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TRADING & QUANTITATIVE RESEARCH REPORT

Momentum — Turnover

Research report examining momentum strategies based on share turnover

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LYNX

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Introduction and Theory

Introduction

The short-term reversal effect is a well-established stock market anomaly, which states that stocks with high returns in the previous month tend to underperform in the following month – and vice versa (Zaremba, Long & Karathanasopoulos, 2019). However, as described in Zaremba et al. (2019), everything that goes up must not necessarily come down – and nor does everything that goes down have to automatically find its way up again. Recent evidence shows a prevalence of the short-run momentum effect in trading data and findings indicate that this pattern is persistent across both space and time. Results from Medhat and Schmeling (2021)'s study on short-term momentum extend to 23 developed stock markets in North America, Europe and the Asia Pacific. Zaremba et al. (2019) further show that this pattern of the previous month's return positively predicting future performance holds across a variety of major asset classes, including equity indices, commodities, government bonds, treasury bills and currencies, applies to developed as well as emerging markets and – where figures are available – can be observed in over two centuries' worth of data. A question that remains unanswered is whether short-term momentum and conventional momentum are related phenomena with markedly distinct characteristics or if they are in fact the same phenomenon, one that has the tendency to appear to manifest in divergent ways (Medhat & Schmeling, 2021). In either scenario, the seemingly widespread nature of the short-run momentum effect makes this an exciting development to follow. It could be that several lessons can be drawn from here for the purposes of constructing new trading strategies.

One of the more notable aspects concerns the positive relationship between share turnover and momentum, wherein share turnover is defined as the total volume of trades divided by the number of shares outstanding (Medhat & Schmeling, 2021). Medhat and Schmeling (2021) show that by excluding the lowest turnover stocks, returns are more likely to exhibit short-term momentum than short-term reversal. The authors moreover depict a picture of short-term momentum and short-term reversal co-existing among the highest turnover stocks in a way that returns are not negatively impacted. This implies that exploring volume-return relations can be of particular relevance.

In collaboration with LYNX Asset Management, this project sets out to evaluate selected momentum-based equity trading strategies. For that purpose, the phenomenon of short-term momentum along with the relationship between short-term momentum and share turnover are explored. An additional objective of the project is to gauge the viability of constructing groups out of certain universes on the basis of data clustering. We construct three groups from the S&P 500 universe based on share turnover by employing Jenks' natural breaks classification as the clustering method and look at how returns from selected momentum trading strategies will differ for the high, medium and low turnover groups. We employ two trading strategies: one built around the close price of the day and the 25-day exponential moving average (EMA25) and another that focuses on the close price and the 200-day simple moving average (MA200). The latter strategy incorporates conventional momentum to provide a comparison to short-term momentum.

Theory

In momentum-based trading strategies, investors take positions in the direction of strong trends: buy high and sell higher – or sell low and sell lower (Lim, Zohren & Roberts, 2019). As seen in Lim et al. (2019), one way to go about this is to compare stocks in a universe and buy the top performers and short the bottom performers. For turnover-based strategies, as in Medhat and Schmeling (2021), high turnover stocks are bought and low turnover stocks shorted or excluded. Constructing groups using Jenks' natural breaks could provide an interesting perspective here for determining which stocks to buy.

Risk adjustments, such as volatility scaling, to momentum-based trading strategies may additionally be vital, as market panic can result in significant crashes (Lim et al. 2019). For the purposes of examining volume-return relationships, it is thus reasonable to assume that high share turnover could also result – for example – from a panic sell-off. The goal then does not necessarily have to be a minimising of the relevant risk measures, e.g. volatility, but instead simply avoiding losses when trading (Dai, Marshall, Nguyen & VIsaltanachoti, 2020). This may prove particularly relevant for momentum strategies. A good risk management tool could then be a stop-loss rule, where a sale is triggered by the price going below – or above – a certain threshold. Using a trailing stop-loss rule, as opposed to a traditional stop-loss rule, is likely to prove beneficial, as this allows for the sale trigger price to move together with profits (Dai et al. 2020). A sound volatility indicator for constructing the trailing stop-loss could be the average true range (ATR), where true ranges for prices within a desired time-period are calculated through high-low-close relationships and the ATR is a moving average of the true ranges (Basdekidou & Styliadou, 2017).

Hypothesis and Methodology

Hypothesis

We expect that it will be possible to make use of data on share turnover in combination with momentum trading strategies to generate gains in the market and that our results will fall in line with the principal findings from Medhat and Schmeling (2021). Consequently, the expectation is that the high turnover group will outperform the medium turnover group while the low turnover group will have the lowest relative gains. This would imply that employing Jenks' natural breaks to construct groups out of broad market universes such as the S&P 500 is a viable method for trading. We presume that there would be implications not only for locating which stocks to purchase, and which stocks not to purchase, but that it may also indicate that employing different trading strategies to different groups could be advisable.

Relying also on the conventional momentum literature, e.g. Lee and Swaminathan (2000), we anticipate the expected relative profitability pattern of the groups to hold for both strategies. Although as short-run momentum may be an independent indicator of future returns from the conventional momentum effect (Medhat & Schmeling, 2021; Zaremba et al. 2019), profits from the strategies could differ notably. Here, our expectation is that short-term momentum will outperform conventional momentum. Divergences from this prediction for only a specific turnover group would prove to be of interest.

Methodology

We look at 20 years' worth of data for 505 single equities currently in the S&P 500 universe. The data is presented in daily intervals, the starting date for the dataset is January 1, 2000 and the end date December 31, 2020. The data has been sourced from Bloomberg.

We begin by constructing groups from the stocks in the S&P 500. Using the JenksPy Python package, the stocks are clustered into three groups in accordance with results from Jenks' natural breaks data classification for average monthly share turnover. Jenks' natural breaks is a powerful data clustering method that forms groups based on characteristics inherent to the data: the difference between groups is maximised and the difference within groups minimised, with the breakpoints being formed where there are relatively large gaps in the data (ESRI, n.d.).

The groups are constructed on the last trading day of the month and reconstructed monthly. Using Jenks' natural breaks, the number of stocks allocated to each group is determined by the values for share turnover. The sizes of the turnover groups are therefore in constant change. The medium turnover group may – for example – feature 232 stocks one month and 217 stocks the following month, with two stocks having moved to the high turnover group and 13 to the low turnover group.

We then set up the signals for our two momentum strategies, wherein we only assume long positions. For strategy one, we assume a long position when the close price of the day moves above the EMA25. For strategy two, a long position is taken on when the close price exceeds the MA200. As the exponential moving average gives more weight to recent price data, we presume it to be an appropriate indicator for short-term momentum and a relatively less appropriate indicator for conventional momentum, where we use the simple moving average.

Following Medhat and Schmeling (2021), we discard the last three days of the trading month to minimise influences from end-of-month liquidity trading on our strategies. Relying on the assumption that short-term momentum is driven by informed trading, the goal here is to exclude signals from non-informed trading (Medhat & Schmeling, 2021). As we mainly strive to eliminate the temporary price pressure from non-informed trading, which Medhat and Schmeling (2021) refer to, we only discard days for the trading phase where we directly interact with momentum. No days are discarded for the grouping, where non-informed trading could still be connected to certain factors that are potentially relevant to volume-return relationships, such as liquidity.

We use a simulated portfolio with an equal distribution of funds that starts from the value of 100 and allocate a maximum of 33% of portfolio value into one stock. We sell when the condition of the strategy is no longer being met.

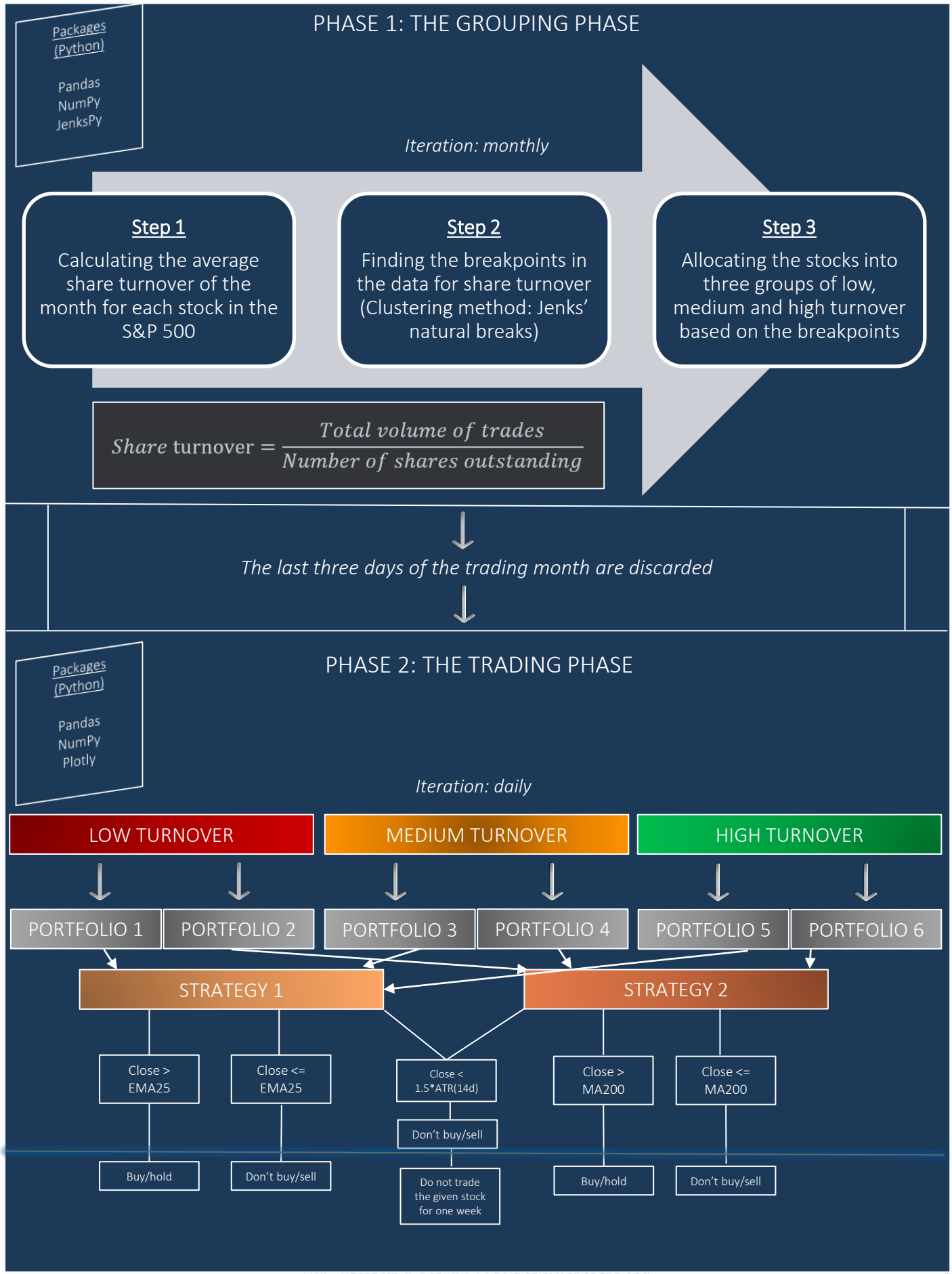
A trailing stop loss rule is further implemented as a risk adjustment measure. For this, we calculate the 14-day average true range (ATR) using the following formulas:

$$TR = \text{Max}[(H - L), \text{Abs}(H - C_P), \text{Abs}(L - C_P)]$$

$$ATR = \left(\frac{1}{n}\right) \sum_{(i=1)}^{(n)} TR_i$$

Here H is the high price of the day, L the low, C_p the close, n the number of days = 14 and Abs the absolute value. When the stock that we are long in moves below 1.5 times the ATR, a sell protocol is initiated. After the initiation, we do not trade the given stock for one week.

A Visual Representation of the Methodology



Results and Analysis

Table 1 displays the cumulative 20-year returns, annualised returns and annualised Sharpe ratios for the two strategies by turnover group. These are further compared to the "no strategy" buy-and-hold benchmarks. Likewise as for the strategies, the portfolios are rebalanced monthly for the benchmarks.

Table 1. S&P500, Returns and Sharpe ratios by turnover group

High turnover	Strategy 1	Strategy 2	No strategy
Return (20 years)	82.9%	140.89%	116.58%
Annualised return	3.06%	4.49%	3.94%
Annualised Sharpe	0.25	0.33	0.28
Medium turnover			
Return (20 years)	-2.43%	-4.64%	232.96%
Annualised return	-0.12%	-0.24%	6.2%
Annualised Sharpe	0.05	0.05	0.37
Low turnover			
Return (20 years)	6.59%	-5.1%	114.58%
Annualised return	0.32%	-0.26%	3.89%
Annualised Sharpe	0.08	0.02	0.31

The results confirm the primary expectation that the high turnover group will have the highest correlation between momentum and share turnover. The returns for the high turnover group are highly pronounced in comparison to the medium and low turnover groups.

Two findings run counter to our prior hypotheses. Turning attention to the herein substantial returns in the high turnover group, it can firstly be observed that our conventional momentum strategy has proven to be distinctly more profitable than our short-term momentum strategy. Moreover, comparisons with the buy-and-hold benchmark reveal that strategy two outperforms the market within the group. Considering the characteristics of the S&P 500, this can be considered notable. Secondly, the anticipated relative profitability pattern for the turnover groups has not fully manifested. Both strategies are unable to generate positive returns in the medium turnover group, performing extremely poorly in comparison to the benchmark. While the conventional momentum strategy also generates negative returns in the low turnover group, the short-term momentum strategy is interestingly able to produce limited positive returns.

As Figure 1 in Appendix I demonstrates, the limited positive returns are nonetheless only generated for a fraction of the 20-year time period that we observe. These returns are also marginal and likely squashed completely after factoring in trading costs, which we do not consider. As our conventional momentum strategy never generates positive returns in the low turnover group, this finding could still provide a vaguely interesting note for the discussion on whether short-term and conventional momentum are different phenomena.

Figure 2 in Appendix I helps illustrate the larger uniformity for medium turnover, where neither strategy generates a positive return for ~19.5 years in a row. The short-term strategy has a brief stint with positive returns around the year 2000, which is absent for conventional momentum. Yet, the general patterns of movement appear similar. The movements of strategy one and strategy two moreover seem strikingly alike in the low turnover group. All of this may however have limited relevance due to the absence of profitability within these groups. For the momentum strategies, investing solely in the high turnover group appears to be optimal here.

Time periods are likely important to examine for most of the results. Both the short-term and conventional momentum strategies only produce relevant gains after 2014, certainly curbing our Sharpe ratios. Figure 3 in Appendix I highlights the odd characteristics of the benchmark in the high turnover group. Profits are only generated during the recent bull market, in contrast with the low and medium turnover groups that almost constantly produce gains. Considering the latest bull runs of certain high-performing stocks in the high turnover group, e.g. Tesla, as a competing determinant of returns could herein be vital. Certain bull runs might serve as a confounder to both turnover and momentum. Bull runs could however also be a channel for volume-return relationships to manifest. Figure 4 in Appendix II shows the post-2018 concentration of relatively high share turnover around a limited number of stocks, which coincides with the relevant return increases.

The allocation of stocks into turnover groups can also be seen to be highly dynamic. It may be that Jenks' natural breaks can offer traders sound opportunities to keep up with changes taking place within a universe, providing a viable alternative to static stock grouping techniques. This dynamicity is however presumably also keeping the Sharpe ratios low. The implications for risk-return relationships require subsequent analysis.

Figure 5 and Figure 6 in Appendix II moreover illustrate that the signals for the two trading strategies seem to move rather alike, with the conventional momentum strategy expectedly producing fewer signals.

Concluding Remarks

This report has demonstrated that it is possible to generate gains in the market by constructing groups based on share turnover and then applying momentum strategies within the groups to determine which stocks to buy. Based on the parameters that we established in regard to the grouping method used, trading strategies employed and risk adjustment measures undertaken, we were able to generate presentable returns in the S&P 500 universe for one short-term momentum strategy and one conventional momentum strategy. In the conventional momentum case, the strategy outperformed the buy-and-hold benchmark. For the gains to be realised, it proved necessary to only trade the group of stocks with the highest share turnover. Although our approach was not always profitable in a 20-year perspective, it has constantly generated gains since 2014. While contextual, time period specific factors have to be accounted for, the current market circumstances appear favourable for the approach presented in the report.

The results of the report generally line up with the expectations in relevant literature with respect to the relationship between share turnover and momentum. Although our results can still speak to the strength of the short-term momentum effect, the conventional momentum effect results in superior outcomes. We have further shown that using Jenks' natural breaks as a method to cluster stocks into groups could be a viable way to determine which stocks would eventually be traded. A closer exploration of risk-return relationships might however be necessary, as large fluctuations in the number of stocks traded may not always be optimal. This could especially prove to be true for time periods where only a few stocks end up being traded in the high turnover group. A question to consider here might be how well a high degree of portfolio volatility can be counter-acted, e.g. by stop loss rules, and whether this can here serve as an effective alternative to the process of reducing portfolio volatility.

There are numerous other opportunities to expand on the results of the report. Employing additional trading strategies for both short-term and conventional momentum would provide further insight, particularly with the incorporation of short positions that would be taken on alongside long positions. Experimenting with parameters could be attempted with the goal of optimising the outcomes for risk and returns. Examples include adjusting the trailing stop loss rule, the number of turnover groups that are formed and traded or the length of the period after which the groups are reconstructed. Increasing the frequency of our trades might moreover prove beneficial, particularly for our short-term momentum strategy. Additional metrics, e.g. the win rate, could be included for an improved understanding of performance. Jenks' natural breaks could be evaluated against other methods used to group stocks based on share turnover in order to measure the effectiveness of natural breaks in a comparative perspective. One such option would be a comparison with choosing a fixed number of the highest – or lowest, if shorting – turnover stocks. Additional universes, such as the FTSE 100 and the Nikkei 225 could further be explored.

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Appendix I

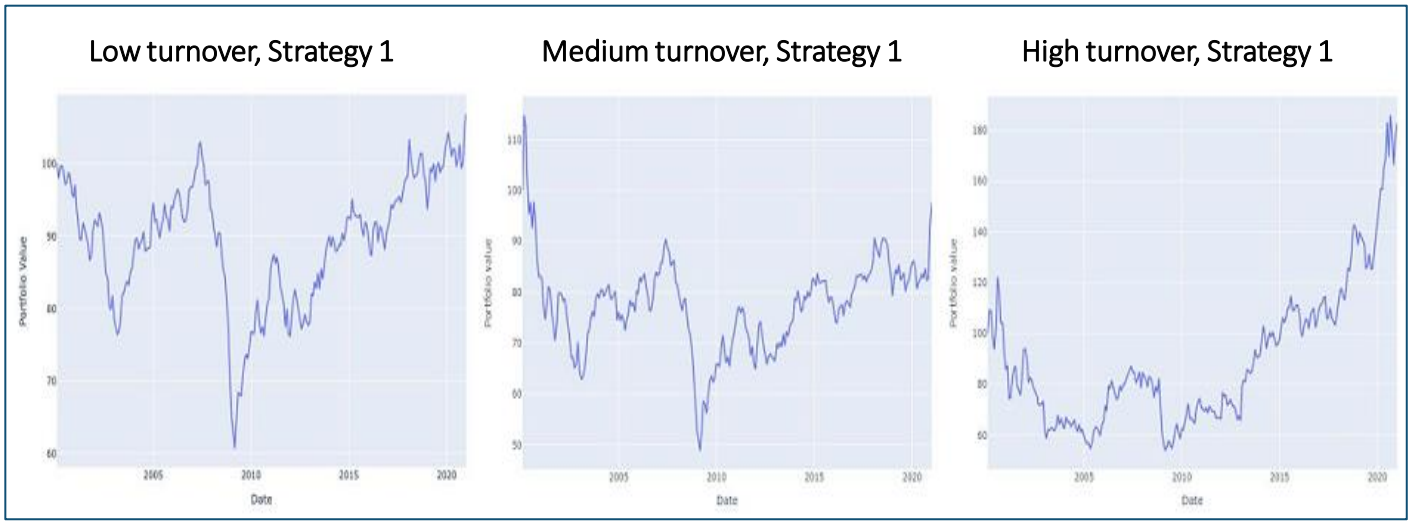

Figure 1. S&P 500, Portfolio value for strategy 1 (Close>EMA25), 2000-2020

Figure 2. S&P 500, Portfolio value for strategy 2 (Close>MA200), 2000-2020

Figure 3. S&P 500, Portfolio value for the buy-and-hold benchmark, 2000-2020

Appendix II

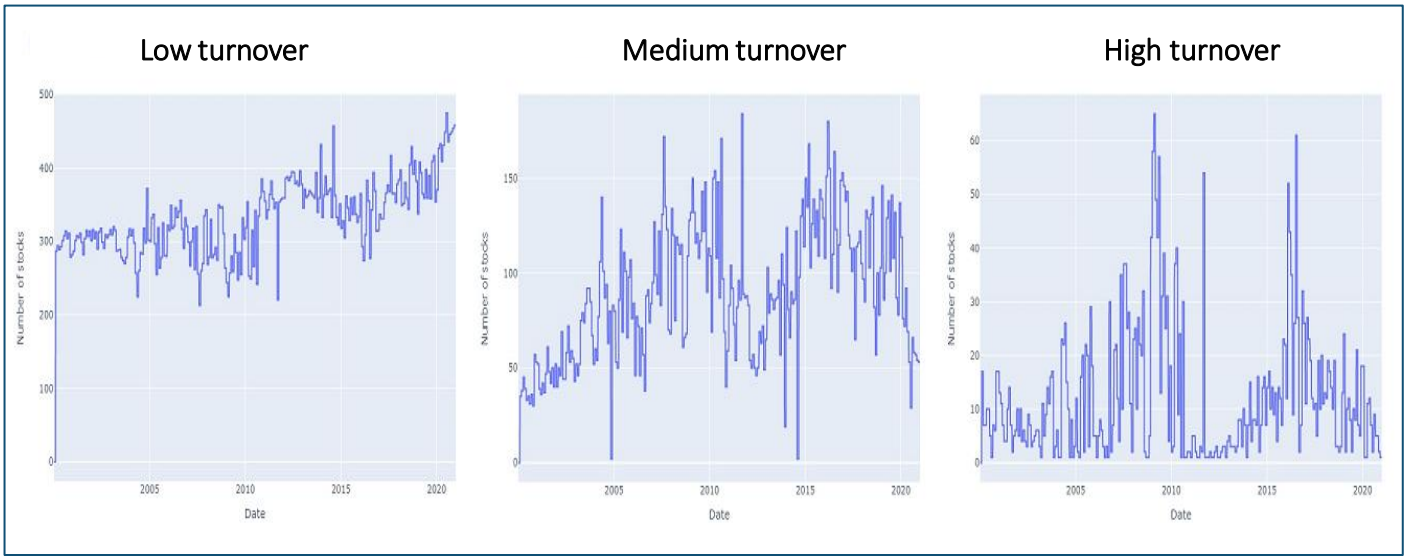

Figure 4. S&P 500, Stocks by turnover group, 2000-2020

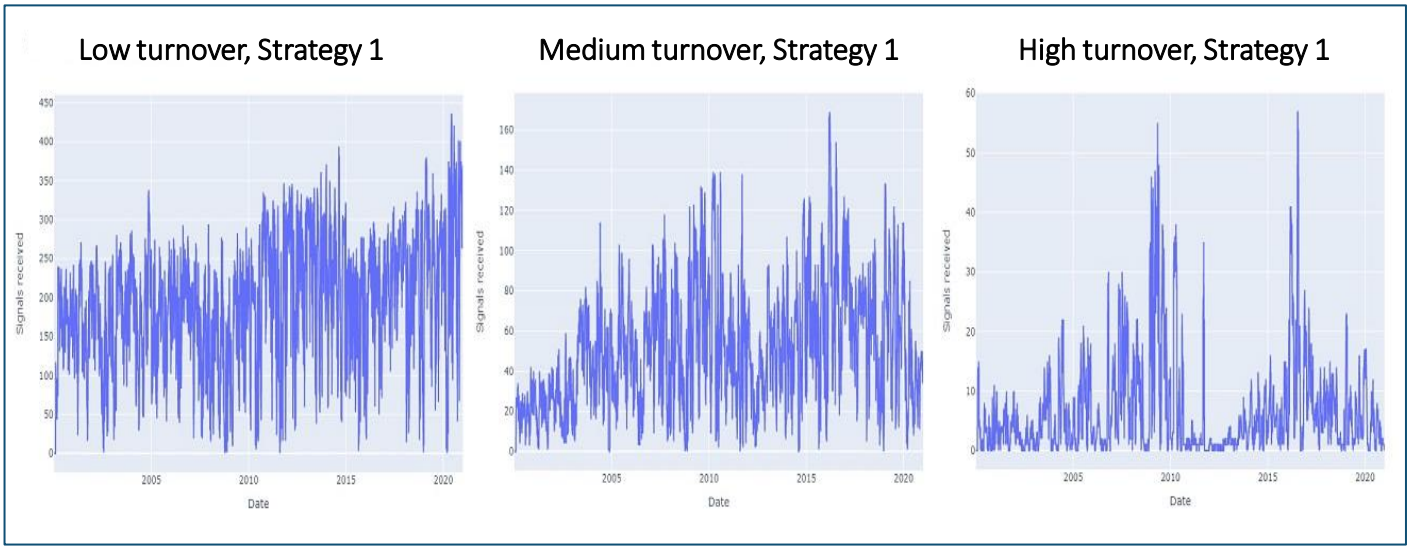

Figure 5. S&P 500, Signals received from strategy 1 (Close>EMA25), 2000-2020

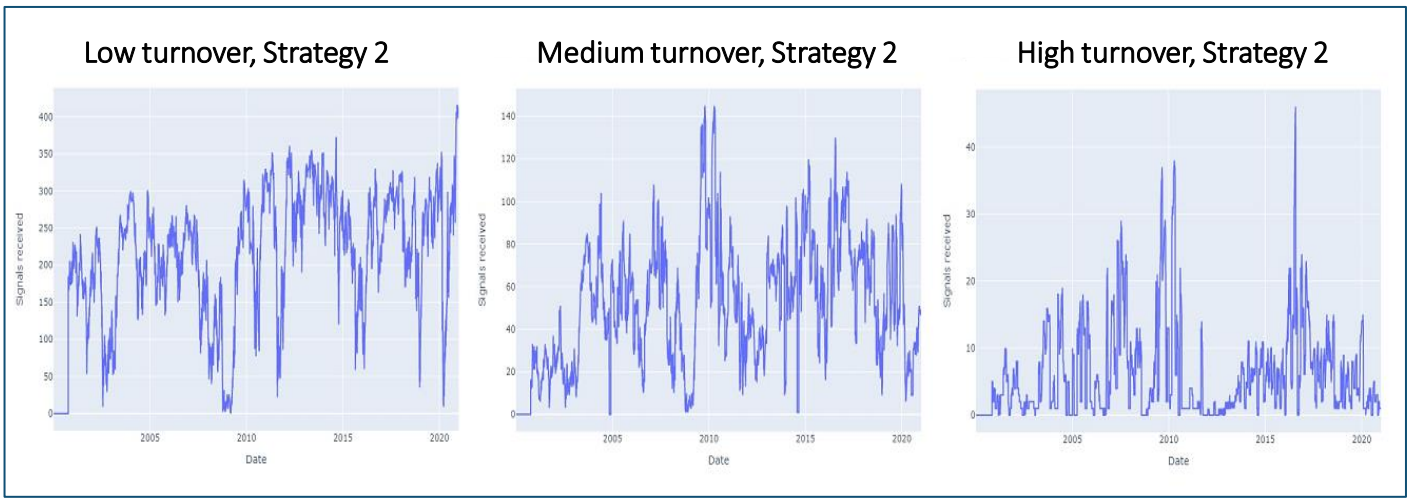

Figure 6. S&P 500, Signals received from strategy 2 (Close>MA200), 2000-2020

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