Cross-sectional predictability of stock returns in Nordic stock markets using machine learning methods

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October 30, 2023

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1 Introduction

Objective of this study is to apply set of machine learning methods to well established asset pricing factors to capture abnormal stock return patterns. This study will focus on four Nordic stock markets namely Denmark, Finland, Norway and Sweden. These four markets are relatively homogenous in many aspects. They are geographically close, politically stable and economically interconnected. Denmark, Finland and Sweden all belong to European union. Additionally, stock exchanges of all these three countries are operated by Nasdaq. Therefore, investors could view them as a single market. Some of the features that are characteristic for Nordic markets make them fertile ground for stock market anomaly studies. As mentioned Nordic countries are geographically closely located in northern Europe and therefore relatively distant from large European and especially American markets. So called periphery effect has been studied by the scholars a lot. It refers to investor behaviour where during times of a crisis investors tend to liquidate their investments first from the markets more distant to them. This increases the volatility of periphery markets and can challenge the efficient market theory. Another common feature that Nordic markets share is a high level of foreign ownership. Share of foreign investments in Nordic stock markets can reach more than 50% [1]. Given the remote location of Nordic stock markets and their high share of foreign ownership it is likely that Nordic countries could be subject to periphery effect. Which again can result abnormal returns.

Structure of this paper goes as follows. In second chapter introduction to related literature is provided. In this chapter performance of different methods and persistence of different anomalies in different regions is discussed. Third chapter introduces the methodology and data. Fourth chapter presents the empirical study and final chapter provides as conclusion.

2 Literature

Being the largest and most prominent stock market in the world US stock market has been subject to majority of asset pricing studies. Despite the dominance of US markets in capturing the the attraction of the academics lot of anomaly asset pricing literature has been conducted in international setting as well. Characteristic for international asset pricing literature is that instead of focusing on single countries they aggregate stock market data to a certain regional level such as Europe or Asia-Pacific. Following chapter provides an overview for pioneering asset pricing anomaly literature. Focus will mainly be on literature on US and European markets. US stock markets are chosen because of their significance on international stock markets and because most anomalies have been discovered there and therefore majority of the initial studies of these anomalies have been conducted there. European studies provide interesting perspective since in many of them Nordic countries are included.

Chapter introduces the most important anomalies in these markets and how they have been exploited

[1] Butt and Hogholm (2020) calculate share of foreign ownership from IMF Coordinated Direct Investment Survey CDIS data. Foreign ownership share of Butt and Hogholm is 52% for Denmark, 42% for Finland, 35% for Norway and 56% for Sweden.

with different methods. This works as starting point to define set of factors that will be used in this study. It can be argued that this kind of process when the set of variables are chosen based on their performance in previous studies is one sort of forward looking information if we try to mimic investors information set. On the other hand Jacobs and Müller (2020) only find reliable post-publication decline in long/short returns in US which emphasizes the practical potential of this study.

Table 1: Stock market anomaly selection

Anomaly	Founded[2]	Description	Frequency
Beta	Black, Jensen, and Scholes (1972)	Stock price's sensitivity to overall market changes	Monthly
Book-to-market	Stattman (1980)	Book value of equity divided by the market value of the equity	Monthly / Yearly
Momentum	Jegadeesh and Titman (1993)	Stock return from month -12 to month -2	Monthly / Yearly
Profitability	e.g., Basu, 1983	Sales minus costs of goods sold divided by the book value of equity	Yearly
Asset growth	Titman, Wie, and Xie, 2004	Growth rate of total assets	Yearly
Leverage	Bhandari (1988)	The sum of costs of goods sold and selling, and general and administrative expenses divided by total assets	Yearly
Accruals	Sloan (1996)	Changes in working capital minus depreciation divided by lagged total assets	Yearly
Volatility	Ang et al. (2006)	Monthly standard deviation, calculated from monthly returns from month -24 to month -1	Yearly
Sales-to-price	Fama and French (1992)	Net sales divided by the market capitalization	Yearly
Earnings-to-price	Basu(1977)	Income before extraordinary items to the market capitalization	Yearly
Cash flow-to-price	Desai, Rajgopal and Venkatachalam (2004)	Net cash flow from operating activities divided by the market capitalization	Yearly
Zero dollar return	Butt and Hogholm (2020)	Number of days with zero return in US dollars divided by number of trading days	Monthly

2.1 US stock market anomalies

Many of the recent cross-sectional stock return studies use framework of Lewellen (2015) as base model. He runs 10-year rolling Fama-MacBeth regressions using lagged firm characteristics to predict out of the sample stock returns. He studies cross-sections of US stock return between 1964 and 2013 using different model settings up to 15 company characteristics. He finds strong positive correlation between expected return derived from rolling Fama-MacBeth regressions and realised returns. Additionally Lewellen shows

[2]Founder of an anomaly can be arguable, but here is listed the paper that is in the literature often referred as initial study for corresponding anomaly

that spread between realised return of portfolio formed from stock with lowest expected returns and portfolio with highest expected return is up to 2.36%. In his study logarithmic market value of equity, logarithmic book-to-market value, momentum and accruals show the strongest statistical power in explaining monthly returns using lagged variables.

Gu, Jelly and Xiu (2020) contribute to the literature by applying machine learning methods to exploit stock market anomalies. By deploying sophisticated models that do not suffer from over parameterization as heavily as OLS Gu et al. are able to include 94 stock characteristics and their interactions as well as eight aggregated time series variables to their models. Gu et al. use large variety of statistical methods including linear regression, generalized linear models with penalization, dimension reduction via principal components regression and partial least squares, gradient boosted regression trees, random forest and different settings of neural networks. Out of these gradient boosted regression trees and neural networks [3]explain the monthly out of sample stock return the best reaching out of sample R^2 0.33 and 0.44 correspondingly where as three factor OLS model introduced by Lewellen (2015) only reaches out of sample R^2 of -3.46.

Similar to Lewellen (2015) Gu et al. construct portfolios based on predicted return of different models. Monthly spread in realized return between portfolio constructed from decile of companies with lowest expected return and decile of stocks with highest expected return [4]is 0.94, 1.62 and 2.12 for models based on OLS, random forest and three layer neural network correspondingly. Gu et al. also show that all methods they examine show somewhat similar patterns on variable importance on return predictability. Most important factors are price trends such as momentum followed by stock liquidity, stock volatility, and valuation ratios.

2.2 European stock market anomalies

As mentioned US market environment is different in my ways compared to Nordic markets. Fortunately lot of stock market studies have been conducted in Europe and since Nordic markets are usually just a subset of European markets it can be beneficial to have a look on European studies. Tobek and Hronec (2021) study machine learning based anomaly strategies in international setting. Their study includes 153 different equity anomalies and they only include anomalies to their data after documented discovery of corresponding anomaly. This way they can mimic the information set investor would have had and avoid forward looking information. Tobek and Hronec examine five different models including weighted least squares, penalized weighted least squares, gradient boosting regression trees, random forest and neural networks. Their data set spans from 1990 to 2018. Similar to Gu et al. (2020) in US, Tobek and Hronec find that strategy using neural networks provides highest returns on quintile long-short portfolios. Mean return for neural network long-short portfolio in Europe was 0.7. Interestingly penalized weighted least square method provided mean return of 0.651 which is higher than return of random forest based portfolio's return of 0.396. Tobek and

[3]Gu et al. (2020) use five different settings of neural networks differing by number of hidden layers. Neural network with three hidden layers reaches the highest R^2_{oos} and is reported here.

[4]Portfolio returns are average value weighted returns.

Hronec find that Industry momentum, lagged momentum, liquidity shocks, 52 week high, book-to-market value and return on equity are the most important variables for neural networks model.[5]

Exploiting stock market anomalies using machine learning methods is also studied by Drobetz and Otto (2021). Their data set contains all companies listed in at least one of the 19 Eurozone countries on December 2020 and spans form 1990 to 2020 [6]. Drobetz and Otto examine performance of ordinary least squares, penalized least squares, principal components regressions, partial least squares, random forests, gradient boosted regression trees and neural networks on predicting monthly stock level return exploiting a set of 22 predictions, their two-way interactions and second- and third-order polynomials. Findings of Drobetz and Otto are similar to Gu et al. (2020). They show that with large number of explanatory variables simple linear regression is not able to explain out of the sample stock returns.

Findings of Drobetz and Otto (2021) are also similar to Tobek and Hronec (2021) in a sense that least squares methods where dimensionality is restricted can actually perform better than tree based methods. Like in majority of other literature, Drobetz and Otto find out that neural networks provide superior framework for stock return prediction model measured in both explanatory power and profitability. Neural network method reaches out of the sample R^2 value of 1.23 and long-short portfolio formed based on expected returns derived from neural networks model provide average value weighted monthly return of 1.94%. Similar to Gu et al. (2020) Drobetz and Otto find that same variables show the most importance across the different models, most notably earnings-to-price ratio and 12 month momentum.

Fieberg et al (2023) study stock market anomalies in 16 European stock markets using machine learning methods over almost the same period as Drobetz and Otto (2021) [7]. Nevertheless they choose a slightly different approach where instead of including vast set of anomalies, they only consider six prominent equity factors. Their conclusion endorses findings of Drobetz and Otto (2021) and Tobek and Hronec (2021) as they shown that more complex machine learning models beat linear approach in terms of both economic and statistical performance.

2.3 Stock market anomalies in Nordic markets

This chapter provides an overview of observed stock market anomalies in different Nordic stock markets. Many studies in this chapter have slightly different objective than this study. Studies show the existence of the anomalies by constructing a portfolio heavily weighted on certain factor. Nevertheless, they do not describe the magnitude of the relationship between the factor and the stock returns. This study has slightly more ambitious objective and tries to derive return expectations from predefined stock market factors. This literature review serves as starting point for choosing most promising stock market factors that have already

[5] Tobek and Hronec (2021) discover possibilities training models either only using historical data from US, using historical data from local markets or using international historical data. Only results for models trained using local data are reported here because that is closest to the setting of this study. Additionally, Tobek and Hronec state that difference between model trained on US data and local data are small.

[6] Finland is the only country included in the study of Drobetz and Otto (2021) that is also included in this study, since it is the only country belonging to Eurozone.

[6] Dataset of Fieberg et al (2023) contains Denmark, Finland, Norway and Sweden

been studied.

Magnitude of value and momentum anomalies in Nordic stock markets are examined in the paper by Grobys and Huhta-Halkola (2019). They combine information from companies listed in main lists of Danish, Finnish, Norwegian and Swedish stock exchanges between 1991 and 2017. Grobys and Huhta-Halkola measure value with book-to-market value and momentum with past 12-month total shareholder equity. Grobys and Huhta-Halkola show that momentum effect exists in Nordics markets and profitability of momentum strategy is not related to size factor. Value factor yields also significant excess return, but according to Grobys and Huhta-Halkola it could be partly driven by the size factor, since value premium reduces when accounted for the size. Among all stocks monthly average equally weighted long-short return is 1.73% and 1.25% for momentum and value strategies correspondingly. Both of the excess returns are statistically highly significant. Grobys and Huhta-Halkola also test combination strategies using signals from both momentum and strategy which yield even stronger results.

Value premium has shown consistency in Finnish stock markets. Davydov, Tikkanen and Äijö (2017) examine profitability of different value investing strategies between 1991 and 2013. Davydov et. al. investigate set of value indicators which included earnings to price, book to price, cash flow to price, dividends to price and earnings before income and taxes to enterprise value ratios. Additionally they test performance of investing strategy developed by Greenblatt (cite here) where portfolios are formed based on combined ranking of company's return on invested capital and earnings before income and taxes to enterprise value ratio. They show that returns of all of the value portfolios not only beat the market return, but can also not be explained by the four factor model of Carhart (1997).

Similar to Grobys and Huhta-Halkola (2019) Leivo and Pätäri (2011) combine value anomaly with momentum anomaly in Finnish stock market for data set between 1993 and 2008. They show that two step portfolio sort that first allocates stocks to three portfolios based on their value indicators and subsequently based on momentum indicator can capture extraordinary stock returns. Leivo and Pätäri show that including momentum further increases returns of already recognised value sorting. Strategy performs even better when authors allow for long position in high value high momentum portfolio and short position on low value low momentum portfolio. Excess returns resulting from the two-fold portfolio construction can not be explained by CAP-model or two factor model including also size factor. It is not a surprise that value and momentum premium show existence in Nordic markets. Value and momentum anomalies are among the most well documented factors showing persistence in multiple cross-sectional studies (e.g, Gu, Jelly and Xiu (2020), Lewellen (2015), Drobetz and Otto (2021), Tobek and Hronec (2021)).

Nordic stock markets have several characteristic features. One is that all Nordic stock markets are considered to be developed, but also small. Especially market capitalization of companies listed in Nordic stock exchanges are on average much smaller than in US. Therefore, it is reasonable to ask whether liquidity of the stock could be driving factor of the stock returns. Impact of illiquidity risk to stock returns in Nordic market setting has been studied by Butt and Hogholm (2020). Butt and Hogholm test variety of different illiquidity measures and find that dollar zero returns is the most profitable illiquidity anomaly measure across all four Nordic market. Dollar zero return measurement is calculated by dividing number of days stocks return in US dollars is zero by total number of trading days. Butt and Hogholm construct five quintile portfolios based on liquidity of the stocks with data spanning from 1988 to 2013. They show that in all Nordic markets there exists large illiquidity premium as annual difference in equal weighted return of most illiquid portfolio and least illiquid portfolio is more than 18% for Finland, Norway and Sweden. For Denmark premium is slightly smaller 8.8%.

Jokipii and Vähämaa (2006) investigate free cash flow anomaly in Finnish stock markets between 1992 and 2002. They construct portfolios from stocks listed in Finnish stock exchange based on predefined thresholds for free cash flow ratios. These ratios include market value to free cashflow and total debt to free cashflow ratios. High free cashflow portfolio yields higher returns than market on average and the excess returns can not be completely explained by weightings in Fama and French (1993) risk factors.

3 Data

4 Methodology

This study will evaluate tested methods from two perspectives. Both of them depend on expected returns provided by the methods. How different methods derive the expected returns is explained in the following subsections. First more economical perspective is how profitable predictions of different models would have turned out to be. Profitability is estimated via portfolio construction following Lewellen (2015). Each month based on the expected return produced by the model all stocks are allocated to quintile portfolios. Object of the interest is the spread between lowest and highest expected return portfolios. Both value and equal weighted returns will be reported for each portfolio. Long-short returns will be calculated from the returns of portfolio with highest and lowest expected returns. These returns will be regressed agains Fama-French (1993) three factor model factors to test if model was able to produce returns that can not be explained with loadings of Fama and French risk factors.

Second more statistical measure is how precise prediction methods was able to produce. Prediction accuracy will be evaluated using out-of-smaple R^2_{oos} from (source).

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{T} \sum_{i=1}^{N} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{t=1}^{T} \sum_{i=1}^{N} r_{i,t}^2} \tag{1}$$

Factors importance

4.1 Linear regression

Benchmark model of this study is Fama-MacBeth (1973) regression. First step of the method is to run rolling cross-sectional regressions with lagged variables. Second step of the method calculates means of the factor loadings obtained from the cross-sectional regressions. Finally expected stock return can be obtained by multiplying the mean factors loading with latest available stock characteristics. Below formulas show one model specification for Fama-French (1993) three factors model.

$$r_{i,t} = \beta_0 + \beta_{1,t}\ Mkt_{i,t-1} + \beta_{2,t} +\ Size_{i,t-1} + \beta_{3,t}\ Value_{i,t-1} + \epsilon_i \tag{2}$$

$$\overline{\beta}_j = \frac{1}{T}\sum_{t=1}^{T}\beta_{j,t} \tag{3}$$

$$E(r_{i,t}) = \overline{\beta}_0 + \overline{\beta}_{1,t}\ Mkt_{i,t-1} + \overline{\beta}_{2,t} +\ Size_{i,t-1} + \overline{\beta}_{3,t}\ Value_{i,t-1} \tag{4}$$

One benefit that linear regression models have is that they do not require hyperparameter tuning. Therefore data does not have to be split to three sub-samples for separate validation of hyperparameters and testing. To obtain the expected return mean of 120 historical regression coefficients is calculated. Due to their high computing cost machine learning models are usually trained only once a year and then used for the rest of the year. Each month recent information is just inserted to the model. Computing requirements for linear model is far lesser than for non-linear models. Nevertheless to ensure comparability between different models also the linear model is trained only once per year. That means that no more recent stock returns than $t-1$ are used to train the model to predict stock return t, but the gap between predicted return and last return used to train the model can grow up to 12 months. Since we use lagged variables, this means that for prediction of stock return t we alway use stock characteristics from $t-1$, but some factors are only updated yearly. To mimic information set investor would have had available in historical periods we have to account for the delay in reporting balance sheet information. Therefore timeline of Fama and French (1993) is followed and models are trained each year at end of June.

4.2 Random forest

4.3 Neural networks

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