Literature review: trading strategies

Harold Heymans

February, 2022

1 Scope of the study

This literature study had as goal to identify a number of trading strategies that can be used in the broader context of developing orthogonal portfolios using canonical correlation analysis and its extensions. The literature on trading strategies is extensive, however, a number of self-imposed constraints reduce the literature that can be considered. The first constraint relates to the input data. In the case the goal is to define a broad framework and therefore only time series of price/returns data can be considered as predictors. A second major goal is to construct a number of different signal types that perform differently in a variety of market scenarios. Given that a single asset is considered, i.e. stocks, strategies that are used for futures, fixed income or currencies (eg. carry) are not discussed.

After Fama and French (1996), a big part of the trading literature focuses on extending or using a number of factors as predictor variables or enhancing models using alternative data sources. Such literature does not fall into the scope of this review. Examples include Rapach and Zhou (2013), Freyberger et al. (2020) and Kozak et al. (2020). Furthermore, a large portion of literature on trading strategies focuses on explaining the reasons behind the performance of certain strategies, eg. Jacobs (2015). Such literature does not fall into the scope of this review either. In sum, papers under consideration solely discuss the profitability of certain strategies applied to the time series of stocks.

This document is organised as follows: section 2 briefly discusses the available literature, section 3 provides an overview of the proposed signals and finally, section 4 proposes further additions that could be considered if time permits.

2 Literature

The strategies in the papers that are explored can be categorized in several (overlapping) areas. These include momentum versus mean-reversion, single versus multi-asset and linear versus non-linear (complex). For momentum strategies, the initial work of Jegadeesh and Titman (1993) provides the initial momentum strategy: 3-to 12 month performers (losers) continue to perform (lose) over the next 3- to 12 months. As mentioned in the scope, we only look at time series momentum (omitting cross-sectional momentum) because we only work with price time series. Chan (2013) also provides a practical implementation of a momentum strategy based on Moskowitz et al. (2012). These simple models have proven robust throughout the years, though performance falters during market crashes and some papers suggest returns from these strategies are increasingly being out-arbitraged. As a result, researchers have extended the simple model by using more advanced techniques, such as deep learning in Takeuchi and Lee (2013). For a further completer review on the literature up to now that is relevant to the scope of this study we refer to section 4.1 in Singh and Walia (2020).

Arguably, in order to develop a profitable stock trading strategy, the asset has to be either trending (momentum) or mean-reverting, which brings us to the second family of trading strategies, i.e. mean-reverting ones. Literature on mean-reversion dates back to the 1980s with popular papers such as Poterba and Summers (1988) and Balvers et al. (2000) providing evidence of excess returns. After the earliest papers, mean reversion is mostly investigated in the context of multiple assets. Gatev et al. (2006) is the simplest implementation and forms the foundation of pairs trading. Over the years, more complicated implementations, such as in d'Aspremont (2011) which uses canonical correlation analysis. Overall, Krauss (2017) provides an excellent overview on the different approaches to pairs trading. From two asset implementations based on distance metrics, cointegration, time series and stochastic control to (quasi-)multivariate implementations in which portfolios and traded against each other.

More recently a popular strand of literature dives deeper into the use of advanced machine learning techniques to develop profitable trading strategies. Notable examples include Kelly et al. (2021), Fischer and Krauss (2018) and Huck (2010). Authors report significant improvements in Sharpe ratios in comparison to simpler strategies.

The above literature study on viable trading strategies is by no means exhaustive. Should time permit, a deeper look into the use of machine learning, and especially market friction could be included.

This brief overview leads us to list a number of proposed strategies, which are outlined in the next section.

3 Proposed Signals

Above literature study leads us to propose a number of strategies that could be implemented within the context of the broader thesis. Strategies, particularly linear single asset are rather simple.

3.1 Single asset strategies

3.1.1 Momentum strategies

- Momentum from literature, i.e. Moskowitz et al. (2012): go long (short) for 1 month/day if past 12-month returns are positive (negative).
- Momentum technical indicators: MACD strategy: buying when fast exponential moving average rises above slow exponential moving average.
- Based on p.135 in Chan (2013): checking auto-correlations with lags (using partial auto-correlations) and trading the most significant relationships.

3.1.2 Mean reversion strategies

- Technical mean reversion: individual mean reversion using bollinger bands (Z-scores are determined based a cross-validation procedure). Similar to Gatev et al. (2006) but with a single asset.
- Khandani and Lo (2011): buy yesterday's lowest N% losers and sell yesterday's highest N% winners (based on over-under reaction of markets).

3.2 Multiple asset strategies

Most of the literature on trading "multivariate" portfolios of assets could be categorized as pairs trading strategies and therefore the momentum section contains a single proposition.

3.2.1 Momentum strategies

- Literature has suggested to apply Moskowitz et al. (2012) but only on the top % winners and % losers in a broad portfolio.

3.2.2 Pairs trading strategies

- Distance-based trading: Gatev et al. (2006) implementation, i.e. use euclidean distance over a 1 year period to identify the closest pair for each asset. Choose the top X% pairs and trade them during the next 6 months based on the divergence in standard deviation from their normalized price series. An extension based on maximizing both spread variance and mean reversion can be included to optimise returns Do et al. (2006).
- Quasi-multivariate implementation: Chen et al. (2019) propose to define a divergence metric for each asset with the following formula $\beta(r_{i,t} - r_f) - (r_{j,t} - r_f)$ where β is the regression coefficient of r_i on r_j, r_i is the i^{th} asset return and r_j is the weighted average of the 50 assets it correlates highest with. The top 10% are long and bottom 1% are shorted. There is a one-month look-back and one-month holding period.
- For the univariate cointegration approach we base ourselves on Huck and Afawubo (2015). In short, the method uses the Johansen cointegration test and trades the pairs with the highest statistic over a period of time.

3.3 Complex strategies

Complex strategies aim to capture highly non-linear relationships in single asset and multi-asset settings. These strategies are more complicated to implement and as of the moment of writing this, less research has been conducted in this area. However, certain strategies could be worth including:

- The highly cited LSTM implementation in Fischer and Krauss (2018) is a form of contrarian strategy whereby the most extreme winners (losers) are sold (bought) on a daily basis.
- In Takeuchi and Lee (2013) they apply deep learning techniques to identify non-linear patterns, which results in a strategy that closely resembles momentum.
- Huck (2010) uses Multi-Criteria Decision Making Methods (MCDM) to rank a number of pairs. It should be noted the method does not specify a prediction model, which is a necessary input to the method.

Alternatively, I could solely work on replicating Krauss et al. (2017) in which deep neural networks, gradient boosting and random forests are benchmarked.

4 Conclusion and further extensions

This short literature study is heavily dependent on the determined scope in section 1 and is not exhaustive. However, its goal is to narrow down the relevant literature for section 2 and provide a solid grounding to justify the proposed strategies in section 3.

In terms of extensions (if time permits), in decreasing order of importance, it is suggested to look at the following: inclusion of market frictions (transaction costs, borrowing costs, liquidity), return construction methodologies (eg. fractional differentiation), further complex strategies based on the latest research such as in Kelly et al. (2021) and finally the optimisation of different trading objectives.

References

Balvers, R., Wu, Y., and Gilliland, E. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. *The Journal of Finance*, 55(2):745–772.

Chan, E. (2013). *Algorithmic trading: winning strategies and their rationale*, volume 625. John Wiley & Sons.

Chen, H., Chen, S., Chen, Z., and Li, F. (2019). Empirical investigation of an equity pairs trading strategy. *Management Science*, 65(1):370–389.

d'Aspremont, A. (2011). Identifying small mean-reverting portfolios. *Quantitative Finance*, 11(3):351–364.

Do, B., Faff, R., and Hamza, K. (2006). A new approach to modeling and estimation for pairs trading. In *Proceedings of 2006 financial management association European conference*, volume 1, pages 87–99.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance*, 51(1):55–84.

Fischer, T. and Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, 270(2):654–669.

Freyberger, J., Neuhierl, A., and Weber, M. (2020). Dissecting characteristics nonparametrically. *The Review of Financial Studies*, 33(5):2326–2377.

Gatev, E., Goetzmann, W. N., and Rouwenhorst, K. G. (2006). Pairs trading: Performance of a relative-value arbitrage rule. *The Review of Financial Studies*, 19(3):797–827.

Huck, N. (2010). Pairs trading and outranking: The multi-step-ahead forecasting case. *European Journal of Operational Research*, 207(3):1702–1716.

Huck, N. and Afawubo, K. (2015). Pairs trading and selection methods: is cointegration superior? *Applied Economics*, 47(6):599–613.

Jacobs, H. (2015). What explains the dynamics of 100 anomalies? *Journal of Banking & Finance*, 57:65–85.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1):65–91.

Kelly, B. T., Malamud, S., et al. (2021). The virtue of complexity in machine learning portfolios. *Swiss Finance Institute Research Paper*, (21-90).

Khandani, A. E. and Lo, A. W. (2011). What happened to the quants in august 2007? evidence from factors and transactions data. *Journal of Financial Markets*, 14(1):1–46.

Kozak, S., Nagel, S., and Santosh, S. (2020). Shrinking the cross-section. *Journal of Financial Economics*, 135(2):271–292.

Krauss, C. (2017). Statistical arbitrage pairs trading strategies: Review and outlook. *Journal of Economic Surveys*, 31(2):513–545.

Krauss, C., Do, X. A., and Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the s&p 500. *European Journal of Operational Research*, 259(2):689–702.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of financial economics*, 104(2):228–250.

Poterba, J. M. and Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of financial economics*, 22(1):27–59.

Rapach, D. and Zhou, G. (2013). Forecasting stock returns. In *Handbook of economic forecasting*, volume 2, pages 328–383. Elsevier.

Singh, S. and Walia, N. (2020). Momentum investing: a systematic literature review and bibliometric analysis. *Management Review Quarterly*, pages 1–27.

Takeuchi, L. and Lee, Y.-Y. A. (2013). Applying deep learning to enhance momentum trading strategies in stocks. In *Technical Report*. Stanford University Stanford, CA, USA.