Bachelor Thesis
Statistical Learning for Trend-Following and Momentum Strategies

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Executive Summary

A characteristic feature of momentum strategies is the look-back period, namely the observation period used. However, there is no rule of thumb that a particular look-back period must always be used as being more efficient in every case, but rather it is more appropriate to select one depending on the situation. The work of Levy and Lopes (2021) is based on precisely this, namely the dynamic selection of the look-back period using a statistical model. The aim of this thesis is the same, but using different statistical methods to select the most appropriate look-back periods and construct portfolios of stocks based on signals from momentum strategies (and/or reversal, depending on the method) with the most efficient look-back periods. This process can be defined as dynamic as it is done at each period and for each asset by using a rolling window analysis. The size of the rolling window may change depending on the model used. Therefore, a look-back period is not chosen a priori, but the statistically most efficient look-back period is chosen according to the asset and the period. Furthermore, it is important to distinguish two types of approaches used to invest with momentum strategies. The first is called time-series, and is an approach in which every available security has a long/short signal (and therefore one invests in all available securities). This method is the one most in vogue in recent years and is the same one used by Levy and Lopes. The second is called cross-sectional, and one selects only a percentage of securities in which to invest, so as to have equal long and short positions. Typically, one selects a certain percentage of securities with higher momentum values in which to go long, the so-called winners, and an equal percentage of securities with lower momentum values in which to go short, the so-called losers. In this thesis, both methodologies will be explored.

For this purpose, data on stocks in the S&P500 are analysed for the last 20 years, where the last 15 make up the performance period for all strategies. To measure performance, the most important measure is the Sharpe ratio, as it incorporates both the return and the risk of a portfolio. In addition to this, the maximum drawdown is measured and a graphical analysis of the development of the portfolios of the various strategies is made, in order to get a clearer idea of how the above-mentioned data were generated (and how important they are). For the cross-sectional approach, the choice is to invest on 10% of the available stocks (5% long positions and 5% short positions), although depending on the method this value could be slightly lower for convenience.

The first method used for this purpose is an algorithm called simple algorithm, as it is not based on a more complex statistical method. The purpose of the algorithm is to assign, at each period and for each asset, a score to each available momentum strategy (i.e., among the various momentum strategies that differ by look-back period). The strategy with the highest score will dictate which momentum strategy to use (i.e., which look-back period to select) for the long/short signal for that particular security in that particular period. That score is called WTS (Weighted Total Score), and it is a kind of weighted average of individual scores called SS (singe scores). In a nutshell, the WTS is composed of the SS of the previous 48 periods, where the SS can have a value

of 1 if that particular momentum strategy has predicted the trend of returns (if momentum strategy and returns have the same sign for the same period), otherwise a 0. After that, these values are weighted in a way that gives more importance to the most recent values. The consequence of this is the WTS. In the time-series approach, one simply selects the momentum strategy with the highest WTS for each asset and for each period. In the cross-sectional strategy, on the other hand, one has to select those with higher WTS for cases where the signals are long (selecting the winners) and those with higher WTS for cases where the signals are short (selecting the losers).

The second method is based on an ARIMA(p,d,q) model. The autoregression is done on returns, and 12 months are set as the limit observation period. Dynamic selection is then done by the R auto.arima() function, which using a rolling window of 60 periods, selects the most efficient parameters. The p and q values are selected by AICc, and the d value by KPSS. Using the parameters of this model, the returns for the next period are estimated, going long in cases where such predicted returns are positive and short if negative. Since many values of the predicted returns are equal to 0, in order to avoid going long on them as well or not investing in them, the choice is to select the momentum strategy signal with look-back period 12 months for such cases. This choice is dictated by the fact that this look-back period is often used as a benchmark in the literature. For the time-series approach, one simply has to follow the signals mentioned above. For the cross-sectional approach, winners are selected from stocks with the highest predicted returns and losers from stocks with the lowest predicted returns.

The last method is based on a logistic regression, which has a given momentum strategy as the explanatory variable and a binary version of returns (1 if greater than or equal to 0 and 0 otherwise) as the response variable. The rolling window size is 48 periods. The resulting logit model outputs the probability that the returns for the next period are positive (correlated with a long position). Thus, a value close to 1 means a higher probability of a long signal and a value close to 0 a higher probability of a short signal. It follows that for the time-series case, for each period and for each asset, the signal that is furthest away from the value of 0.5 is selected, going long if it is greater or equal than 0.5 and going short otherwise. For the cross-sectional approach, losers are selected from among the most important short signals (which deviate most from the value of 0.5 on the downside) and winners from among the most important long signals (vice versa).

The results confirm that dynamic selection using statistical methods brings benefits in terms of performance. For both cross-sectional and time-series cases, the best performance is given by statistical methods. In general, the CS-ARIMA model stands out, being the one with the highest Sharpe ratio of all (0.49). In terms of maximum drawdown, the most efficient strategy is the TS-ARIMA (24.80%). In terms of volatility, CS-Logit stands out above all others (8.03%). It follows that the paper stresses the importance of dynamic (statistically based) selection of the look-back period, which cannot be sidelined.

References

[1] Levy, B. P. C., & Lopes, H. F. (2021). Trend-Following Strategies via Dynamic Momentum Learning. *arXiv preprint arXiv:2106.08420*. doi:10.48550/ARXIV.2106.08420.