check that the absence of industry momentum documented in Section IV is not an artifact of poor industry classification. We apply a one-month ranking period ($L = 1$) and a one-month holding period ($H = 1$) strategy to evaluate industry persistence. Our results confirm that the industry groupings behave as coherent economic sectors in which winners and losers appear equally across industries, rank correlations are stable and partial autocorrelations are economically negligible across all horizons. These diagnostics confirm that industry momentum does not exist in the Swedish market, implying that individual stock momentum cannot be explained by industry effects.

For each of the five industries, we report how often it appears as the top-ranked (winner) or bottom-ranked (loser) industry. The maximum number of consecutive winner or loser months is reported (in parentheses). Industries receive a monthly winner ranking between 36 and 82 times (maximum of 5 consecutive months), with Healthcare being the most frequent winner. Industries receive a monthly loser ranking between 32 and 77 times (maximum of 4 consecutive months), with High Tech being the most frequent loser. Thus, winner and loser classifications are spread across all industries. The average ranks for each industry are clustered around the middle and range between 2.90 and 3.16, further indicating that no industry persistently holds a winner or loser position.

To measure the persistence of relative industry performance, we compute the rank correlation between month t and month $t-1$. Compared to Moskowitz and Grinblatt (1999), we find higher rank correlation, ranging from roughly 0.66 to 0.75, indicating stable relative industry positions. This result reflects the higher probability of an industry maintaining its relative position from one month to the other due to fewer industries in the sample.

To test whether stable rankings translate into return persistence, we compute the partial autocorrelation coefficients of industry returns at lags 1, 6, 12, and 36 months. We find weak average positive autocorrelation at lags 1 and 6, followed by negative autocorrelation at longer horizons: a pattern consistent with (Moskowitz and Grinblatt, 1999). However, all coefficients are economically negligible and close to zero. The absence of meaningful autocorrelation at any horizon confirms that despite stable industry rankings (high rank correlation), actual return dynamics show no exploitable persistence at the industry level.

Table V
Industry Momentum Ranking and Persistence Diagnostics

Table V presents summary statistics for a short-term industry momentum strategy using a one-month ranking period ($L = 1$) and a one-month holding period ($H = 1$). The table reports the total number of months an industry is ranked as a winner or loser over the sample period, with the maximum number of consecutive winner or loser months (in parentheses). The winner (loser) is the industry with the highest (lowest) past one-month return. We also report the average rank of each industry and the correlation between the rank of each industry at time t and its rank in the prior month at time $t-1$. Finally, we report the partial autocorrelation coefficients for each industry at 1-, 6-, 12-, and 36-month lags. Our effective sample for the industry diagnostics spans September 2000 to September 2025 (301 months). Each statistic is estimated using the maximum number of months available given its lag length. t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

		No. of Months in				Partial Autocorrelations			
No.	Industry	Wi (max.)	Lo (max.)	Avg. Rank	Rank Corr.	$\hat{\rho}(t-1)$	$\hat{\rho}(t-6)$	$\hat{\rho}(t-12)$	$\hat{\rho}(t-36)$
1	Consumer	48 (5)	47 (3)	3.01	0.7046	-0.0194	-0.0283	-0.0904	-0.0114
2	High Tech	55 (3)	77 (4)	3.16	0.7157	0.0982	-0.0325	-0.0395	-0.0111
3	Healthcare	82 (4)	69 (3)	2.90	0.6632	0.0039	0.0829	-0.0113	-0.0447
4	Manufacturing	56 (5)	52 (4)	2.98	0.7523	-0.0000	0.0038	-0.0423	-0.0634
5	Other	36 (2)	32 (2)	2.95	0.6606	0.0034	-0.0126	-0.0355	0.0218
Mean		55.4 (3.8)	55.4 (3.2)	3.00	0.6993	0.0172	0.0027	-0.0438	-0.0218

C. Industry Momentum Returns by Size and Trading Value

In Table VI, we decompose the short-term industry momentum strategy to test whether size effects, illiquidity, or lead-lag patterns explain the absence of industry momentum in Sweden. Panel A shows that the absence of industry momentum in Sweden cannot be attributed to size or trading volume distortions. Panel B shows that, across both raw and DGTW-adjusted returns, industry-momentum profits are concentrated almost entirely in the largest and most liquid firms, while smaller and less-traded firms contribute almost nothing.

The decomposition considers *SIZE* and trading value. We compute industry momentum profits using a one-month ranking period ($L = 1$) and a one-month holding period ($H = 1$). Each month, we rank industries based on their one-month raw return. Within the top- and bottom-ranked industries, stocks are sorted into quintiles based on one-month lagged *SIZE* (or trading value). For each quintile, we subtract the value-weighted return of the bottom industry from that of the top industry. We compute profits using both rebalanced and non-rebalanced weights.

In Panel A, weights within each quintile are rebalanced to sum to one, so each quintile forms a self-contained value-weighted portfolio. We report raw and DGTW-adjusted returns. Our results show that lead–lag effects do not hide industry momentum. The largest firms earn negative and statistically insignificant momentum profits, while the smallest firms earn positive and statistically insignificant profits. Size differences therefore do not reveal hidden industry momentum. Results based on trading value are similar. The most liquid firms earn negative and statistically insignificant profits, and the least liquid firms earn positive and statistically insignificant profits. If the smallest or most illiquid firms adjust prices slowly, we would expect positive industry momentum profits in this group. The absence of such a pattern indicates that liquidity-related frictions do not hide industry momentum.

Panel B keeps each stock's original share of its industry portfolio rather than rebalancing within quintiles. This approach measures each quintile's contribution to the overall short-term industry momentum profit. We report both raw and DGTW-adjusted profits and each quintile's percentage contribution. We compute the average monthly return of the value-weighted industry momentum portfolio separately for *SIZE* and trading value. The total profits differ because the two samples include different sets of firms with available data. In both cases, the total profits are negative, indicating no industry momentum at these horizons.

The firms with the largest size account for 94.53% of total raw profits, and 99.79% of total DGTW-adjusted profits. The remaining size groups contribute near 0%. Trading value produces the same pattern: the most actively traded firms generate 89.25% of total raw profits and 101.14% of total DGTW-adjusted profits. These contributions are larger than those documented by Moskowitz and Grinblatt (1999) for the United States, where the largest firms contribute 76.94% of total DGTW-adjusted profits and the most liquid firms contribute 62.25%.

The results from Table VI show that industry momentum profits are generated almost exclusively by the largest and most liquid firms. This pattern is consistent with Bali, Cakici, and Whitelaw (2011), who document that small, illiquid and volatile "lotterly-like" stocks in the U.S. do not exhibit return persistence, instead, momentum arises primarily among large liquid firms. Applied to Sweden, this finding can explain why our size and trading value decompositions do not reveal any hidden industry momentum. Swedish industries are dominated by a few large firms, which means that industry portfolios show momentum only if these dominant firms exhibit return persistence. Our findings indicate that they do not: large-firm quintiles generate nearly all industry-momentum profits, yet these profits are negative or statistically insignificant. Thus, the absence of industry momentum reflects a lack of persistence among the dominant firms.

Table VI
Industry Momentum Returns by Size and Trading Value

Table VI presents the decomposition of the short-term industry momentum strategy, using a one-month formation ($L = 1$) and holding period ($H = 1$). The decomposition is related to firm size and liquidity. Panel A reports the industry momentum profits for the top and bottom quintiles of stocks based on one-month lagged market capitalization (*SIZE*) and trading value, with weights within each subset rebalanced to sum to one. Momentum profits are reported using raw returns and DGTW-adjusted returns alongside Newey and West (1987) t-statistics with one lag. Panel B decomposes the industry momentum profits following the same procedure as in Panel A, but without rebalancing the weights to sum one within each group. For all five quintiles, we compute their average contribution to the overall momentum profit, as well as their percentage share of the total profit, using both raw and DGTW-adjusted returns. The average return from the value-weighted industry momentum portfolio prior to decomposition is reported as "Total" for both *SIZE* and trading value. Results are reported for the period September 2000 to September 2025. t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

Panel A: Rebalance to Sum to One

	SIZE				Trading Value			
	Raw	(t-stat)	DGTW	(t-stat)	Raw	(t-stat)	DGTW	(t-stat)
Largest 20%	-0.59	(-1.60)	0.04	(0.15)	-0.56	(-1.46)	0.05	(0.16)
Smallest 20%	0.60	(1.46)	1.55	(1.46)	0.03	(0.07)	0.29	(0.23)

Panel B: No Rebalancing

	SIZE				Trading Value			
Quintiles	Raw	%	DGTW	%	Raw	%	DGTW	%
(low) 1	-0.00	0.25%	-0.00	0.21%	-0.01	1.17%	-0.00	0.01%
2	-0.00	0.07%	-0.00	0.86%	-0.00	0.36%	-0.01	2.46%
3	-0.02	4.17%	-0.01	3.67%	-0.02	3.09%	-0.00	0.04%
4	-0.01	0.98%	0.01	-4.52%	-0.03	6.14%	0.01	-3.65%
(high) 5	-0.49	94.53%	-0.23	99.79%	-0.45	89.25%	-0.24	101.14%
Total:	-0.52	100.00%	-0.23	100.00%	-0.50	100.00%	-0.24	100.00%

**, * indicate significance at the 1% and 5% levels.

VI. Cross-Sectional Return Dynamics and the Role of Stock- and Industry-Level Momentum

In this section, we run monthly Fama–MacBeth regressions to examine how individual stock and industry momentum variables explain the cross-section of (*SIZE*)- and (*BE/ME*)-adjusted stock returns. Each month, we regress these adjusted stock returns on firm characteristics, together with individual stock and industry momentum variables. The regressions also include short-term and long-horizon return variables. Table VII reports the time-series averages of the monthly coefficients. Using Fama–MacBeth regressions also provides a robustness check to the portfolio-level results from Section IV because we use every stock each month, rather than relying on portfolio sorts. This approach avoids results being driven by sorting choices or portfolio-weighting rules. We drop months where no stock has a full set of characteristics.

Following Moskowitz and Grinblatt (1999), the dependent variable is the stock return adjusted for *SIZE* and *BE/ME*, constructed using the same characteristics-matching procedure described earlier in the paper. We include *SIZE* and *BE/ME* as regressors to capture remaining cross-sectional variation associated with these characteristics.

In Panel A, we test whether individual stock momentum predicts adjusted stock returns. The first regression includes the independent variables: log-*SIZE*, log-*BE/ME*, β, *OP*, *INV*, and *ret (-6, -1)*. Unlike Moskowitz and Grinblatt (1999), who only include β, *SIZE* and *BE/ME* as firm characteristics, we also add *OP* and *INV*, following Fama and French (2015). *ret (-6, -1)* is the stock's average monthly return from $t-6$ through $t-1$. We estimate market β for each stock using a 36-month rolling regression of the stock's excess return on the excess return of our value-weighted market index. We compute the market return each month as the value-weighted average return of all stocks in our sample, using market capitalization at the end of month $t-1$ as weights. This approach follows Moskowitz and Grinblatt (1999), who estimate from a regression of each stock's past 36 months of excess returns on the CRSP value-weighted market return.

The second regression in Panel A adds two additional independent variables: the stock's past one-month return *ret (-1, -1)*, which controls for short-term return effects, and the long-horizon return from month $t-36$ to $t-13$, *ret (-36, -13)*, which helps isolate the momentum variable *ret (-L, -H)* from slower long-horizon return patterns.

Following Moskowitz and Grinblatt (1999), we re-estimate the regressions using three alternative momentum variables: (6,6), (12,1) and (12,12). For the (12,1) strategy, the momentum variable is redefined as the average monthly return from month $t-12$ to $t-1$, replacing the six-month measure *ret (-6, -1)* used in the (6,1) regressions. For the (6,6) strategy, we form six overlapping six-month return measures: one ending in month $t-6$, one ending in $t-5$, and so on, up to the six-month period ending in $t-1$. The (6,6) variable is the equal-weighted average of these six six-month returns:

$$ret_{6,6} = \frac{ret_{-11:-6} + \cdots + ret_{-6:-1}}{6}.$$

The (12,12) strategy is constructed in the same way but using twelve overlapping twelve-month windows ending in months $t - 12$ through $t - 1$.

Panel A shows that individual stock momentum predicts adjusted stock returns. Across all (L, H) strategies, the momentum coefficients *ret (-L, -H)* are positive and significant at the 1% level, with estimates between roughly 0.10 and 0.16. These results are consistent with our earlier findings that momentum in Sweden exists at the individual stock level at intermediate terms. Adding the short-term *ret (-1, -1)* and long-horizon variables *ret (-36, -13)* in the second regression leaves the momentum estimates essentially unchanged. The coefficients for the short-term return variable *ret (-1, -1)* are small, positive, and significant across all (L, H) strategies, with magnitudes between roughly 0.02 and 0.03. This finding indicates weak short-term continuation rather than the short-term reversal documented in U.S. data by Moskowitz and Grinblatt (1999). The long-run return variable *ret (-36, -13)* remains insignificant throughout, in contrast to the modest long-term reversal found in U.S. data by Moskowitz and Grinblatt (1999).

In Panel B, we test whether industry momentum predicts adjusted stock returns by repeating the regressions in Panel A, but using industry-level momentum variables instead. We replace each stock's past return with the corresponding value-weighted industry return over the (L, H) window. We find no evidence that industry momentum predicts adjusted stock returns, as all *ind (L, H)* coefficients are statistically insignificant across all (L, H) strategies. Adding short-term and long-horizon industry return variables does not change this pattern. These results align with our earlier evidence that industry momentum is absent in the Swedish market.

In Panel C, we test whether individual stock momentum continues to explain adjusted stock returns after controlling for industry momentum. The results show that individual stock momentum remains a strong predictor of adjusted returns, while industry momentum adds no explanatory power. Across all (L, H) strategies, the individual momentum coefficients *ret (-L, -H)* are positive and significant at the 1% level, with magnitudes between roughly 0.10 and 0.14 in both regressions. Including short-term *ind (-1, -1)* and long-horizon *ind (-36, -13)* industry return variables in the second regression leaves these estimates essentially unchanged. All industry variables remain statistically insignificant throughout, reinforcing that momentum in Sweden is driven by individual stocks rather than industries. As in Panel A, the short-term return variable *ret (-1, -1)* is small, positive, and statistically significant across all strategies, while the long-horizon return variable *ret (-36, -13)* is statistically insignificant.

Panel D repeats the Panel C regressions but introduces a one-month gap between the formation and holding periods by shifting all momentum windows one month earlier, excluding the most recent return $t-1$. Thus, the (6,1) and (12,1) variables become returns ending at $t-2$, and the overlapping strategies drop the window ending in $t-1$. The (6,6*) variable is the equal-weighted average of five six-month windows ending between $t-2$ and $t-6$, and the (12,12*) averages the eleven twelve-month windows ending between $t - 2$ and $t - 12$. Industry momentum variables are shifted in the same way. The results show that the individual momentum coefficients remain positive and statistically significant at the 1% level, though slightly smaller than in Panel C, while short-term continuation becomes marginally stronger. The long-horizon return variable *ret (-36, -13)* remains statistically insignificant. Industry momentum stays statistically insignificant in all but one specification, and that isolated coefficient is not supported by similar patterns elsewhere.

Overall, our Fama–MacBeth regressions show that momentum in Sweden operates at the individual stock level, and that industry momentum adds no explanatory power for adjusted stock returns. This finding contrasts with Moskowitz and Grinblatt (1999), who document that industry momentum is strong and often dominates individual stock effects in the U.S. market. Our results therefore indicate that, unlike in the U.S., momentum in Sweden operates at the stock level rather than industry level, consistent with our earlier findings.

Table VII
Cross-Section of Expected Size- and BE/ME-Adjusted Returns

Table VII reports time-series averages of coefficients from monthly Fama–MacBeth cross-sectional regressions of stock returns adjusted for market capitalization (*SIZE*) and book-to-market equity (*BE/ME*) over September 2000 to September 2025. Each month t, we regress these characteristically adjusted stock returns on an intercept (omitted), firm characteristics, and the stock- and industry-level return variables shown in the table. Since the dependent variable is already adjusted for $SIZE$ and BE/ME and we also include *SIZE* and *BE/ME* as regressors, the regressions control for these effects on both sides of the equation. The firm characteristics are log-*SIZE* (the natural logarithm of market capitalization at $t-1$), log-*BE/ME* (the natural logarithm of book value of equity divided by market capitalization at $t-1$), market beta (β) (estimated using a 36-month rolling regression), operating profitability (OP), and investment (INV). Across all panels, the table reports Newey and West (1987) HAC t-statistics with three lags (in parentheses).

Panel A reports the time-series average coefficients from regressions that use individual stock momentum variables *ret (-L, -H)*, where (L, H) (6,1), (6,6), (12,1), (12,12). For (L, 1), we define the momentum variable as the average stock return over the past L months ending at $t-1$. For (L, L) we define the momentum variable as the equal-weighted average of the L overlapping L-month average-return windows ending at $t-L$, $t-(L-1)$, $\ldots$, $t-1$. Each momentum variable is estimated twice: once on its own, together with the firm characteristics, and once jointly with the short-term return variable *ret (-1, -1)* and the long-horizon return variable *ret (-36, -13)*, again including all firm characteristics.

Panel B reports the time-series average coefficients from regressions that use industry momentum variables, *ind (-L, -H)*. We construct the industry return variables from value-weighted returns of the industry to which each stock belongs. Each industry momentum variable is estimated twice, following the same regression structure as in Panel A, but applied at the industry-level.

Panel C reports the time-series average coefficients from regressions that include both individual stock momentum variables *ret (-L, -H)* and industry momentum variables *ind (-L, -H)*. The momentum variables follow the same (L, H) constructions as in Panels A and B. Each regression is estimated twice: first with both individual stock and industry momentum variables included together with the short-term and long-horizon return variables *ret (-1, -1)* and *ret (-36, -13)*, and then with the short-term and long-horizon industry return variables *ind (-1, -1)* and *ind (-36, -13)* added. All regressions include the firm characteristics.

Panel D reports the time-series average coefficients from regressions that use individual stock momentum variables *ret (-L, -H)* and industry momentum variables *ind (-L, -H)* constructed with a one-month skip between the formation and holding periods. In these skipped strategies, we shift the return windows one month earlier, so the formation period ends at $t-2$ rather than $t-1$. The skipped strategies are: (7,2), (6,6*), (12,2), (12,12*), where (6,6*) and (12,12*) are defined as the equal-weighted average of the L–1 overlapping L-month average-return windows ending at $t-L$, $t-(L-1)$, $\ldots$, $t-2$. Each skipped strategy is estimated twice, following the same regression structure as in Panel C.

t-statistics above 2.58 and 1.96 indicate significance at the 1% and 5% levels, respectively.

(L,H)	SIZE	BE/ME	β	OP	INV	$ret_{-L,-H}$	$ret_{-1,-1}$	$ret_{-36,-13}$	$ind_{-L,-H}$	$ind_{-1,-1}$	$ind_{-36,-13}$
Panel A: Individual Stock Momentum											
(6,1)	0.0008	0.0015	0.0010	-0.0013	-0.0013	0.1297**					
	(1.36)	(0.44)	(0.81)	(0.81)	(-1.16)	(7.84)					
(6,1)	0.0009	0.0028	0.0006	-0.0007	-0.0007	0.1086**	0.0151*	0.0008			
	(1.39)	(0.79)	(0.46)	(0.46)	(-0.63)	(6.39)	(2.33)	(1.15)			
(6,6)	0.0005	0.0011	0.0010	-0.0015	-0.0015	0.1136**					
	(0.88)	(0.32)	(0.81)	(0.81)	(-1.33)	(6.37)					
(6,6)	0.0008	0.0026	0.0005	-0.0007	-0.0007	0.0986**	0.0315**	0.0007			
	(1.27)	(0.73)	(0.39)	(0.39)	(-0.61)	(5.58)	(4.90)	(1.06)			
(12,1)	0.0010	0.0011	0.0006	-0.0013	-0.0013	0.1624**					
	(1.79)	(0.31)	(0.49)	(0.49)	(-1.18)	(7.00)					
(12,1)	0.0012	0.0024	0.0002	-0.0006	-0.0006	0.1378**	0.0224**	0.0008			
	(1.81)	(0.68)	(0.15)	(0.15)	(-0.55)	(6.20)	(3.55)	(1.15)			
(12,12)	0.0002	0.0006	0.0008	-0.0019	-0.0019	0.0996**					
	(0.38)	(0.19)	(0.62)	(0.62)	(-1.66)	(4.40)					
(12,12)	0.0005	0.0020	0.0006	-0.0007	-0.0007	0.1055**	0.0346**	-0.0006			
	(0.91)	(0.54)	(0.48)	(0.48)	(-0.64)	(4.32)	(5.22)	(-0.84)			
Panel B: Industry Momentum											
(6,1)	-0.0007	0.0012	0.0019	-0.0021	-0.0021	-0.0026					
	(-1.35)	(0.37)	(1.49)	(1.49)	(-1.82)	(-0.04)					
(6,1)	-0.0007	0.0013	0.0021	-0.0022	-0.0022	-0.1353	-0.0604	-0.0027			
	(-1.41)	(0.38)	(1.64)	(1.64)	(-1.83)	(-0.65)	(-0.98)	(-0.37)			
(6,6)	-0.0007	0.0012	0.0021	-0.0019	-0.0019	-0.0146					
	(-1.42)	(0.36)	(1.68)	(1.68)	(-1.65)	(-0.11)					
(6,6)	-0.0009	0.0013	0.0021	-0.0021	-0.0021	0.0385	-0.0255	0.0032			

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Table VII — continued

(L,H)	SIZE	BE/ME	β	OP	INV	$ret_{-L,-H}$	$ret_{-1,-1}$	$ret_{-36,-13}$	$ind_{-L,-H}$	$ind_{-1,-1}$	$ind_{-36,-13}$
	(-1.62)	(0.37)	(1.70)	(1.70)	(-1.80)	(0.19)	(-0.50)	(0.36)			
(12,1)	-0.0009	0.0012	0.0019	-0.0020	-0.0020	0.0644					
	(-1.69)	(0.37)	(1.45)	(1.45)	(-1.70)	(0.75)					
(12,1)	-0.0009	0.0013	0.0021	-0.0021	-0.0021	0.0172	-0.0431	-0.0037			
	(-1.80)	(0.37)	(1.68)	(1.68)	(-1.79)	(0.08)	(-0.72)	(-0.35)			
(12,12)	-0.0009	0.0013	0.0019	-0.0021	-0.0021	0.0905					
	(-1.69)	(0.38)	(1.46)	(1.46)	(-1.76)	(0.73)					
(12,12)	-0.0008	0.0012	0.0020	-0.0021	-0.0021	0.0703	0.0475	-0.0307			
	(-1.56)	(0.35)	(1.64)	(1.64)	(-1.78)	(0.11)	(0.49)	(-1.58)			
Panel C: Individual Stock and Industry Momentum											
(6,1)	0.0010	0.0028	0.0009	-0.0008	-0.0008	0.1091**	0.0155*	0.0007	-0.0152		
	(1.57)	(0.78)	(0.65)	(0.65)	(-0.66)	(6.42)	(2.38)	(1.06)	(-0.21)		
(6,1)	0.0009	0.0028	0.0011	-0.0009	-0.0009	0.1055**	0.0159*	0.0007	-0.1364	-0.0700	-0.0017
	(1.40)	(0.77)	(0.80)	(-0.75)	(-0.75)	(6.12)	(2.41)	(1.09)	(-0.68)	(-1.13)	(-0.25)
(6,6)	0.0008	0.0026	0.0009	-0.0006	-0.0006	0.0984**	0.0315**	0.0007	-0.0242		
	(1.30)	(0.72)	(0.67)	(0.67)	(-0.48)	(5.57)	(4.88)	(0.95)	(-0.21)		
(6,6)	0.0007	0.0026	0.0010	-0.0008	-0.0008	0.0956**	0.0316**	0.0007	0.0410	-0.0416	0.0038
	(1.03)	(0.71)	(0.74)	(-0.68)	(-0.68)	(5.45)	(4.87)	(0.94)	(0.20)	(-0.84)	(0.47)
(12,1)	0.0011	0.0024	0.0004	-0.0005	-0.0005	0.1368**	0.0220**	0.0007	0.0511		
	(1.65)	(0.68)	(0.31)	(0.31)	(-0.48)	(6.14)	(3.48)	(1.06)	(0.62)		
(12,1)	0.0010	0.0024	0.0007	-0.0007	-0.0007	0.1317**	0.0227**	0.0008	0.0125	-0.0547	-0.0008
	(1.48)	(0.68)	(0.51)	(0.51)	(-0.62)	(5.91)	(3.53)	(1.10)	(0.06)	(-0.95)	(-0.09)
(12,12)	0.0004	0.0021	0.0007	-0.0007	-0.0007	0.1052**	0.0346**	-0.0006	0.0592		
	(0.65)	(0.56)	(0.52)	(0.52)	(-0.65)	(4.27)	(5.19)	(-0.82)	(0.47)		
(12,12)	0.0004	0.0020	0.0009	-0.0008	-0.0008	0.1018**	0.0348**	-0.0006	0.0772	-0.0037	-0.0281
	(0.71)	(0.55)	(0.70)	(0.70)	(-0.70)	(4.15)	(5.20)	(-0.78)	(0.13)	(-0.05)	(-1.62)

Continued on next page

Table VII — continued

(L,H)	**SIZE**	**BE/ME**	β	**OP**	**INV**	$ret_{-L,-H}$	$ret_{-1,-1}$	$ret_{-36,-13}$	$ind_{-L,-H}$	$ind_{-1,-1}$	$ind_{-36,-13}$
Panel D: Full Specification											
(7,2)	0.0009	0.0028	0.0009	-0.0006	-0.0006	0.0948**	0.0349**	0.0008	0.0072		
	(1.48)	(0.79)	(0.64)	(0.64)	(-0.56)	(6.65)	(5.35)	(1.15)	(0.11)		
(7,2)	0.0008	0.0028	0.0011	-0.0008	-0.0008	0.0918**	0.0341**	0.0007	0.0067	-0.0302	-0.0062
	(1.34)	(0.78)	(0.82)	(0.82)	(-0.67)	(6.37)	(5.19)	(1.10)	(0.04)	(-0.45)	(-0.89)
(6,6*)	0.0006	0.0026	0.0009	-0.0006	-0.0006	0.0850**	0.0345**	0.0006	0.0072		
	(1.02)	(0.72)	(0.72)	(0.72)	(-0.49)	(5.16)	(5.23)	(0.89)	(0.07)		
(6,6*)	0.0006	0.0026	0.0010	-0.0008	-0.0008	0.0835**	0.0347**	0.0006	-0.2804	0.0343	0.0134
	(0.88)	(0.72)	(0.77)	(0.77)	(-0.70)	(5.14)	(5.24)	(0.87)	(-0.90)	(0.55)	(0.99)
(12,2)	0.0009	0.0023	0.0005	-0.0004	-0.0004	0.1240**	0.0344**	0.0004	0.1063		
	(1.43)	(0.64)	(0.34)	(0.34)	(-0.39)	(5.90)	(5.21)	(0.63)	(1.16)		
(12,2)	0.0009	0.0021	0.0008	-0.0006	-0.0006	0.1195**	0.0342**	0.0005	0.3280	-0.0207	-0.0020
	(1.36)	(0.59)	(0.56)	(0.56)	(-0.55)	(5.62)	(5.11)	(0.73)	(1.07)	(-0.32)	(-0.18)
(12,12*)	0.0003	0.0021	0.0008	-0.0008	-0.0008	0.0942**	0.0354**	-0.0006	0.0757		
	(0.47)	(0.58)	(0.57)	(0.57)	(-0.69)	(3.89)	(5.28)	(-0.80)	(0.59)		
(12,12*)	0.0003	0.0021	0.0010	-0.0008	-0.0008	0.0909**	0.0355**	-0.0006	1.2294*	-0.0375	-0.0218
	(0.54)	(0.58)	(0.70)	(0.70)	(-0.71)	(3.77)	(5.29)	(-0.77)	(2.12)	(-0.51)	(-0.82)

**, * indicate significance at the 1% and 5% levels.

VII. Conclusion

This paper analyzes the existence of momentum and its source in the Swedish equity market by assessing whether return continuation is driven by firm-specific return components or by industry-level return factors, following the framework of Moskowitz and Grinblatt (1999). Specifically, we test whether individual stock and industry momentum exist and whether stock-level momentum persists after controlling for industry effects.

Our results show that momentum exists in Sweden and is a firm-level phenomenon. Individual stocks exhibit robust momentum across intermediate horizons, and this effect remains after controlling for industry effects, firm characteristics, short- and long-horizon return patterns, and alternative formation and holding periods. In contrast, our findings suggest that industry momentum is absent. Across both portfolio-level tests and cross-sectional regressions, stock-level momentum remains strong and statistically significant when both sources are considered jointly, whereas industry momentum exhibits no statistically significant return patterns.

The absence of industry momentum is robust across all checks. Alternative formation and holding periods, characteristic-adjusted returns, and skipped-month strategies all yield no significant positive industry momentum returns. Although industries maintain similar positions in the return ranking from month to month, indicating that the classification captures economically coherent sectors, this stability does not translate into return persistence, as industry returns show no autocorrelation at any horizon. Size and trading-value decompositions further show that, when industries are value-weighted, their returns primarily reflect the performance of a few large and liquid firms rather than broad sector-wide patterns.

While we find clear evidence that momentum in Sweden operates at the stock-level rather than through industries, several factors limit how broadly this result can be generalized. The five-industry classification is coarse and leaves one industry poorly diversified, while placing many firms into a broad 'Other' category. Swedish industries are concentrated and often dominated by a few large firms, which limits the extent to which industry portfolios diversify firm-specific movements. The available sample period is shorter than in Moskowitz and Grinblatt (1999), which is a constraint in a smaller market with fewer listed firms. Future research could address these limitations by examining whether similar patterns arise in other small or concentrated markets, or whether other non-industry risk-based sources, such as factor momentum, can explain part of the stock-level momentum profits.

Our findings offer implications for both asset pricing and investors. We find that momentum does not arise from the same sources in all markets. Given the absence of industry momentum, exposure to nondiversifiable industry-level risk cannot explain momentum profitability in Sweden. This finding suggests that the source of momentum lies outside nondiversifiable industry shocks, whether in behavioral explanations or in other risk-based explanations that operate at the firm level. For asset-pricing models, this means that industry-level risk is unlikely to rationalize momentum in the Swedish market. For investors seeking to capture it, the evidence shows that momentum signals reside in individual stocks rather than in sector movements. These findings illustrate that momentum patterns depend on market structure and need not mirror those documented in large U.S. markets.

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AI Appendix

We have used the AI tools ChatGPT and Claude for assistance with coding, methodological guidance, and grammar checking.