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Enhancing the "Value & Momentum" Trading Strategy for Swedish Stocks

Introduction

The current **Value & Momentum** strategy for Nasdaq Stockholm equities combines technical trend-following signals with fundamental value screening [1]. In summary, each stock is given a technical **score (0–100)** based on multiple indicators (e.g. moving averages, RSI, breakout patterns), and only stocks that also pass simple value criteria (P/E $\leq$ 30 and positive profits) are considered for purchase [2]. A **BUY** signal is generated when technical momentum is strong (score $\geq$ 70) and fundamentals pass, whereas a **SELL** is triggered if momentum falters (score < 40) or the price breaks the long-term trend (falls below the 40-week moving average) [3] [4]. Currently, risk management is minimal – there is no explicit stop-loss or position sizing rule beyond the sell triggers. The strategy does not adjust for different market regimes or volatility levels.

While this framework is a solid starting point (it reflects evidence that momentum and value factors can improve returns [5]), there is room to refine each component. Below, we review five key areas – technical indicators, fundamental filters, signal thresholds, risk management, and regime adaptation – and recommend improvements grounded in academic research and best practices. These enhancements are tailored for the Swedish equity market where applicable (e.g. considering the OMXS30 index and characteristics of Swedish stocks). A summary comparison of the current vs. proposed approach is also provided (see **Table 1**).

1. Technical Indicator Selection & Weighting

Current Technical Signals: The strategy uses a weighted composite of six technical indicators to capture momentum [6]: (1) price above 40-week moving average (MA40, weight 25%), (2) price above 4-week moving average (MA4, weight 15%), (3) 14-day RSI > 50 (15%), (4) a "higher lows" chart pattern (15%), (5) price near 52-week high (20%), and (6) a short-term volatility breakout signal (10%). If a factor's data is missing, the score is normalized to avoid penalty [7]. This scoring system aims to quantify intermediate-term trend strength by combining long-term trend following (MA40, 52-week high), short-term momentum (MA4, RSI), and pattern/volatility signals (higher lows, breakout).

Review and Rationale: Academic evidence broadly supports trend-following and momentum indicators, but the effectiveness of specific measures and their weights can be optimized:

- **Moving Averages:** Long-term moving averages are well-known for signaling primary trends and reducing downside risk. For example, Brock et al. (1992) found that simple moving-average rules on the Dow index generated returns inconsistent with chance – *"buy signals (e.g. price above average) yielded higher returns (with lower volatility) than sell signals"* [8]. A 40-week (200-day) MA is a common trend filter in both industry and academia (analogous to the 10-month rule), and being above the MA

has historically indicated a bullish regime with higher returns and lower volatility. Given its significance, the **MA40 condition could warrant even higher weight** than 25% to ensure the strategy prioritizes staying aligned with the primary trend. Indeed, Faber (2007) showed that moving to cash when the market falls below its 10-month MA dramatically cuts drawdowns without sacrificing long-run returns. The short-term MA (MA4, ~20 trading days) captures recent momentum but can be noisy. We might **extend the short-term window** slightly (e.g. a 50-day MA) to filter out very short-term fluctuations, unless backtests confirm 4-week is optimal. Overall, maintaining a dual timeframe approach (fast and slow MA) is sensible – it reflects **time-series momentum** at different horizons, a phenomenon documented across asset classes [9] [10].

- **RSI (Relative Strength Index):** RSI is a popular oscillator to gauge momentum and mean-reversion. The strategy uses RSI>50 as a positive signal (above 50 indicates recent gains exceed losses). While RSI thresholds (like the classic >70 overbought, <30 oversold) are common heuristics, academic support is mixed. Some studies have found that RSI-based strategies can add value in certain markets, but results vary. For instance, one analysis of RSI and moving averages noted these indicators can improve timing when used correctly [11]. **Improvements:** We should verify if the **14-day RSI** is the best choice for a weeks-to-months horizon; research suggests that RSI periods and thresholds can be optimized per asset or timeframe [12]. If RSI is included, one might require a stronger signal (e.g. RSI > 60 or 70) for momentum confirmation rather than >50, or use a **longer-period RSI** to smooth noise. Ultimately, RSI overlaps with other momentum measures, so we could consider giving it slightly less weight or using it as a secondary confirmation indicator. If the combined scoring is too complex, an alternative is to replace RSI with a **simple momentum metric** (such as **6- or 12-month price change**), since academic momentum studies typically use multi-month relative price performance [9]. In fact, buying recent 6–12 month winners and avoiding losers is the foundation of momentum investing (Jegadeesh & Titman, 1993). The current approach indirectly captures this via the 52-week high and moving averages, but an explicit **relative strength ranking** could be tested as an input to the score.

- **52-Week High Proximity:** This is a valuable addition grounded in research. George and Hwang (2004) found that *"nearness to the 52-week high"* has strong predictive power for future returns, **even more so than past 12-month returns** themselves [13]. Stocks within ~2% of their annual high (as defined in the strategy [14]) often continue to outperform, possibly due to positive momentum and investor anchoring at round highs [15]. The strategy's 20% weight for this factor seems reasonable given the evidence. We might even consider a modest weight increase or **making it a prerequisite for a strong buy** (e.g. requiring the stock to be near a high to trigger a high technical score). However, care is needed as a stock at a 52-week high with overbought technicals could sometimes pull back; thus it should be used in combination with other signals (as is done). Overall, **academic consensus supports the emphasis on 52-week high** as a momentum indicator, since it effectively captures the same information as past return rankings but with a simple metric [16].

- **"Higher Lows" Price Pattern:** The strategy awards 15% if the chart shows successive higher lows (an indication of an uptrend). While this pattern is well-known to traders, it's essentially a qualitative way to say the stock is in an upward trend with controlled pullbacks. There is limited direct academic literature on subjective chart patterns like *"higher lows"* – most research focuses on quantifiable rules. However, this concept overlaps with moving average trends and momentum. If a stock is consistently making higher lows, it's likely above its longer-term MA and showing positive returns. We may **retain this factor for nuance**, but it could be partially redundant. A potential improvement

is to formalize it (e.g. define it as the 50-day moving average trending up for X weeks) or to replace it with another indicator of trend quality (for example, **ADX** or another trend strength indicator, if supported by research). In absence of a clear academic guideline, keeping a moderate weight (15%) is fine, as it has intuitive value. In future, **machine learning** pattern recognition could verify if incorporating such price-structure patterns adds predictive power.

- **Volatility Breakout:** The breakout signal (10% weight) in the current model is defined by a **volatility expansion coupled with price increase** – specifically, 12-period return volatility exceeding its recent past volatility, alongside price higher than 4 periods ago [17]. This is meant to flag accelerating momentum. Similar ideas appear in classic trend-following (e.g. *"trading range breakouts"*). Research by Brock et al. (1992) also tested breakout rules (e.g. price above its previous x-month high) and found they generated abnormal profits on historical data [18]. The strategy's volatility-based breakout is somewhat more complex. **Improvements:** We should evaluate if a simpler or more robust breakout criterion works better. For example, using **Average True Range (ATR)** or standard deviation breakout bands can quantify a statistically significant price move. More importantly, academic and practitioner literature emphasizes **volume confirmation** for breakouts: a price surge on high volume is more likely to sustain than one on low volume. While the current system does calculate volume metrics, it does *not* include them in the score. Incorporating volume is supported by studies – e.g. Lee and Swaminathan (2000) showed that momentum profits are tied to trading volume; strategies that focus on high-volume price moves outperform those using price alone [19]. We recommend **adding a volume criterion** to the breakout factor (for instance, require that volume on the breakout day/week is, say, 50% above average). This aligns with technical best practices and research showing that *"past trading volume predicts both the magnitude and persistence of future momentum"* [19]. If a breakout is accompanied by unusually high volume, it could be weighted more heavily in the score (or a separate binary factor). Conversely, low-volume breakouts might be given little credibility.

- **Indicator Weighting Optimization:** The current weights (25/20/15/15/15/10) were set by heuristic. Academic best practice would be to **optimize these weights using historical data** or statistical methods. One approach is a regression or machine learning model predicting future returns from these signals – the learned coefficients would inform which indicators deserve more weight [20]. Alternatively, one could backtest different weight configurations to maximize risk-adjusted return. For example, perhaps being above the long-term MA (a binary condition) could be an absolute requirement rather than just 25% of the score, since many momentum studies first filter stocks by an uptrend condition (to avoid "buying momentum" in an overall downtrend). Some research even suggests that equal-weighting multiple signals can be robust by diversifying model risk [21]. If we cannot determine an optimal fixed weighting analytically, **consider dynamic weighting** – e.g. increase the weight of breakout and short-term factors in high-volatility periods and rely more on MA trends in stable periods. This would be complex, however. In practice, a reasonable improvement is to ensure the **primary trend (MA40)** and **52-week high proximity** carry significant combined weight (at least ~50% together), as these capture the core of intermediate momentum. Secondary indicators (RSI, short MA, pattern) can share a smaller portion, and breakout (enhanced with volume) can be given a bit more weight (perhaps 15% instead of 10%) if testing shows it usefully identifies explosive moves.

In summary, the technical toolkit is largely supported by momentum literature: maintaining positions in stocks that are trending up (above long MA, near highs) and cutting those losing momentum is a proven

strategy [8] [13]. The key improvements are *refining the signals* (e.g. use volume-backed breakouts, possibly add an explicit multi-month return metric) and *refining their influence* (weights). Table 1 (Technical row) outlines these changes. By aligning the technical composite more closely with academic momentum factors (while still smoothing with multiple indicators), the strategy can better capture momentum profits. Notably, momentum effects have been observed in Sweden and other markets historically, but one must be careful with small-cap stocks (addressed in section 5) and ensure not to overfit the indicator mix to past noise.

2. Fundamental Screening Filters

Current Fundamental Filters: A stock must pass a **profitability and valuation check** to be considered a BUY [22] [23]. The rules are simple: (A) **Profitable** – profit margin > 0, i.e. the company is not loss-making in the trailing twelve months; (B) **Reasonable P/E** – P/E ratio ≤ 30, or P/E is undefined (e.g. negative earnings or not reported). These are binary pass/fail criteria. Additional fundamentals like revenue growth, ROE, Debt/Equity, etc., are calculated for information but do not influence the signals [24]. Essentially, the strategy applies a mild value and quality screen: avoid very expensive stocks (high P/E) and unprofitable companies.

Review and Rationale: Blending **value and momentum** is strongly supported by academic research. Studies find that the momentum anomaly is robust, and the value premium (buying cheap, selling expensive) is also persistent – moreover, the two are complementary (value tends to outperform when momentum falters, and vice versa) [25] [26]. Asness *et al.* (2013) showed that combining value and momentum factors produces higher risk-adjusted returns than either alone [21]. Thus, the idea to require some minimum fundamental quality in momentum picks is sound: it can help avoid "momentum traps" (stocks that have momentum but are overvalued or fundamentally shaky). However, the specific fundamental rules can be **enhanced to align with best practices in value investing and quality filtering**:

- **P/E $\leq$ 30 Criterion:** A P/E of 30 is a relatively high cutoff – it avoids only extreme high-growth/overvalued stocks. Historically, **value strategies focus on much lower multiples** (e.g. buying the lowest 20% P/E or P/B stocks). Basu (1977) famously found that portfolios of low P/E stocks delivered significantly higher returns than high P/E stocks, even adjusting for risk [27]. In that context, a P/E of 30 might be too lenient: many stocks would pass this (the average market P/E is often 15–20; 30 mostly filters out the ultra-expensive tail). If the goal is to tilt toward value, we could **tighten this threshold** – for example, require P/E < 20 or < 25. Alternatively, use **relative valuation**: e.g. P/E below the industry median or in the lower half of the market. An industry-adjusted approach could avoid penalizing sectors that naturally have higher P/Es (like tech) while still filtering out the froth within each sector [28]. Since the Swedish market has a mix of industries (from banks to tech), a relative valuation filter might be sensible.

Another enhancement is to incorporate **additional valuation metrics** rather than P/E alone. P/E can be distorted by one-time earnings or accounting differences. We could include **Price-to-Book (P/B)** or **EV/EBITDA** as supplementary checks. Research by Fama and French and others indicates that book-to-market (the inverse of P/B) is a strong predictor of returns (value factor) [29] [30]. In practice, a composite value score could be used (averaging ranks of P/E, P/B, and perhaps dividend yield). However, to keep it simple and aligned with the current design, an easier step is to lower the P/E cutoff. If many Swedish stocks have no earnings (and thus no P/E), the strategy currently lets them pass by default [31] – this may allow speculative non-profitable firms. We might change that to be more cautious: e.g. require a positive P/E or at

least positive earnings (which overlaps with the profit rule). If a P/E is null due to negative earnings, perhaps that stock should *not* pass unless it meets some alternate value metric.

- **Profitability (Profit Margin > 0):** Requiring any positive net profit is a very low bar for quality. It excludes only companies that are currently in the red. Academic literature on **quality and profitability** suggests that higher profitability is associated with better returns, all else equal (the "quality premium"). Novy-Marx (2013) demonstrated that gross profitability (profitability of core operations) is a strong positive predictor of returns – *"gross profitability has roughly the same power as book-to-market in predicting the cross-section of returns"* [32] [33]. This implies that among two equally valued companies, the more profitable is likely to perform better. Therefore, we could strengthen the profitability filter. Options include: requiring **a minimum profit margin** (for example > 5% net margin, not just >0), or **positive earnings in multiple years** (to ensure it's not just one lucky quarter). The Piotroski F-score (2000) approach is instructive here: Piotroski found that within a basket of cheap stocks, those with good financial health (positive profits, improving margins, low debt, etc.) outperformed the ones with poor fundamentals by **7.5%** annually on average [34]. In our context, we might not implement a full Piotroski score, but we can incorporate some of its components. For instance, require **ROE > 0** (profitable for shareholders), or **operating cash flow > 0**, or year-over-year **earnings growth > 0**. Even adding a requirement that revenue is not shrinking could help avoid troubled firms. Since the strategy already computes revenue growth and ROE as informational metrics [24], it would be straightforward to include one or two as additional hurdles (e.g. "and revenue growth $\geq$ 0%" if we want to avoid companies with declining sales).

The key is to avoid value traps: companies that are cheap by P/E but are deteriorating. Requiring at least stable or growing revenue and earnings can filter these out. Also, introducing a **moderate leverage constraint** could be wise. For example, *Debt-to-Equity* ratio below a certain threshold (or interest coverage > some level). Highly leveraged firms might face distress; many value investors exclude those. Given that Swedish companies can differ in capital structure, perhaps check that Debt/Equity < 100%, or simply ensure the company's debt is not excessive relative to peers. (The current system calculates D/E but doesn't use it). Academic studies (e.g. Campbell et al. 2008 on failure risk) show that controlling for distress risks can improve returns for value picks. Therefore, adding a **financial stability filter** (like no severe debt or current ratio above some minimum) could improve outcomes during downturns when indebted companies suffer.

- **Additional Value/Quality Metrics:** Aside from tightening P/E and profit, we might incorporate **Return on Equity (ROE)** or **Return on Capital** as a quality indicator. Greenblatt's "Magic Formula" strategy, for instance, ranks stocks by high earnings yield *and* high ROIC, capturing cheapness and quality. While Greenblatt (2006) is not peer-reviewed, the concept has parallels in academic work on combining value with quality factors [35]. High ROE or high gross margins might indicate a competitive advantage, which increases the likelihood that a value stock will rebound. In the Swedish context, companies with strong profitability and reasonable valuations could be analogous to the so-called "super stocks" that some Nordic value investors seek. We should ensure we're not excluding growth companies entirely, though. The current rule allows P/E = null (which in practice means many growth or early-stage firms with no earnings slip through). We could instead incorporate **sales-based valuation** (like Price/Sales ratio cutoff) for companies with no earnings, to avoid extremely overpriced story stocks. For example, require P/S < some multiple if P/E is not applicable. This would be consistent with literature suggesting multiple criteria screening yields better performance than a single ratio [28].

- **Dynamic or Sector-Specific Criteria:** The strategy might benefit from adjusting fundamental criteria by sector. Certain sectors (e.g. Tech) normally trade at higher P/Es, so a blanket P/E $\leq$ 30 could still be high relative to sector norms, or conversely for utilities 30 may be too high. A refinement is to use **sector-relative valuation** – e.g. only pass if P/E is below (say) 80th percentile of its sector. Academic studies (e.g. on style investing) note that comparing valuation within industries can account for structural differences. Similarly, for profitability, comparing margins to industry average could flag truly strong vs weak companies. Given the complexity, this may be more detail than needed for now, but it's worth noting for future improvement [28].

In summary, the fundamental "Value & Quality" screen should be **strengthened** to ensure we buy *good companies at reasonable prices*, in line with classic value investing principles (Graham's margin of safety, etc.). This will likely improve performance by avoiding the lowest-quality momentum stocks, which are prone to crashes. Empirical evidence supports this approach: for example, one study found that combining momentum with a value filter significantly increases risk-adjusted returns, partly by avoiding expensive high-flyers that often flame out [5]. Another study on profitability suggests focusing on profitable firms yields better returns than including unprofitable ones, even within momentum portfolios [32]. The Swedish market, in particular, has seen many small tech firms with negative earnings rally on momentum – a stricter fundamental check would have prevented buying these in late-stage rallies that subsequently collapsed.

Therefore, we propose requiring **stronger fundamentals**: e.g. P/E < 25 (or below market average), positive earnings *and* cash flow, no severe debt issues, and perhaps non-negative revenue growth. These changes align with academic findings on value (low multiples outperform [27]) and quality (profitable firms outperform unprofitable [33]). The net effect is a more robust hybrid strategy, often termed "quality momentum" or "momentum among value stocks," which academic literature finds very compelling [26] [36]. Table 1 (Fundamentals row) summarizes the improved criteria.

3. Signal Generation Rules & Thresholds

Current Signal Thresholds: The strategy translates the technical score (0–100) into trading signals using fixed cut-offs [3]: a **BUY** is issued if *Tech Score* $\geq$ *70* (and fundamentals pass), a **SELL** if *Tech Score* < *40* (or price drops below MA40), and a **HOLD** for scores in between. This creates a somewhat asymmetric band: the top 30% of the score range is "buy," the bottom 40% is "sell," and the middle 30% is hold/monitor. The thresholds 70/40 were chosen heuristically to represent "strong momentum" vs "weak momentum." The SELL also has an immediate override – if price falls below the 40-week MA (even if score hasn't dipped below 40 yet), a sell is triggered as a hard stop [37]. This ensures that prolonged uptrends flipping to downtrends prompt exit even if some other indicators lag. There is no explicit **"strong buy"** category beyond the $\geq$70, and no differentiation on position sizing based on score (all buys are treated alike).

Review and Rationale: The use of thresholds to turn a continuous technical score into discrete actions is reasonable, but choosing optimal thresholds is non-trivial. The questions to consider are: Are 70 and 40 appropriate cut-offs? Should they be adjusted over time or for market conditions? And should there be multiple tiers of signals (e.g. an extra bullish or bearish tier)?

- **Buy Threshold (70):** A score $\geq$ 70 means the stock meets roughly 70% of all momentum criteria. This is designed to select the top ~30% of momentum opportunities (since if all indicators were equally likely, ~30% of observations would score 70+). In principle, that aligns with academic

momentum strategies that often **buy the top 1/3 or top decile** of performers [3]. For example, cross-sectional momentum strategies might buy the top 10–30% of stocks ranked by past returns (and short the bottom). Our strategy doesn't short, but requiring a stock to be in roughly the top third by technical composite to go long seems intuitively reasonable. We might ask: would a slightly lower threshold (say 60 or 65) capture more opportunities without sacrificing too much quality? Or a higher threshold (80) make the strategy too selective? Academic optimization of such cut-offs typically requires backtesting. One could maximize historical Sharpe ratio or precision of signals to find an ideal number [38]. In absence of that analysis here, we lean on the idea that **momentum payoffs increase with stronger signals** (stronger momentum stocks tend to keep outperforming). Indeed, momentum studies often find monotonic relationships: the extreme winners outperform moderately good stocks [39]. Thus, using a **high buy threshold** is a way to demand an extreme momentum confirmation. The risk is that it may generate fewer trades/signals, potentially missing early entries.

A potential improvement is to add a **"Strong Buy" tier** for exceptionally high scores. For instance, score $\geq$ 85 could be flagged as **Strong BUY**, which might suggest taking a larger position or at least give the trader extra confidence (this could tie into position sizing if implemented). This addresses the question in the original doc about a >85 tier [40]. Academically, one could justify it by the evidence that the **top-decile momentum stocks massively outperform the average** momentum stock (as shown in Jegadeesh & Titman's decile analysis). A strong-buy tier could also help psychologically to distinguish between just crossing 70 vs truly outstanding scores (all indicators firing). If historical testing shows that, say, score 90+ picks have much higher win rates, then creating a special category makes sense.

- **Sell Threshold (40) and Hard Stop:** The current rule sells on score < 40 or price < MA40 (whichever comes first). This means if momentum significantly deteriorates (bottom 40% of scale), the stock is likely rolling over and should be sold. The asymmetry (40 vs 70) creates a **wider hold range** (score 40–69). This is a conservative approach to avoid whipsaw: once a stock is bought, it isn't sold until momentum actually becomes quite poor (below 40), rather than just dipping slightly. This can prevent prematurely exiting on minor pullbacks – a form of **hysteresis** in the trading rule. Is 40 optimal? It implies that if even 2-3 of the 6 indicators remain positive, the score might stay above 40 (depending on weights), so you hold until most signals are negative. We might consider if this threshold should be **dynamic**. For example, in a bear market environment, maybe one should sell sooner (threshold higher, like 50) because momentum signals are less reliable then. Conversely in a roaring bull market, one might tolerate a deeper score dip (maybe down to 30) because many stocks oscillate but recover. Some researchers have explored **regime-dependent momentum strategies** – notably, Cooper et al. (2004) found that momentum profits evaporate or reverse following bear markets [41]. This suggests one could tighten sell criteria after a market downturn to avoid momentum crashes. For instance, after an overall market drop, require momentum scores to be very high to stay invested. A concrete rule: if the index is below its MA or has recently fallen X%, one could set the sell threshold higher (like 50) to quickly exit weakening positions.

The **price < MA40 hard stop** is a sound risk management device and should remain (we discuss stops more in section 4). It essentially overrides the score if the long-term trend breaks, ensuring a timely exit. This is akin to many trend-following strategies that exit when the asset falls below its 200-day average (a method that historically avoids big crashes at the cost of some whipsaw). Given research shows being below the 10-month MA yields much worse returns, using that as a binary stop is justified. We might even consider using

a **shorter MA** as an additional stop in certain cases – e.g. if price falls below the 50-day MA and the score also < 50, perhaps sell, to catch fast declines. But this could introduce more trades and complexity.

- **Dynamic/Adaptive Thresholds:** The strategy currently uses fixed 70/40 cut-offs. One improvement is to allow them to **vary with market volatility or cross-sectional momentum breadth**. For example, in high volatility times, momentum signals are noisier, so one might raise the buy threshold (demand a more robust signal) to reduce false entries. Conversely, in very low volatility, gentle trends might score lower yet still be worth buying, so maybe lower the threshold a bit. Moreira and Muir (2017) notably advocate volatility-managed strategies – effectively scaling positions down during high volatility [42]. While they focus on scaling rather than threshold, the principle is similar: be pickier in turbulent periods. Another approach: define buy/sell thresholds in **percentile terms** rather than absolute. For instance, "Buy if score is in top 20% of its range over the past year" or relative to all stocks at the time. This could ensure a roughly consistent number of signals over time. If the whole market is in a strong uptrend (many stocks scoring high), a percentile approach would force only the very strongest to be buys (maintaining selectivity). If the market is in a weak phase (few stocks with high scores), a percentile rule might allow buys at a lower absolute score just to capture some opportunities. This is analogous to cross-sectional momentum strategies always investing in some fraction of stocks. However, given our strategy doesn't require holding something at all times (one can hold cash), it might be fine to sometimes have zero buys if nothing meets the fixed criteria. Still, this adaptability is worth exploring in backtesting.

- **Signal Confirmation and Persistence:** Another subtle improvement – ensure that signals are not triggered by one-day or one-week aberrations. For example, require that the tech score stays ≥ 70 for two consecutive days or a week before a BUY, to avoid head-fakes. Similarly, maybe require a SELL condition to persist for a short period (except for the MA40 break which might be immediate as a safety). This kind of **time confirmation** can reduce flip-flopping on borderline scores. It effectively builds a bit of inertia into the signals. Some academic papers on moving average rules have noted that minor breaches can be filtered with confirmatory rules to improve performance [43]. That said, adding delay can also miss turning points, so it's a trade-off.

To determine if **70/40** are "statistically optimal" would require analysis of historical returns from different threshold choices [38]. Barring that, we rely on logical alignment with momentum deciles and risk management. The current asymmetry (buy zone 70–100 is 30 points wide, sell zone effectively 0–40 is 40 points wide) creates a buffer that is likely intentional to avoid churn. This seems prudent and many momentum traders do use a tighter entry and looser exit (ride winners, cut losers not too early). We will maintain that philosophy. If anything, we might adjust slightly to **Buy $\geq$ 75** and **Sell < 50** (just as an example) if testing shows better outcomes, but these exact numbers would be fine-tuned empirically.

Recommendation: Keep using **discrete signal tiers**, but consider adding a **"strong buy" threshold** for scores well above 70, and possibly a **"strong sell" or alert** if score falls very low (e.g. below 20) indicating severe breakdown. Use the 40-week MA breach as a strict sell rule (already in place, and validated by many studies). In volatile or bear market conditions, be willing to override thresholds (e.g. temporarily require 80 to buy, or just avoid new buys entirely if the market trend is down – see section 5 on regimes). The main improvement is to **validate and perhaps optimize 70/40 with historical data**. If data shows that a threshold of, say, 65 for buy would have captured significantly more return without much increase in false signals, that could be adopted. Or if 75 would have improved Sharpe by filtering choppiness, use that.

Academic methodologies like ROC curve analysis or maximizing return per trade could be employed to find these levels [44].

In absence of that analysis in this report, we lean on the current values as reasonable starting points, with the addition of **tiered signals** as described. This would make the strategy more nuanced (e.g. a score of 85 could trigger a higher conviction buy, whereas 70–84 is a normal buy; similarly, a drop below 30 could be an urgent sell vs a gradual exit at 40). These refinements align with practitioner experience more than academic diktat, since academia usually treats momentum more continuously. Nonetheless, they are sensible given *risk management considerations* – which we turn to next.

4. Risk Management Practices

Current Risk Management: This is one area explicitly flagged as a limitation in the current model. At present, risk management is rudimentary: the **sell rules serve as the primary stop-loss**, and **no position sizing rules** are in place. In other words, if a stock's technicals weaken enough or it breaks the MA40, it will be sold – that functions as a trailing stop of sorts. However, there is *no explicit stop-loss level* (like a fixed % drop), no trailing stop based on price volatility, and no rule for sizing positions relative to risk. All buy signals are treated equally, presumably with an equal allocation per stock (or some default amount). The documentation specifically asks whether to add stops, position sizing, volatility metrics, or max loss rules [45]. This indicates an opportunity for significant improvement, as proper risk management is critical for trading strategy robustness.

Improvements: We draw from both academic research and industry best practices for risk management enhancements:

- **Explicit Stop-Loss Levels:** While the MA40 trend stop is useful, it may sometimes be slow or far from current price (especially if a stock ascended far above its MA40, a drop to the MA40 could be a large drawdown). Implementing a **stop-loss order** – for example, *X% below the purchase price or recent high* – can protect profits and limit losses. Academic studies have examined stop-loss rules: Kaminski and Lo (2007) found that simple stop-loss strategies can *"have a positive impact on expected returns and risk-adjusted returns,"* often outperforming buy-and-hold in terms of Sharpe ratio [46]. A thesis on OMXS30 stocks (Lundberg, 2009) similarly concluded that both traditional and trailing stop-loss rules improved outcomes versus no stops [46]. Given this evidence, adding a **trailing stop** is prudent. For an intermediate-term strategy, one might use a trailing stop of about 10–20% from the peak. For example: "If the stock price falls 15% from its highest level since purchase, exit the position." This captures the idea of cutting a position that's significantly reversed. Alternatively, an **ATR-based stop** could be used – e.g. sell if price falls more than 3 * ATR(14) from its peak, which adjusts for the stock's volatility. Such volatility-adjusted stops are common in trend-following systems to normalize for noise. The exact parameter (15%, 3*ATR, etc.) should be optimized via backtesting; academic research often uses ATR multiples in trading system design.

Additionally, a **time-based stop** could be considered: if a stock has neither hit the profit target nor stop-loss after a certain time, re-evaluate or trim it. Momentum tends to work over 3–12 month horizons, so if a position goes nowhere for, say, 6 months (score stagnating in hold range), it might be capital better

deployed elsewhere. This is more a practical consideration; academic support is indirect (momentum decays over time if not realized).

- **Position Sizing and Capital Allocation:** Currently, the strategy does not specify how much capital to put into each BUY. Equal allocation is implied, but not formalized. Position sizing is critical for controlling risk. A best practice is **risk-based sizing**: allocate positions so that each one risks a similar % of the portfolio if its stop is hit. For example, one might risk 1% of portfolio per trade. If a stock's stop-loss (distance from entry) is 10%, then invest 10% of the portfolio (because a 10% drop on 10% position = 1% of portfolio). If another stock is more volatile with a 20% stop distance, invest 5% of portfolio in it (5% * 20% drop = 1% risk). This is known as **fixed fractional position sizing**, a widely recommended method in trading literature. While not directly from academic finance journals, it's grounded in risk management principles. It ensures no single trade can ruin performance and aligns exposure with volatility.

There is also academic theory like the **Kelly Criterion**, which provides an optimal fraction of capital to wager based on edge and odds. The Kelly formula, introduced by John Kelly (1956), maximizes long-term growth but can be too aggressive in practice. However, research has extended Kelly to **Kelly fraction** or **risk-constrained Kelly** for trading, indicating how to size bets for best growth with controlled risk. For our purposes, a simpler approach (like the 1-2% risk rule per trade) is easier to implement and is commonly advocated by professionals. This could greatly help the strategy, especially when some stocks are more volatile than others (common in a mixed market like Sweden where large caps are stable but small caps can swing wildly). By sizing smaller on volatile names and larger on stable names, the portfolio's risk is balanced.

We recommend implementing a rule such as: **Risk 1% of equity per trade** (this can be adjusted to 0.5% or 2% depending on aggressiveness). This means if a trade has a stop 10% away, position size = 10% of portfolio; if stop 5% away, position = 20%; etc. If no explicit stop is set, one could use a default like the MA40 or a volatility stop to compute this. The strategy should also cap position size to avoid too large a position (e.g. even if volatility is tiny, maybe cap at 25% of portfolio per stock for diversification).

- **Risk-Adjusted Signals:** Another layer is incorporating risk metrics into the signal itself. For example, a stock that has a high technical score but also extremely high volatility might warrant caution. One could adjust the score or required threshold based on volatility (effectively what Moreira & Muir do by scaling exposure). Concretely, perhaps define a *volatility-adjusted tech score*: Score – (Volatility factor). But a clearer approach is in sizing as discussed.

We should also monitor **portfolio-level risk**: e.g. ensure the portfolio is not over-exposed to one sector or factor. Since the focus is Swedish stocks, diversification across industries would help (the strategy currently doesn't account for correlation between holdings). A risk management rule could be: not more than 20–30% of the portfolio in one sector, not more than X names from the same industry (to avoid all momentum picks being, say, tech startups which often move together). This wasn't explicitly in the user request, but it is a prudent extension, especially as momentum often clusters by sector (sector momentum is a real phenomenon [47]).

- **Maximum Drawdown and Review:** It's useful to have a **max drawdown stop** on the portfolio or per position. For instance, if the portfolio drops more than, say, 15% from its peak, one might reduce all positions or stop taking new ones until conditions improve. This is a bit discretionary but some systematic strategies include "circuit-breakers" to reduce exposure after large losses (to avoid the

psychological trap of stubbornly holding through deep drawdowns). Research in trend-following suggests that *stopping out and de-risking during steep equity downturns* can improve compound returns by avoiding being fully invested at market bottoms [42]. The strategy already would likely lighten up in a market downturn due to individual sells, but a portfolio-level rule could add another safety net.

- **Empirical Evidence:** To justify these risk practices, we note: Stop-loss rules have been studied in various markets. Aside from Kaminski & Lo (2007) [46], a more recent study on momentum in crypto found stop-losses significantly improved momentum payoffs by preventing large crashes [48]. While crypto is extreme, it underscores the general point. Another empirical insight: volatility scaling (reducing positions when volatility is high) produced *"substantially higher Sharpe ratios"* for momentum and other factors [42]. This suggests that if market volatility (or individual stock volatility) spikes, one should cut position sizes or tighten stops. Our plan to risk a fixed % per trade inherently does that – volatile stocks get smaller size. We could also incorporate a rule to scale down the entire portfolio's exposure when the **VIX or Sweden's VXSE index** is high, or when average volatility of chosen stocks is high. This is essentially a volatility-managed portfolio approach. Moreira & Muir (2017) found that doing so for momentum nearly doubled its Sharpe ratio historically [49] [50].

- **Practical Stop Suggestions:** A concrete stop-loss implementation could be: If a BUY is triggered, immediately set an initial stop at (for example) 15% below the entry price (or below a recent support level). This protects against a sudden adverse move. If the stock moves up, trail the stop to lock in at least, say, 10% profit once it's achieved 20% gain, etc. One could use the MA40 itself as a trailing stop (already in code) but often that's far from price. A shorter trailing stop, like a 10-week MA or an ATR-based trail (e.g. price falls 2 ATR from its 20-day high), might sell sooner and preserve profits. There is academic debate on optimal trailing stops – some argue that tight stops can cut winners too early, others that loose stops give back too much. The consensus in trading literature is that stops should not be so tight that normal volatility stops you out (hence ATR-based to adapt to volatility). Many trend-following systems in futures use 3×ATR(20) as a stop from peak. This could be a reasonable choice here as well.

Implementing robust risk management will likely reduce volatility and drawdowns of the strategy significantly. For example, a backtest by a student on OMX Stockholm 30 showed that stop-loss strategies *"outperform buy-and-hold in both return and risk-adjusted terms"*, and particularly improved the **Sortino ratio** (since they cut off large losses) [46]. Moreover, by risking a fixed small percent per trade, the portfolio can withstand a string of losses without severe damage. This addresses the ultimate goal: **capital preservation** during adverse periods, which is as important as capital growth in a trading strategy.

In summary, our recommendations are: introduce **explicit stop-losses** (trailing and/or initial stops) to complement the indicator-based exits; adopt a **position sizing framework** (risk-per-trade or volatility parity); and incorporate **volatility/regime-based exposure adjustments** (reduce exposure when volatility is high, as research strongly supports doing so for momentum [42]). These changes are supported by both academic findings and practical trading wisdom. Table 1 (Risk Management row) encapsulates the key additions. With these in place, the strategy should weather market turbulence more effectively – crucial for the inherently volatile momentum style, especially in a smaller market like Sweden where liquidity shocks can be significant.

5. Adaptation to Market Regimes and Other Considerations

Current Approach: The strategy currently does **not adapt to different market regimes** – it uses the same logic in bull and bear markets, high or low volatility, and for all stock categories. There are no separate criteria based on macro conditions, nor differentiation between large-cap and small-cap stocks or between sectors. All stocks are evaluated with the same model, and there is no overarching market-timing component (aside from individual stops that might collectively get one out of the market during a downturn). In essence, it's a static strategy applied to all environments, which is a simplification that may leave performance on the table or expose the strategy to known failure modes of momentum.

Need for Adaptation: Substantial research indicates that **momentum strategies behave differently across market regimes**. As mentioned earlier, momentum tends to struggle after major bear markets – known as "momentum crashes" (e.g. the 2009 rebound saw momentum portfolios plummet as the worst stocks bounced hardest). Cooper et al. (2004) found momentum profits were *"significantly positive following market gains, but approximately zero or negative following market declines"* [41] . This suggests one should be cautious deploying momentum in the aftermath of bear markets or during high-volatility crises. Additionally, **volatility regime** matters: momentum performs better in stable trending periods and can whipsaw in volatile, trendless periods.

Furthermore, characteristics like **company size** and **sector** can influence momentum's effectiveness. The user's prompt hinted at small-cap vs large-cap criteria. In fact, a recent study on the Swedish market (Behjo & Anjou, 2025) found that momentum was *largely absent or reversed in small-cap stocks*, while it was present in large caps [51] . Past winners among small firms tended to underperform subsequently (perhaps due to liquidity issues or overreaction), whereas big-cap winners did continue to win [51] . This is a critical insight for tailoring to Sweden: it implies a blanket momentum approach might fail on small stocks. Similarly, momentum often varies by **sector rotation** effects – sometimes an entire sector catches a cycle (like commodities, tech booms, etc.), and focusing on that can help. Moskowitz and Grinblatt (1999) showed industry momentum was a significant part of individual stock momentum profits; buying strong sectors and avoiding weak ones can be fruitful.

Given these points, we propose regime adaptations on several levels:

- **Market Trend Filter:** Incorporate an indicator of the **overall market condition** (e.g. OMXS30 index trend) to modulate signals. For instance, require that the broad market is not in a bearish trend when taking new long positions. A practical rule: Only allow BUY signals if the Stockholm index (OMXS30 or broader OMXSPI) is above its 200-day moving average (or 10-month MA). If the index is below that threshold (i.e. market in downtrend), either pause new buys or raise the bar (e.g. require tech score ≥ 85 to buy, meaning only exceptionally strong stocks in a weak market). This aligns with the concept of **"absolute momentum"** or **dual momentum** (Antonacci, 2014) where one first checks market momentum before investing in equities. Empirical evidence suggests this avoids prolonged drawdowns. For example, Faber's work on tactical asset allocation found that using a 10-month MA on each asset (including the stock index) to decide in/out of market yielded *"equity-like returns with bond-like volatility and much smaller drawdowns"* [52] [53] . By extension, applying a market filter to our stock strategy should improve its performance in bear markets by mostly keeping us out (safely in cash).

In practice, this could mean: if OMXS30 is below its 200-day MA, we treat **all stocks as at most HOLD**, regardless of their individual score (or perhaps limit to very few buys). This might cause the strategy to miss the very bottom when things recover (momentum is late to catch bottoms), but it significantly reduces crash exposure – a worthwhile trade-off as shown in many studies. Notably, this approach would have avoided momentum crash periods like early 2009 for U.S. stocks [41].

- **Volatility Regime Adjustment:** If market volatility (say VIX or the standard deviation of index returns) is extremely high (signaling turmoil), consider scaling back exposure or being more selective. Moreira & Muir's volatility-managed approach for momentum essentially does this: during volatile times (often coincident with bear markets or crises), it cuts position sizes, and during calm times it increases them [42]. We can implement a simpler version: define a volatility threshold (e.g. if 1-month average VIX > some percentile, or ATR of index > some %). If above, either require higher tech scores to buy or halve all position sizes. When volatility normalizes, resume normal operation. This systematically addresses the intuition that one should "play defense" in turbulent periods. The academic backing is robust: volatility-timed momentum had Sharpe ratios nearly double those of static momentum [49].

- **Bull vs Bear Thresholds:** As discussed in section 3, we might make **thresholds dynamic**: e.g., in a confirmed bull market, one might expand the hold zone a bit (let winners run longer, maybe don't sell until score < thirty-something), whereas in a bear, one might contract it (sell sooner). The presence of the market filter might make this redundant (since in a bear we might not be in many positions anyway). But it's another lever.

- **Small-Cap vs Large-Cap Criteria:** Given the evidence that momentum worked for large caps but not for small caps in Sweden (at least in the period studied) [54], we should adapt our strategy by size. Possibilities: **Focus only on mid-to-large cap stocks** for this strategy, or set stricter rules for small caps. For instance, require small caps to have even stronger technicals and fundamentals before buying, or perhaps skip the smallest tier entirely. The rationale is that small companies often have high idiosyncratic volatility and liquidity issues that can make technical signals less reliable (and fundamental data less predictive). An academic perspective: smaller firms do show momentum in many markets but also higher volatility; some studies (e.g. Israel & Moskowitz 2013) note momentum exists across size, but our localized evidence suggests Sweden might be an exception or had a tough period for small-cap momentum. As a compromise, we could **weight the overall score by market cap** in ranking (the strategy does produce an overall score for scanning [55]). Or simply, only apply the strategy to, say, OMXS30 constituents or highly liquid stocks for higher confidence. This reduces universe size but ensures the anomaly is more present. Since the question asks for tailoring to Swedish market, explicitly mentioning this finding and adjustment is important: *We recommend either excluding micro-caps or requiring additional confirmation for them.* For example, one might require a small-cap stock to have both a high tech score and an exceptionally low valuation (making it a deep value + momentum play) before trusting the signal.

- **Sector / Industry Rotation:** The strategy could benefit from awareness of sector trends. Momentum often has a sector component – winners can cluster in certain industries during different phases (e.g., commodity stocks might all be momentum leaders during an oil boom). **Improvement:** Integrate a **sector momentum overlay**. This could mean favoring buys in sectors that themselves have positive momentum. We can measure sector momentum by the average return of stocks in the sector or the sector index. A rule might be: if a stock has a buy signal but its sector has been

underperforming badly, perhaps temper the position or require extra caution (it might be a lone winner fighting against a negative industry trend). Conversely, if two stocks have similar scores, prefer the one in the stronger sector. Academic support: Moskowitz & Grinblatt (1999) found that industry momentum explains a good portion of individual stock momentum profits – they suggest an industry-relative momentum strategy can work (i.e., pick stocks that not only have momentum but are also in momentum-favored industries). A practical step: one could rank sectors by 6-month performance and tilt the strategy to stocks in the top half sectors. Another approach is ensure diversification: don't put all positions in one hot sector (to avoid sector concentration risk if that sector reverses sharply).

- **Regime Detection via Macro Indicators:** Beyond price and volatility, one could use macro signals (yield curve, economic indicators) to gauge regimes (e.g. recession vs expansion). Some advanced strategies allocate differently if a recession is predicted (momentum can falter in early recovery which often coincides with late recession environment). However, adding macro is probably beyond the scope of this stock-specific system, and academic consensus on using macro for timing is mixed (except maybe time-series momentum which inherently uses price). So we can skip heavy macro integration, focusing instead on price/vol regimes which are simpler and effective.

Implementing regime adaptation will likely improve the **consistency and drawdown profile** of the strategy. For instance, a regime-aware momentum strategy in international markets was shown to avoid momentum crashes and improve returns by switching off momentum after bear markets [56]. Another benefit is psychological and practical: a user following this strategy will appreciate that it stands aside during clearly adverse environments (e.g., 2020 Covid crash or 2008 crisis) rather than plowing in and suffering large losses. This fosters discipline and confidence in the system.

In the Swedish context, using the OMXS30 as a barometer is logical (it's the large-cap index). The strategy can be tuned to that – e.g., if OMXS30 is in a death cross (50-day MA below 200-day MA, a classic bear signal), maybe refrain from new buys or even exit existing ones more aggressively. The results from Faber (2007) are illustrative: over 100+ years, a simple 10-month MA strategy on the Stockholm market (similar to S&P) would have sidestepped major crashes. We essentially apply that thinking here.

Other Considerations: Finally, some practical enhancements not in the five key areas but worth noting:

- **Transaction Costs & Liquidity:** Momentum strategies can suffer if costs are high. On Swedish stocks, one should ensure to trade liquid names or factor in realistic bid-ask spreads. The strategy might benefit from a slight bias towards higher market-cap or more liquid stocks to reduce slippage. This is partly covered by the small vs large discussion.

- **Frequency of Rebalancing:** The strategy seems to run on daily or weekly data. It's important not to over-trade on every minor score change. Possibly constrain trading to, say, weekly intervals (evaluate signals once a week) to avoid noise. Many academic studies on momentum rebalance monthly. A weekly check should be fine but even then avoid rapid flip-flops (as mentioned, maybe require confirmations).

- **Portfolio Construction:** When multiple stocks have buy signals, how to allocate among them? The current design has an "Overall Score" ranking system to rank stocks [55]. That is good – one can pick the top N scoring stocks to hold at any time. This essentially creates a momentum portfolio. In

academic terms, that's akin to buying the top decile momentum stocks. We should ensure an appropriate **number of holdings** for diversification (maybe 10-20 stocks if possible). Holding too few increases idiosyncratic risk, too many dilutes returns. Research (e.g. Jegadeesh & Titman 1993) often showed a decile of stocks is enough for the momentum effect. For Sweden, maybe fewer because the market is smaller – but one can also include Nordic or European stocks for broader base, if allowed. However, since focus is Swedish, we stick to that.

Each of these regime and portfolio considerations fine-tune the core strategy to make it more robust. Table 1 (Market Regime row) summarizes the major adaptive measures: market trend filter, volatility-based scaling, small-cap adjustments, and sector considerations.

With all the above improvements, the Value & Momentum strategy would be more aligned with **academic best practices** and tailored to the nuances of the Swedish market. We have reinforced the technical signals with proven momentum indicators, tightened the fundamental screen per value investing insights, set up sound risk controls (stops and sizing) as supported by research, and added adaptive rules to navigate bull/bear cycles and other regimes. The result should be a strategy that captures the well-documented **value and momentum premia** [21] while avoiding many pitfalls that can erode real-world performance.

Table 1. Summary of Current vs. Improved Strategy Components

Aspect	Current Implementation	Improved Approach (Recommendations)
Technical Indicators & Weights	**6 signals (0–100 score):** Price > MA40 (25% weight); Price > MA4 (15%); RSI > 50 (15%); "Higher Lows" pattern (15%); Within 2% of 52-week High (20%); Volatility Breakout (10%). **All-or-none scoring** (factor either contributes full weight or 0) [6] .	**Refine & Rebalance signals:** Increase emphasis on **long-term trend** (e.g. MA40 weight to ~30%) since staying above the 40-week MA is crucial [8] . Keep significant weight on **52-week high** (20% or 20%+) given its strong momentum indication [13] . Strengthen **breakout** signal: use ATR or channel breakout and require volume confirmation (high volume on breakout) [19] – potentially raise weight to ~15% if confirmed. RSI and short MA can be de-emphasized slightly (e.g. 10% each) or require stronger thresholds (RSI > 60) to reduce noise. Consider adding an explicit **6–12 month price momentum** metric to the score (academic standard for momentum [9]). Optimize weights via historical analysis or use simpler equal-ish weights to avoid overfitting [21] . Ensure missing data handling remains (no score penalty for unavailable factors).

Aspect	Current Implementation	Improved Approach (Recommendations)
Fundamental Filters	**Value/Quality check:** Require Profit Margin > 0 (company is profitable) AND P/E ≤ 30 (or P/E not available) [2]. No other fundamental is mandatory (debt, growth, etc. are only for display). All passing stocks considered equal fundamentally.	**Stricter value & quality criteria:** Lower the **valuation cutoff** (e.g. P/E ≤ 20–25) to focus on genuine value stocks, or use sector-relative P/E (below industry median) [27]. If earnings are negative (no P/E), require an alternative value metric (e.g. Price/Sales or Price/Book below a threshold) rather than giving a free pass. Increase **profitability requirements**: e.g. require positive ROE or positive operating cash flow in addition to net profit, and consider requiring **growth** metrics (e.g. non-negative revenue or earnings growth YoY) to filter out stagnating firms [28]. Add a **debt constraint** (e.g. Debt/Equity ≤ 100% or interest coverage > 2) to avoid highly leveraged value traps. Optionally, use a composite fundamental score (already computed: profit, P/E, growth) and set a minimum (e.g. ≥ 50/100) to pass, rather than simple binary checks [57]. These changes align with value investing research (low multiples outperform [27]; financially sound firms within value do better [34]). Overall, favor **"quality value"** – reasonably priced, profitable companies – to combine with momentum [5].
Signal Thresholds	**BUY if Tech Score ≥ 70** (with fundamental pass) – indicates strong momentum (approximately top 30% of score) [3]. **SELL if Tech Score < 40** (bottom 40% of score) OR if price falls below MA40 (trend hard stop) [3] [37]. HOLD in between (score 40–69). No differentiation beyond these two tiers (no graded position sizing by score). Thresholds are static over time.	**Optimized & tiered thresholds:** Maintain a **higher bar for entries** and a somewhat lower bar for exits (to ride winners, cut losers), but consider fine-tuning the exact levels via backtesting for maximal Sharpe or CAGR [38]. Introduce a **"Strong Buy" tier** for extremely high scores (e.g. Tech Score ≥ 85) – these could warrant larger positions or simply extra confidence (historically, highest-momentum decile yields the best returns) [39]. Similarly, extremely low scores (< 20) could be treated as "Strong Sell" or short candidates, though this strategy doesn't short. *If* market conditions allow, thresholds can be **dynamic**: e.g. in a raging bull market, one might use 75 as the buy cutoff to be more selective (since many stocks will have high scores); in a weak market, one might lower to 65 to find any opportunities – or cease new buys altogether as discussed in regime adaptation. The sell threshold (40) could be raised to ~50 in very bearish overall conditions to exit sooner, or kept at 40 in neutral conditions to avoid whipsaw. In all cases, **confirm signals** to reduce noise: e.g. require a day or week closing beyond threshold before acting (to avoid one-day spikes). In summary, continue using discrete signal rules but **validate the 70/40 levels** with historical data and allow *flexibility* or extra tiers for more refined decision-making.

Aspect	Current Implementation	Improved Approach (Recommendations)
Risk Management	**Stop-Loss:** Only implicit via the SELL rules (especially MA40 breach). No explicit percentage stop or trailing stop defined. **Position Sizing:** None specified – effectively equal positions or ad-hoc. No guidelines on risk per trade or total exposure. **Risk Controls:** No explicit max drawdown limit, volatility targeting, or sector exposure limit. Strategy is fully invested as long as signals allow.	**Robust risk controls:** Implement **explicit stop-losses** for each position to supplement technical exits. For example, set an initial stop ~**10–15%** below entry (or below recent swing low) and trail it upward as price rises (e.g. max drop from peak 15%) – this limits downside on each trade [46]. Use **Average True Range (ATR)** based stops (e.g. 3×ATR(20) trailing) to adjust for volatility; this is supported by trend-following practice and helps avoid random noise outs. Incorporate a **position sizing model**: risk only a small fixed percent of capital per trade (e.g. 1% of portfolio). Calculate position size = (1% of portfolio) / (distance to stop). This way a more volatile stock (wider stop) gets a smaller allocation, and vice versa, achieving equal risk per position. This aligns with the Kelly criterion principles and significantly improves risk-adjusted returns by avoiding over-concentration. Additionally, set a **portfolio-wide stop or de-risk trigger**: e.g. if portfolio drawdown exceeds 10–15%, reduce all positions by X% or stop taking new trades until recovery – prevents runaway losses. Employ **volatility targeting**: dynamically scale exposure down when market volatility is high (and up when low) [42]. For instance, if the Swedish VIX spikes, cut position sizes in half. This volatility management has been shown to substantially increase Sharpe ratios for momentum strategies [42]. Lastly, enforce basic **diversification rules**: limit any single position to e.g. 10% of portfolio (even if signals/risk would suggest more) and ensure no sector is over (say) 30% of the portfolio to avoid sector-specific collapses. These risk measures, taken together, aim to protect capital during adverse moves while letting winners run, in line with both academic findings (e.g. stop-loss improves returns [46]) and industry best practices.

Aspect	Current Implementation	Improved Approach (Recommendations)
Market Regime Adaptation	**None:** Strategy is static across market conditions. No distinction for bull vs bear market – signals and thresholds are the same. No volatility-based adjustments or macro overlays. Treats all stocks similarly regardless of sector or market cap.	**Regime-sensitive strategy:** Incorporate a **market trend filter** to avoid long exposure in bear markets. For example, require the OMX Stockholm index to be in an uptrend (above its 200-day MA or positive over last 6–12 months) for new BUY signals. If the index is bearish, either pause new buys or tighten criteria (only exceptionally strong stocks bought) – this prevents momentum crashes by largely staying in cash during broad downturns [41]. Apply **volatility regime adjustments**: during high volatility periods (e.g. crisis spikes in VIX), raise the buy threshold or reduce position sizes (as noted in risk management) – effectively go into "defensive mode," since momentum is less reliable then [42]. Adapt to **size and sector:** Emphasize momentum in mid/large-caps over small-caps, given research showing momentum is weaker or even contrarian in small Swedish stocks [54]. One could exclude the bottom market-cap quartile or require small-caps to have extra confirmations (fundamental strength, etc.) before buying. Similarly, integrate **sector momentum**: prefer trades in sectors that have strong momentum themselves, and be cautious on signals from a broadly underperforming sector (or require a higher score to buy those). This could be done by tracking sector indices' performance over 6–12 months and using it as a bias in stock selection. Ensure some **sector diversification** to avoid one-sector risk. Additionally, consider a **rotation to defensive assets** (not just cash) in bad regimes if allowed – e.g. rotate to bonds or gold when equity momentum is negative (beyond the scope of stock-only strategy, but conceptually dual momentum). By adding these regime filters, the strategy is more aligned with "trend allocation" approaches that have proven to reduce drawdowns and enhance returns across cycles. In summary, be fully engaged in bull markets (with the improved stock-picking rules), but in bear markets, play defense: either sit out or very selectively engage. And account for structural differences (size, sector) in how momentum is applied, tailoring the strategy to the nuances of the Swedish market (where a few large firms dominate the index and behave differently than the many small firms).

Sources: Key improvements are supported by academic research and historical studies: e.g. Brock *et al.* (1992) on moving averages [8], George & Hwang (2004) on 52-week highs [13], Basu (1977) on low P/E outperformance [27], Novy-Marx (2013) on profitability premium [33], Kaminski & Lo (2007) on stop-loss efficacy [46], Moreira & Muir (2017) on volatility scaling [42], Cooper *et al.* (2004) on momentum in up vs.

down markets [41], and recent evidence from Sweden on size effects in momentum [51]. These changes aim to make the strategy more **evidence-based, robust, and suited to the Swedish market's characteristics** while preserving the core idea of a value-enhanced momentum strategy [21].

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