Automated Stock Picking using Random Forests

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Abstract

We derive a stock ranking by applying a technical features based random forest model on an international dataset of liquid stocks. We show that portfolios based on an outperformance profitability ranking are more profitable than those constructed on the basis of predicted returns. When applying a decile split, equally (value) weighted long-short portfolios achieve a highly significant yearly six factor alpha of 23.49% (17.51%) and a Sharpe ratio of 2.37 (1.95). Unobserved risk factors identified via RP-PCA may not explain the outperformance. Moreover, we show that outperformance probabilities serve as a superior measure of future returns. Mean-variance portfolios of large stocks using our return measure are less volatile and more profitable than equally or value weighted portfolios. The results are not explainable by limits to arbitrage as they are robust to firm size, regional restrictions and non-crisis periods.

Keywords: Keywords: Stock Picking, Machine Learning, Random Forest, Portfolio Optimization

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1. Introduction

Picking stocks that outperform in the future is one of the challenges asset managers face. As active investing requires accurate return estimations, various researchers proposed respective prediction models. As in line with the Efficient Market Hypothesis (EMH), most of these models fail to predict future stock price movements. In a comprehensive study, Welch and Goyal (2008) show that the vast majority of suggested models not only performed poorly out-of-sample, but also in-sample.

With the increase in computation power, researchers started to apply machine learning algorithms to predict short-term stock price trends using models like support vector machines (Liu et al., 2016), deep learning (Dos Santos Pinheiro and Dras, 2017) or ensemble models (Basak et al., 2019) with promising results. Rather than predicting up- or downward movements, some researchers also tried to forecast whether individual stocks generate a return higher than some absolute return threshold. For example, Milosevic (2016) defines stocks as "good" if they increased by at least 10% in the subsequent year. More recently, Gu et al. (2020) compare the performance of neural networks and random forests with traditional models to predict future stock prices and find that Machine Learning models indeed outperform traditional ones. They argue that this overperformance may be traced back to the capability of machine learning algorithms to capture non-linear patterns. Avramov et al. (2021) find a similarly strong performance for ML driven investment strategies. While they agree with Gu et al. (2020) that the profitability likely originates in non-linear anomalies that ML models may successfully identify, they claim that these anomalies mainly occur in stocks that are subject to serious trading frictions. As a consequence, when controlling for transaction costs and excluding stocks with a low market capitalization or missing credit rating information, the performance of these strategies barely generate alpha, questioning the applicability of ML driven investment strategies.

Within this paper we tackle this problem by training a Random Forest classification model on technical indicators of international liquid stocks to identify outperformers, stocks that yield an above-average return. By excluding stocks with less than $300 million market capitalization and less than 15 trading days per month within the previous year, the model aims at identifying abnormal return patterns that are present in liquid stocks. Furthermore, by predicting outperformance probability rather than absolute returns, our proposed model solves a considerably less ambitious problem which might positively affect the accuracy of the model. Our strategy is similar to Moritz and Zimmermann (2016) who use tree-based models to derive portfolio sortings, however we provide a more granular stock ranking.

By comparing the performance of long-short portfolios based on the stock ranking suggested by our model with the ranking obtained from a random forest regression model predicting returns, we find that portfolios based on the rankings produced by our model are more profitable and less risky. We explain this observation by the reduced focus on extreme return behaviour during training. Furthermore, we observe that the feature importances are almost in line with their relative frequencies, suggesting that the calculated outperformance probabilities are derived from a diverse feature space and thus should be non-linear.

To further evaluate the performance of our baseline model, we split the dataset into deciles based on the predicted outperformance probability and calculate the return spread between the average return per decile and the average return of the whole dataset. We find that the return spread is largest (smallest) for stocks with the highest (lowest) probability of outperformance. Moreover, the average monthly return difference between the largest and lowest decile is positive in all considered years. We also do not observe a substantial decrease within recent years, indicating that the identified abnormal patterns do not seem to be traded.

To test the performance of ranking-based investment strategies more extensively, we construct equally and value weighted portfolios of different sizes based on the derived stock ranking. We obtain a Sharpe ratio (SR) of 1.93 by equally investing into the hundred highest ranked stocks (monthly rebalancing) which is substantially larger than the SR of the MSCI World Index over the same time horizon (0.33). Adding short investments into the hundred lowest ranked stocks yields a substantially higher SR of 3.23. For value weighted portfolios, we obtain Sharpe ratios of 1.25 for the long and 1.95 for the long-short portfolio respectively. The results are also robust for portfolio size. While larger portfolios generate lower Sharpe ratios on average, they remain significantly larger than the Sharpe ratio of the market. This effect is driven by both, higher returns and lower volatilities. High ranked portfolios also seem more resilient during market turmoils.

To test whether the results may be explained by any of the commonly known risk factors, we run a Fama French six factor model, using international factors. Note that we control for country-specific effects by weighting country-specific factors in accordance with the country exposure of our portfolio. We obtain highly significant yearly alphas of up to 23.49% before transaction costs for equally weighted portfolios and 17.51% for value weighted ones. The t-statistics are 6.82 and 5.33 respectively. Additionally, we identify three relevant unobserved risk factors within the cross section by running a RP-PCA as suggested by Lettau and Pelger (2020). By extending the six factor model by those three factors, we find that they may explain the performance of the top and bottom portfolio to some extent. Nevertheless, the alpha remains significantly larger than zero in the top portfolio. At the same time, the alpha obtained from shorting the bottom portfolio increases in magnitude. As a consequence, the unobserved risk factors do not explain the profit obtained from equally and value weighted long-short investments. Instead, the obtained alphas slightly increase to 25.14% for equally weighted and 18.61% for value weighted ones respectively.

To ensure that the results are not driven by small and mid-cap stocks, we repeat the analysis on large capitalized stocks using an absolute (larger than $10 billion) and a relative threshold as suggested by Chen et al. (2020). We achieve Sharpe ratios of up to 1.55 and a yearly alpha of 16.2%. As the profitability is mainly driven by the long-leg, we argue that short-selling constraints may not explain the outperformance of the model. If we compare the value weighted portfolio with the MSCI world index, we do not only observe a return more than twice as high, but also a roughly twenty percent lower volatility.

Next to stock picking, asset managers also try to determine weights that optimize the return-to-volatility ratio of the portfolio, a problem which has been heavily investigated within academia since the mid of the last century ((Ban et al., 2018), (DeMiguel et al., 2009) and (Jagannathan and Ma, 2003)). When Markowitz (1952) proposed the concept of the Mean-Variance Portfolio, practitioners quickly discovered a poor out-of-sample performance, as the approach requires good estimates of future returns which are hard to come up with. To circumvent this problem, some researchers suggest to invest in the Minimum Variance Portfolio (MinVP) as the expected returns do not enter the optimization objective. However, a decrease in the volatility is usually accompanied by a decrease in the portfolio return. As a consequence, these optimization strategies often fail to achieve higher Sharpe ratios than equally weighted portfolios out-of-sample.

We suggest an alternative proxy for future returns, a linearly shifted version of our outperformance probabilities that is centered around 0. When constructing mean-variance portfolios based on a random selection of large stocks using our future return measure, we observe a substantial increase in the performance. On average, without short-selling, the portfolio yields a SR of 1.01 which is not only substantially higher than the SR of a MeanVP using past returns as a measure of future returns, but also more than three times as high as the MSCI World Index generated within the same time horizon. What is striking is that the concentration of both mean-variance variants is comparable, indicating that the reduction in the observed volatility may be explained by stock selection rather than fewer concentration. With short-selling, we observe a similar pattern. While the obtained Sharpe ratio is lower, the mean-variance portfolio generates a return almost three times as high as an equally weighted long portfolio, leading to a yearly alpha of 13.7%. This is impressive, given that we only consider large stocks. In general, these findings strongly suggest that investors may be able to achieve higher alpha without increasing their risk exposure by considering our ML driven performance forecasts as measures of future return.

We further test whether the results are driven by specific regions. We therefore restrict investments into European, American, Pacific and Emerging markets. As before, we apply decile splits based on the outperformance probability of our internationally trained prediction model. We find that the highest return and Sharpe ratio may be obtained in the Pacific (2.46), which translates into a large and highly significant alpha of almost 33% per year. As in line with our expectation, the lowest Sharpe ratio is obtained in the US (1.55). However, the realized returns of around 21% remain substantially above the returns predicted by a six-factor model.

According to Avramov et al. (2021), ML driven investment strategies tend to perform extraordinarily well during crisis periods. We therefore conduct median splits among various dimensions to test whether our suggested stock ranking is also valuable in non-crisis periods. Indeed, we obtain a highly significant alpha of up to 9.1% in the long-leg in non-crisis periods. Shorting instead seems to be profitable only in periods of economic distress. While we observe a slight decrease in profitability in the long-leg recently, suggesting that markets got more efficient over time, the results may also identify underpriced stocks in non-crisis periods.

Finally, we investigate the net profitability of different investment strategies by considering estimated trading costs for portfolios of non-financially distressed stocks. We find that long-only investments yield around 7% yearly six factor alpha after transaction costs. Our less trading-intense investment strategy performs slightly better.

We contribute to the literature in two dimensions. First, we introduce a random forest classification model that recognizes high-dimensional patterns which predict abnormal return behaviour of liquid stocks in international markets. Second, we show that the derived out-performance probabilities serve as a superior measure of future returns, allowing investors to maximize their returns by optimizing their portfolio weights.

The remainder of this paper is organized as follows. First, we introduce the identification strategy in section 2, then we present the dataset and some constructed features in section 3. The results are evaluated in section 5, followed by some robustness checks in section 6 before we conclude our findings.

2. Identification Strategy

The vast majority of researchers tries to predict stock prices based on technical or fundamental data, as summarized by Nti et al. (2019). Taking into account that prices are determined by millions of individual trades, precise stock predictions are hard to come by. Moreover, not all of the stock market trades are based on expectations, some trades can be allocated to liquidity traders (Tirole, 2010), which further exacerbates price prediction, leading to a low signal-to-noise ratio within capital markets.

By predicting prices in a long-term, one may be able to reduce the impact of liquidity trades, but the problem remains complex, as next to firm-specific variables, macroeconomic variables also affect stock prices. Moreover, when training models to predict future returns, those models usually focus on those stocks with the most extreme return behaviour during training. These are usually the smallest and most illiquid stocks. As a consequence, the suggested stock ranking is not aligned with the requirements of investors. To circumvent the above-metioned problems by breaking down the regression- into a classification problem. More specifically, we predict whether a stock will perform better or worse than a certain performance benchmark. By doing so we do not only reduce the complexity of the problem, our model should also be less biased towards small and illiquid stocks.

The simplest approach is to fix some return threshold to distinguish between "good" and "bad" stocks. For example, Milosevic (2016) uses a threshold of 10%. However, this approach bears a major problem. If we assume that the majority of stocks in the training set performs better than 10% in the subsequent year, the dataset is unbalanced. This imbalance will be incorporated into the model such that it predicts a return larger than 10% for the majority of stocks. Consequently, the accuracy score would appear artificially high (low) on a test set that mostly contains stocks with a return larger (smaller) than 10%. This could lead to a misinterpretation of the model's prediction power.

A better approach is to label stocks according to their relative performance in the consecutive month. A stock is an *outperformer* (labelled 1) if it's next month stock return is higher than the median next month stock return of all stocks in the dataset and an *underperformer* (labelled 0) otherwise. This leads to a more robust performance as the return difference is less affected by macroeconomic variables and the market environment in general. Moreover, setting a relative threshold is in line with the mindset of active investors who aim at beating the market rather than achieving some yearly return threshold.

One may argue that labelling stocks according to their relative return is not optimal because the volatility of a security should also play a role. By calculating the Sharpe ratio (Sharpe, 1994), we could also incorporate the volatility when labelling. However, due to the diversification effect that occurs when investing in multiple assets, a highly volatile security may be less of a problem. In principal, a portfolio of highly volatile stocks might experience a low volatility as long as the correlation among the stocks is sufficiently low. Thus, we argue that there is no need to consider the volatility of a stock during the labelling process.

In general, there are two major forms of stock market analysis. Technical analysts try to predict future stock prices by analysing historical prices and trade volumes (Lo et al., 2000) while fundamental analysts believe good investment opportunities may be discovered by analysing the fundamental ratios of a company (Abarbanell and Bushee, 1998). Additionally, with the latest advancements in Natural Language Processing, researchers started to investigate whether textual data may reveal information regarding the future performance of equities (Cohen et al., 2020). In this paper we will entirely focus on technical features.

We calculate a large amount of technical features that can broadly be categorized as either momentum-, trend-, volume- or volatility-based.[1] In order to ensure that the model does not capture extreme return behaviour of particularly small and illiquid stocks, we restrict our international dataset to stocks that were traded on at least 15 days per month and have a market capitalization of $300 million.

We decided to construct the training set as follows. One year of stock market information is used to create features whereas the label is assigned by subtracting the average next month stock return from the consecutive individual stock return. If the return difference is negative, we assign a zero, if it is larger or equal to zero, a one. We then repeat this process by shifting the starting date by one month. Following this approach we come up with 156 subsamples that are then merged into one large training set with close to three million observations. This approach has two main advantages. On the one hand, we construct our model on a large time horizon (1990 to 2003) that covers both bullish and bearish market environments. This should lead to a more robust prediction model. On the other hand, since ML algorithms usually profit from larger datasets, we presumably increase the prediction power of the model by using a rolling window. The test set is created in a similar manner using stock market data from 2004 to 2018.

As a next step, a Machine Learning algorithm needs to be selected. As we plan to limit the size of these portfolios, we will need an algorithm that is able to calculate a probability of class membership rather than returning the classes itself. We may then use this information to create a stock ranking allowing investors to pick promising investment opportunities.

In case the classification task is non-linear, meaning that there is no clear linear distinction between the two classes, one should apply an algorithm that is able to identify high-dimensional relationships. In order to test for non-linearity, we follow Basak et al. (2019) and reduce the dimensionality of the model from almost hundred to two dimensions using the so-called Principal Component Analysis (PCA) and plot the convex hulls of both classes. If they do not intersect, a hyperplane that separates both classes exists (De la Fuente, 2000), indicating that the problem could be solved by some linear algorithm.

[Figure 1 about here.]

[1] Further information may be found in section 3.

Figure 1 reveals that the convex hulls clearly intersect such that a separating hyperplane does not exist. Thus, we will need to employ a non-linear algorithm to the classification problem. Among others, neural networks, support vector machines and random forests are the most prominent ones.

In this paper we decided to construct a random forest, a model suggested by Breiman (2001). Random forests are basically a combination of multiple *Decision Trees* whereas each tree is trained on a random subsample of the dataset only. A Decision Tree itself is capable of learning non-linear relationships but tends to overfit on the training data. Random forests may reduce this problem by averaging the results of multiple Decision Trees that are fitted to random subsamples of the dataset.(Horning et al., 2010)

Random forests have been successfully applied within quantitative finance (Emerson et al., 2019). They are robust, automatically handle missing values and work well on discrete and continuous variables Obthong et al. (2020).

3. Data

We collected international stock market data from Refinitiv (Datastream), covering stocks from 68 countries between 1990 and 2018. All technical indicators are calculated by considering not more than one year of previous stock price data as we argue that the future price development is mostly affected by recent price movements. Additionally, as all technical indicators should be calculated using the same length of price history, extending the time frame would lead to a reduction in the number of stocks as some stocks in the dataset might be relatively new.

We restrict the dataset to sufficiently liquid stocks and thus ensure that our results are not driven by small and iliquid stocks. We define a stock as sufficiently liquid if its market capitalization is larger than $300 million dollars and the average monthly amount of trading days within the last year was above 15 days. We also considered adding a liquidity threshold for the average daily traded amount. However, as the variable is usually highly positive correlated with market capitalization and at the same time often missing in our dataset, we refrained from doing so. To reduce the probability that the dataset contains data errors that significantly affect our results, we further drop the 0.1% of stocks that show the highest (lowest) return in the forecasting period. In total, our dataset comprises 18973 stocks across 67 countries. Note that not all of those stocks fulfill the required liquidity constraints throughout the entire investment horizon. We therefore restrict investments to those stocks that match the criteria at the month of investment. As a result, the number of possible investment opportunities ranges between 3000 and 10000 over time.

We calculate technical indicators like *Moving Average*, *Relative Strength Index* and others. We also added features like volatility, skewness and kurtosis. In total, we calculate 96 features that can broadly be categorized as either momentum, trend, volatility or volume-based[2]. To get rid of the price levels some indicators contain by construction, we further relate all indicators to their last available share price such that a comparison among different stocks is possible. The full list of calculated features may be found in figure 15 and 16 in the appendix.

[Table 1 about here.]

Table 1 provides an overview of the stocks contained within our dataset. We observe that the majority of stocks originates in the US, China and Japan. However, we also include some stocks from smaller countries like Bahrain or Serbia that match our liquidity criteria. The average market capitalization within our dataset is $3.74 billion. We also provide the average monthly return for a country across time and observe substantial differences. For countries that on average show a negative monthly return usually contain only few stocks, for example Ukraine or Bahrain. In contrast, countries like South Africa and Turkey show high monthly returns across more than hundred stocks. This is the reason we control for country-fixed effects when running factor models later on.

4. Model Construction

4.1. Model comparison

Within this paper we argue that ranking stocks according to their probability of outperformance is better than using predicted returns, since the model focuses less on stocks with an extreme return behaviour during training. To test whether our argument holds, we compare

[2]Note that some of the features could be associated with more than one category, therefore we decided to allocate those to a fifth category called ”other”.

value weighted investments based on our classification approach with an investment guided by a random forest regressor predicting future returns. Note that we use default parameters, namely a forest size of 100 trees and no restrictions on the tree depth or the maximum features a decision tree may use to split a node.

[Table 2 about here.]

We observe high portfolio returns for the equally weighted long-short portfolio based on our random forest model 2. What is striking is that the volatility of the portfolio is relatively low at the same time, leading to a sharpe ratio of 2.18. If we look at the value weighted portfolio, we observe a lower sharpe ratio which is in line with our expectation. A sharpe ratio of 1.52 remains a strong result though, taking into account that the msci world index yielded a SR of 0.33 only. Even with default parameters, the classification model seems to be quite powerful. If we compare those results with the regression ones, we make multiple observations. Most importantly, the return of the equally weighted regression model is substantially lower with 14.5% compound annual growth rate. At the same time, the volatility is higher, this translates into a sharpe ratio of 1.4 for the equally weighted portfolio which is around thirty percent smaller than the returns of the classification driven portfolio. This underperformance also persists in value weighted portfolios. The results obtained so far strongly support our argument that reformulating the prediction problem as a classification one leads to better prediction results.

Some might argue that in contrast to training a model once, refitting a model over time should yield better prediction results since relationships between variables might change over time. Irrespective of the effect on the models accuracy, refitting the model means loosing the ability to assess whether the patterns captured by the model remain valid over time. To shed some light on the difference in accuracy, we will compare the performance of our baseline model with a yearly refitted one. At the beginning of each year, we train the model again by extending the training period by the most recent year and dropping data from the oldest one. This should ensure a comparable dataset size during training and is also in line with the idea that the oldest data should be least relevant.

According to table 2, refitting the model does not lead to improved prediction results. This is surprising, taking into account that using more recent data is often associated with more prediction power. These results could either be arbitrary or indicate that newer stock price data has a lower signal-to-noise ratio. Consequently, the model captures more patterns within variables that are not predictive but rather occur randomly. Since we are interested in observing whether learned relations remain predictive over time and thus may not be allocated to known anomalies, we will analyze a non-refitted model within the upcoming sections.

4.2. Parameter optimization

When comparing different model setups, we used default parameter settings so far to avoid any systematic bias. However, tuning parameters in a random forest model often improves prediction results. Therefore, we will optimize the parameters of our random forest classifier to maximize the accuracy of the model. There exist multiple parameters that may have an influence on the accuracy of the model. However, optimal parameter settings might differ substantially based on the given task and dataset. For example, the signal-to-noise ratio might have an impact on the parameter choice. If there is a low signal to noise ratio which probably is the case within stock markets, restricting the tree depth is probably a good idea. Otherwise the model overfits on the training set and learns complex relationships that occured randomly and have no predictive power will improve the classification results. By default, there is no restriction on the depth of an individual decision tree, random forest will be as deep as necessary to ensure that all samples are correctly classified. To identify the maximum tree depth for our data, we we randomly divide the training set into two equally sized subsets. Then a random forest model is fitted to one of them and evaluated on the other using different values for the maximum tree depths.[3]

[Figure 2 about here.]

As shown in figure 2, we observe that restricting the depth of the trees too much leads to a performance reduction on the validation set. With an increase in depth, the accuracy of the model on the training set converges to 100%, which is a sign for overfitting. Therefore, we fix the maximum tree depth to 23 as this seems to maximize the out-of sample prediction power.

[3]Note that we keep all other parameters at their default values.

Another important parameter is the maximum number of features available per node. By default, each Decision Tree may consider all features when looking for the best split. In order to further reduce overfitting, it is possible to restrict the number of features that a decision tree may consider to find the best split. To identify an optimal *max feature* parameter, we follow the process described above.[4]

[Figure 3 about here.]

According to figure 3, even though there is a local optimum around 80, the model achieves the best performance if we do not restrict the amount of features that may be assessed at each node. Note that the performance difference between these two parameter settings is marginal anyways, suggesting that both settings will probably lead to similarly powerful models.

Finally, we have to determine the size of the forest. In general, more trees should lead to better classification results even though this effect diminishes with an increasing forest size (Breiman, 2001). A common strategy is to plot the Out-of-Bag (OOB) error rate for different forest sizes to check when the generalization error converges. More precisely, we fix a specific forest size and fit the model on a subsample of the training data. Then, the model is applied to previously unseen data of the training set to calculate the mean prediction error, which is the OOB error rate.

[Figure 4 about here.]

We find that the model converges when the number of estimators is approximately 2000 which we consequently set as forest size. The plot may be found in figure 4.

5. Results

5.1. Feature evaluation

In order to assess which of the used features are most important within our model, we extract feature importances from the model. Feature importances are obtained by counting the nodes where a specific feature was used for splitting and relating it to the total amount of

[4]Note that we use the optimal tree depth parameter within our evaluation.

nodes. Since focusing on 96 different features is not feasible, we calculate feature importances for each category. Note that simply comparing feature importances might be misleading in case some categories contain a lot more features than others. We therefore also relate the amount of features per category with the total amount of features.

[Table 3 about here.]

Table 3 shows the feature importances as derived from our worldwide random forest model. We further present the feature importances of random forest models that were trained on stocks from certain regions only. This enables us to test whether feature importances vary across regions.

By looking at the raw feature importances, one might conclude that trend-based features seem to be most relevant for our international model. In around 36.95% of all cases, the random forest model chose a trend-related feature to split a node. However, given that 37.88% of all features are trend-based, trend features seem to be less important. Instead, momentum and volume factors seem to be favored more often than expected. In total, we obtain a relatively similar image for regionally restricted models. Even though they are trained on different subsamples, the obtained feature importances are mainly in line with the ones from the international model. We observe the largest difference for volume-based features in Europe. Here, volume based features seem to be less important than in other regions. These results strongly indicate that the patterns learned by the model are diverse and thus do not load on specific features.

5.2. Model evaluation

When assessing the performance of a classification model, researchers usually evaluate the accuracy, the precision and the recall. However, taking into account that the amount of correct classifications is less important in our setting, we will focus on the actual return difference for correct and wrong classifications. The reason is that a high accuracy could still mean that an investor looses money, if the underperformance of wrong classifications is sufficiently larger than the outperformance of correct classifications. Therefore, we calculate the deviation between the mean stock return of the dataset and the mean return of the stocks that share similar class probabilities to get an intuition whether the model produces high return spreads.

[Figure 5 about here.]

Figure 5 depicts the relationship between the return spread and the model's estimated class probabilities for the test set. As desired, the spread is positive for stocks with a high probability of outperformance. In contrast, the spread is strongly negative for stocks with only small probabilities. We also observe that stocks, which have a probability of at least 50%, perform better than the average stock in the dataset. Consequently, we may conclude that picking stocks according to the calculated probability of outperformance should be a profitable investment strategy.

[Figure 6 about here.]

To better illustrate the performance of a ranking-based long-short portfolio let us consider the average monthly return spread between equally weighted portfolios with high and low probabilities (decile split) and plot the it for different years. According to figure 6, the average monthly return spread is positive in all considered years. The highest average monthly return spread with around 5.8% was obtained in 2008, amidst the financial crisis. This is in line with Avramov et al. (2021), who argues that ML driven long-short investments tend to be most profitable in crisis periods.

5.3. Portfolio Construction

So far we have seen that the model produces positive return spreads. However, we have not yet considered potentially different levels of volatility of the stocks with the highest (top portfolio) and lowest (bottom portfolio) probabilities of outperformance.

[Table 4 about here.]

Table 4 depicts several performance metrics of differently sized equally weighted top and bottom portfolios. As expected, the return of the top portfolio is substantially larger than the return of the bottom portfolio. For a portfolio of hundred equally weighted stocks, the difference is around 41 percentage points annually. Surprisingly, the annualized volatility of the top portfolio (10.57%) is smaller than the annualized volatility of the bottom portfolio (20.85%). This is in contrast to the Capital Asset Pricing Model (CAPM) that predicts higher volatilities for portfolios with higher returns. Furthermore, we observe that the maximum monthly drawdown of our value weighted long-only portfolio ranges between 15% and 17%, whereas the value weighted MSCI World Index looses up to 22.41% on a monthly basis. We therefore argue that our long-only portfolios are not only less risky on average, but also more robust during crisis periods. Combining long and short investments thus yields extraordinary high profits. For example, an equally weighted long-short portfolio with hundred long and short position yields yields a SR of 3.23. Taking into account that the average market capitalization is $2.65 billion, these results might potentially be driven by smaller stocks. If we consider value weighted portfolios, the obtained SR decreases to a still high 1.95. If we investigate larger portfolios, in example investments into stocks with the 10% highest probabilities, meaning holding around 600 stocks on average, the obtained SR decreases to 1.51 for equally and 1.12 for value weighted portfolios. Combined with short investments, the Sharpe ratios remain impressively high with 2.37 equally and 1.59 value weighted. All of the observed Sharpe ratios are substantially larger than the Sharpe ratio of the MSCI World Index (0.33) and thus indicate market superiority.

To ensure that our dataset does not suffer from a selection bias, we apply a bootstrap approach by comparing our equally and value weighted portfolios with equally and value weighted, randomly constructed portfolios. Those portfolios are constructed in a similar manner as our top and bottom decile portfolios, meaning that the holding period and the portfolio size are the same. The only difference is that we use a random ranking before conducting the decile split.

[Figure 7 about here.]

The results are illustrated in figure 7. We find that both, equally and value weighted portfolios have a higher return-to-volatility ratio than any of the equally or value weighted, randomly constructed portfolios. On the one hand, model-based long-only portfolios are substantially less volatile than their randomly constructed counterparts. The observed volatility difference is around 3% for value weighted and 3.75 percent for equally weighted portfolios. On the other hand, model-based portfolios are also more profitable. The average return difference between model-based portfolios and the random portfolio with the highest return-to-volatility ratio is around 8% equally and 5% for value weighted portfolios. The opposite is true for model-based short-only portfolios. These portfolios not only yield a substantially lower return, they are also more volatile. The average difference in volatility is around 4.5%.

Based on these findings we may conclude that model-based portfolios do not only promise better performance but seem to be even less volatile than randomly constructed ones.

Some might argue that the large returns obtained so far might be explained by some well known factors. We therefore run a six factor model using international factor data for long, short and long-short portfolios. More specifically, we calculate portfolio weights per country and date and group the respective country factors according to those weights. By doing so, we are able to control for country fixed effects. For example, in case our portfolio overweights countries that showed a strong performance in general, we control for this country-specific overperformance. As a consequence, if we obtain significant alphas, we argue that our model identified new potentially high non-linear relationships that may be exploited by investors.

[Table 5 about here.]

Table 5 shows the factor exposure of different model-based portfolios. On the one hand, we obtain a highly significant yearly positive alpha of 11.36% when equally investing in 10% of stocks with the highest probability of outperformance (monthly rebalancing). When using value weighting, the alpha is slightly lower (7.07%), but still highly signficant. On the other hand, equally investing in the 10% of stocks with the lowest probability of outperformance yield a highly significant alpha of -9.84%. When using value weights, the alpha is smaller in magnitude with -7.44% but still highly significant at the 1% level. If we form a long-short portfolio, we obtain even higher alphas of up to 23.49% (equally weighted) and 17.51% (value weighted). If we focus on the long-leg, next to the expected high correlation with the market, we mainly find a strong correlation with the SMB factor in the equally weighted portfolio, suggesting that the portfolio contains a lot of smaller stocks that drive the profitability of the portfolio. As expected, this dependency disappears when using value weights. A similar observation may be found in the short-leg. What is striking is that both long-short portfolios are highly correlated with the market. This is surprising, taking into account that this a long-short strategy and both portfolios are highly correlated with the market themselves.

So far we have shown that the obtained stock ranking may be used to construct market superior portfolios and none of the other five commonly used factors may explain the outperformance. However, it could be that the top and bottom portfolios load on unobserved factors, meaning that investors would face some unobserved risk. We therefore run a RP-PCA analysis as suggested by Lettau and Pelger (2020) to identify the most important factors within the cross-section of stocks. Note that not all of the stocks were available within the full time-horizon, meaning that we lack the required return information for some stocks. To circumvent this problem, we restrict the dataset to those stocks where we have return information throughout the time horizon. In total, this subsample comprises around 3200 stocks. Once having identified the most important factors, we subdivide the dataset into 25 portfolios with monthly rebalancing and test how much of the variance within portfolio returns may be explained by the most common factors.

[Table 6 about here.]

[Table 7 about here.]

Table 6 shows the model exposure of the portfolio with the largest outperformance probabilities. We observe that the most important factor on its own already explains 69% of the variations within the portfolio. Adding the second most important factor, the R^2 increases to 79%. A regression model that contains the five most important factors explains 82% of the variance, however only the first three factors are highly significant. We find similar results for the portfolio with the lowest outperformance probabilities (see table 7). Here, only factor one is significantly different from zero. The explained variance is only slightly smaller (73%).

Now that we have identified relevant unobserved factors in the cross-section, we are able to test whether these unobserved factors may explain the high alphas obtained before. We therefore compare the obtained alphas from an eight factor model, which is the six factor model extended by the two relevant factors, with those previously reported. By assuming that there is no additional unobserved factor in our dataset of liquid stocks that is not available within the dataset on which we constructed the factors, we should be able to isolate the idiosyncratic component from the unobserved factor loadings.

[Table 8 about here.]

According to table 8, we find that the three unobserved risk factors are highly significant for equally and value weighted investments into the stocks with the 10% largest (lowest) outperformance probabilities. At the same time, the exposure to the other factors remains relatively unchanged, indicating that the new factors are indeed unobserved risk factors and no plain linear combinations of the previous ones. However, the reduction in the obtained alpha appears rather low. For equally weighted top portfolio, the alpha decreases by around three percentage points and remains significantly larger than zero (8.18%). Value weighted, the alpha is smaller, but still significantly larger than zero at the 1% level (4.67%).

Given that top and bottom portfolios share the same factor loading sign for factor 1, a reduction in the alpha in the top portfolio will also mean a reduction in the bottom portfolio. As a consequence, the observed negative alpha increases in magnitude by p7 percentage points to a highly negative 16.62% for equally weighted and to -13.71% for a value weighted portfolio. What is striking is that neither of the two unobserved factors may explain a large share of the overperformance in the long-short portfolio. While we observe that factor 2 is significant, we see an increase in the alphas for equally and value weighted portfolios. We therefore argue that the highly significant alphas may not be explained by unobserved risk factors.

To ensure that our results are also valid for the largest stocks, we could increase our threshold for the minimum market capitalization to a higher value, for example $10 billion.

[Table 9 about here.]

According to table 9, an equally (a value) weighted long-short investment into the 10% highest ranked large firms yields a highly significant yearly six factor alpha of 13.80% (12.09%). Those results strongly indicate that the model identified patterns within the data that may also help to predict the performance of large caps. The performance seems to be mainly driven by the long-leg. An equally weighted long-portfolio already yields a highly significant alpha of 6.75%. Taking into account that the average market capitalization is around $31 billion, our proposed stock ranking might also be highly relevant for large institutional investors that may not want to enter short selling positions. For large firms, the bottom portfolio yields a return of around zero percent. Thus, adding short selling does not increase the return of the portfolio. However, as we hedge against certain risk factors, the obtained alpha increases to 11.94% for equally weighted and 10.1% for value weighted portfolios.

Some might argue that, in general, setting an absolute threshold is not ideal, since the value of the Dollar is not constant over time. We therefore rerun the previous analysis by following Chen et al. (2020) and classify a stock as large if its market capitalization represents more than a certain threshold of the total market capitalization at a given point in time. For the US stock market, they suggest a threshold of 0.01% to roughly obtain stocks contained in the SP500.

[Table 10 about here.]

Using the alternative classification for large firms, we observe a SR of 1.55 and a monthly six factor alpha of 16.2% for an equally weighted long-short portfolio in table 10. These results are mainly driven by the long-leg. An equally (a value) weighted long investment into the 10% highest ranked large firms yields a highly significant yearly six factor alpha of 14.91% (12.93%). Those results strongly indicate that the model identified patterns within the data that may also help to predict the performance of large caps.

5.4. Portfolio Optimization

Rather than equally or value weighting, investors might also construct portfolio weights using optimization techniques. One of the most famous one is the mean variance portfolio (MeanVP). The idea is that portfolio weights are chosen such that the SR is maximized. However, the performance of this approach depends heavily on the accuracy of the return forecasts. Investors often model future returns using past returns, however this often leads to heavily concentrated portfolios where past winners are strongly overweighted. To circumvent this issue, we suggest to use a modified version of our calculated probabilities of outperformance as a measure of future returns. We substract 0.5 from the outperformance probability such that underperformers are associated with negative values. Since this measure is bounded by -0.5 and 0.5, we expect to see less extreme weights in the portfolio compared to a mean variance portfolio that uses past returns. Potentially, this also translates into lower volatilities.

We test these hypotheses by comparing the performance and the amount of non-zero positions for mean-variance portfolios using different measures for future returns. Note that we have to select stocks randomly rather than forming portfolios based on the stocks with the highest probability. The reason is that the expected returns for high-ranked stocks would be very similar by construction. In the extreme case, when all considered stocks in the long-leg (short-leg) have the same calculated probabilities of outperformance, we would have zero variance within expected returns. Since including a variable without variation is the same as excluding it from the objective function, we would simply come up with the weights for a minimum variance portfolio, where expected returns do not enter the objective function. As Avramov et al. (2021) point out, ML driven investment strategies tend to overweight stocks that face strong limits to arbitrage and thus the reportedly high profitability of ML driven investments is often hard to realize in practice. To ensure that our results are not biased by limits to arbitrage, we restrict the dataset to large stocks[5]. Moreover, we will consider both, MeanVP with and without short-selling.

[Table 11 about here.]

Table 11 compares different portfolio strategies based on fifty randomly selected stocks with a large market capitalization (monthly rebalancing). Without short-selling, we find that the $MeanVP$ using past returns as return proxy is indeed highly concentrated with only twelve non-zero weights out of fifty investment options. It yields a Sharpe ratio of 0.16 which is lower than those obtained from equal and value weighted investments. Not only the volatility is higher, but also the return is lower suggesting that past returns are indeed a bad measure for future returns. In contrast, using probabilities of outperformance as a measure of expected returns yields a substantially higher Sharpe ratio of 1.01 which is more than twice as much as an equally weighted portfolio generates. This is striking, taking into account that the amount of non-zero positions is not different from the mean-variance portfolio using past returns. The outperformance may not be explained by any of the factors included in our six-factor model, leading to an alpha of 6.38% which is significant at the 5% level. A similar image may be obtained when allowing short selling. We observe a substantially higher Sharpe ratio for $MeanVP_{proba}$ compared to the $MeanVP_{ret}$ which is driven by both, a larger return and a smaller volatility. Overall, this translates into a yearly alpha of 13.7% which is significant at the 10% level.

Based on these findings, we argue that outperformance probabilities may serve as an accurate proxy for future returns. Given that the only consider large stocks, limits to arbitrage or

[5] We define stocks as large stocks, if there market capitalization was larger than \$10 billion in the previous month.

short-selling restrictions may not explain the performance gain. It seems that investors may improve their return-to-risk ratios by constructing mean-variance portfolios using our proxy for future performance.

6. Robustness

6.1. Regional Differences

Intuitively, one may hypothesize that the derived stock picking approach works better in regions with less developed stock markets, as stocks within these markets should be less efficiently priced. On the contrary, Jacobs (2016) finds that there are at least as many market anomalies in developed markets as in emerging markets. Therefore, we calculate the performance of the previously discussed investment approach with restrictions to specific regions. We follow the classification of MSCI to allocate all stocks to the regions *Emerging Markets, Europe, North America, Pacific and Frontier Markets*. Note that we do not test the performance on frontier markets as there are not enough sufficiently liquid stocks available.

[Table 12 about here.]

As suggested by table 12, the stock picking approach yields highly significant positive alphas in all tested regions. We find that the Sharpe ratio is highest for investments into Europe for both equally and value weighted portfolios. This is mainly driven by the extraordinarily small volatility of the long-short portfolios. With respect to the obtained yearly six factor alphas, Europe yields the smallest one. The highest alpha may be obtaines within Emerging Markets for both equally and value weighted portfolios. With highly significant alphas of up to 23.05%, these portfolios are very profitable. What is striking is that we also obtain a highly significant alpha in the US for both, equally and value weighted portfolios. Based on the observed high Sharpe ratios, we conclude that the suggested stock picking approach works on markets with different development status.

6.2. Profitability over time

One may argue that the profitability of our investment approach might deviate over time. Among others, Avramov et al. (2021) finds evidence that ML driven investment strategies tend to perform substantially better within periods of economic distress. To test whether investments based on the suggested stock ranking also generate positive alpha in non-crisis periods, we conduct multiple median splits using different indicators for crisis periods. We use a volatility index for international markets obtained from Refinitiv, the market sentiment obtained from Baker and Wurgler (2006) and the average monthly bid-ask spread within our dataset as splitting variables. We further investigate whether we observe a decrease in the profitability within more recent years.

[Table 13 about here.]

Table 13 shows the performance of the previously studied portfolios for different time periods. We conduct a median split based on the VStoxx volatility index and find that the alphas obtained from long-short investments are substantially higher in periods of high volatility. While the equally weighted long-short portfolio generates a yearly alpha of 31.31% in more volatile periods, the obtained yearly six factor alpha is smaller with 15%, which is still significantly larger than zero. We obtain a very similar image when using the average bid-ask spread as proxy for economic distress. What is striking is that for periods of lower volatility and lower spreads, shorting the lowest ranked stocks does not generate a significant profit, whereas we observe substantially high alphas in periods of economic distress. Conducting a median split based on investor sentiment as measured by Baker and Wurgler (2006), we do not observe significantly different alphas though. We further show that the investments of the portfolios remain profitable within more recent years, however with a lower magnitude. We trace this reduction back to the lack of strong economic downturns within the last century rather than increased market efficiency, as the reduction in profitability is mainly driven by the short leg.

6.3. Net Profitability of portfolios

So far we have not considered transaction costs when evaluating the different portfolio strategies. One may hypothesize that the suggested investment strategy requires frequent trading and thus faces high transaction costs which ultimately reduce profitability. We therefore suggest an alternative investment strategy that should require less trading. An investor initially buys (sells short) a predetermined amount of stocks based on the calculated probability of outperformance. He holds those stocks as long as their probability is above (below) a certain threshold, otherwise he will dissolve his investment and replace it with a new investment that is highly ranked at that point in time. By assessing the performance of this investment strategy, we should additionally get an intuition on how stable the predictions of the model are. Another aspect which might influence our results is the financial distress of individual firms. Stocks that are in financial distress are often associated with anomalously low return patterns. While investors could theoretically profit from this overpricing by short selling the respective stocks, these securities often experience serious trading frictions around credit rating downgrades.Avramov et al. (2013) To ensure that our results are not biased by such stocks, we drop stocks that have a default probability of more than 10% based on the failure measure suggested by Campbell et al. (2008).

[Table 14 about here.]

Table 14 shows the average exit rate, which is the percentage of stocks that are replaced per month, for our baseline and alternative investment strategy (threshold 50%). Indeed, we observe a high average exit rate between 83% and 87% for equally weighted investments into the highest (lowest) ranked 100 stocks. Applying our alternative strategy instead, we observe a substantially lower AER of just 6.83% for the long leg.[6] Based on this finding, we argue that the estimated outperformance probabilities are relatively robust. A stock which gets a high ranking in one month is unlikely to receive a low one in the subsequent month. As expected, the alternative investment strategy is less profitable *before* transaction costs. To test which of these portfolios performs better *after* transaction costs, we calculate the net alpha, which is a six factor alpha minus the estimated relative yearly transaction costs. We estimate transaction costs by multiplying the average monthly exit rate by the portfolios' average bid-ask spread of 0.73% and scale it to a yearly figure. After controlling for transaction costs, both strategies yield similar high significant net alphas of 7-8%. We may conclude that long-only investments into stocks that are favoured by our model yield highly significant alphas even after controlling for transaction costs. For the short leg, we observe a similar effect. Here, the AER drops to

[6] We also tested different thresholds. As expected, we find a positive correlation between the threshold and the AER.

22.94%, which is substantially lower than the baseline strategy, but higher than the long leg of the alternative strategy. We hypothesize that the AER is higher in the short leg because stocks either turn around or drop out of the market eventually. Using the same proxy for transaction costs as before and assuming zero lending fees, both short investments yield around 9% net alpha. We therefore conclude that our suggested stock ranking should not only be relevant for hedge funds, as the long investments yield significant alphas also.

7. Conclusion

While most researchers focus on return prediction, we propose a model that predicts the relative outperformance of a stock during the subsequent month. We train a random forest model based on technical indicators and test it on a fifteen year horizon with monthly investments into liquid stocks. The obtained results indicate that out- and underperformers indeed share common technical attributes that may be discovered by Machine Learning models which questions the weak-form efficient market hypothesis. We observe Sharpe Ratios of up to 3.23 for equally weighted and 1.95 for value weighted portfolios. None of the risk factors within a six factor model may explain the outperformance (underperformance) of stocks with a high (low) probability of outperformance. For equally (value) weighted portfolios, we obtain highly significant yearly alphas of up to 23.34% (17.51%).

To ensure that the outperformance of long-short portfolios may not be explained by some unobserved risk factors, we run a RP-PCA to identify the most relevant factors within the cross section. While one of those three identified factors is highly significant for the long-short portfolio, we obtain an even larger alpha. This indicates that the strong performance of our model is probably not driven by some unobserved risk factor.

We further investigate whether the calculated outperformance probabilities may be used to model future returns when constructing a mean-variance portfolio. We find that using outperformance probabilities rather than past returns leads to a substantially higher return-to-volatility ratio. These results even persist when restricting the optimization to long investments.

As a robustness check, we analyze the performance of our model within different groups of countries. As expected, the observed returns are smaller in the US and Europe, whereas investments into the Pacific and emerging markets yield the highest returns. Nevertheless, we obtain highly significant alphas in all considered regions.

We also show that the suggested stock picking approach is profitable in different market environments. We observe that the alpha is larger in periods of higher volatility and higher bid-ask spreads, but remains significantly positive throughout all other periods. While we observe lower profitability in more recent years, we find some evidence that this effect is mainly driven by the lower amount of economic crisis rather than a substantial increase in market efficiency. We have also proposed an alternative ranking-based investment strategy that requires significantly lower transactions and thus trading costs. By comparing net alphas, we find that both, the baseline and the alternative investment strategies are highly profitable.

Given the robust results, our findings are of high relevance for fund managers pursuing an active stock selection. Not only does our stock ranking approach can serve as a guideline for future investments, it may also be combined with other stock rankings derived by fundamental or textual data by simply averaging outperformance probabilities on the stock level. Future research might therefore investigate whether adding fundamental or textual data to the model may lead to an even more valuable stock ranking.

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8. Appendix

[Table 15 about here.]

[Table 16 about here.]

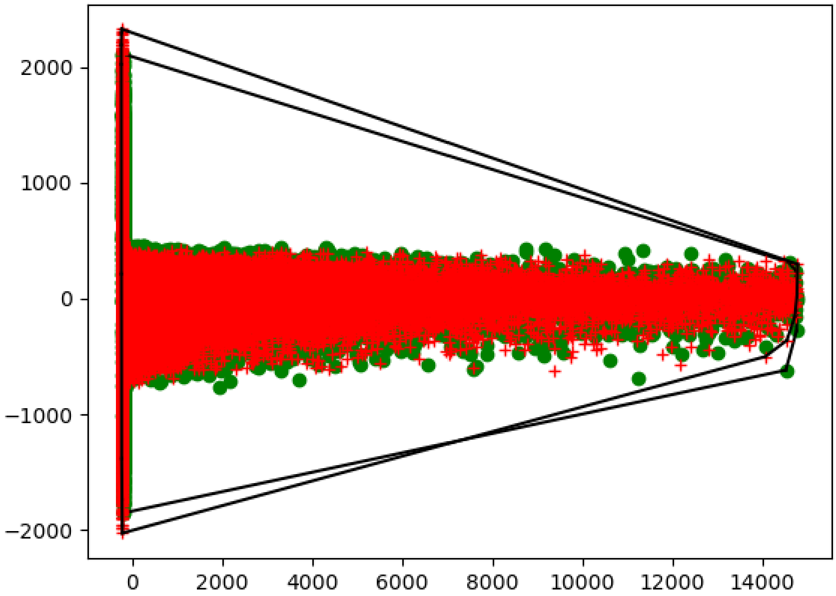

Figure 1: Convex hulls of good and bad stocks

Principal component analysis of outperformers (green) and underperformers (red). We reduce the dimensionality of the feature space to visualize whether a linear separation of both classes is possible.

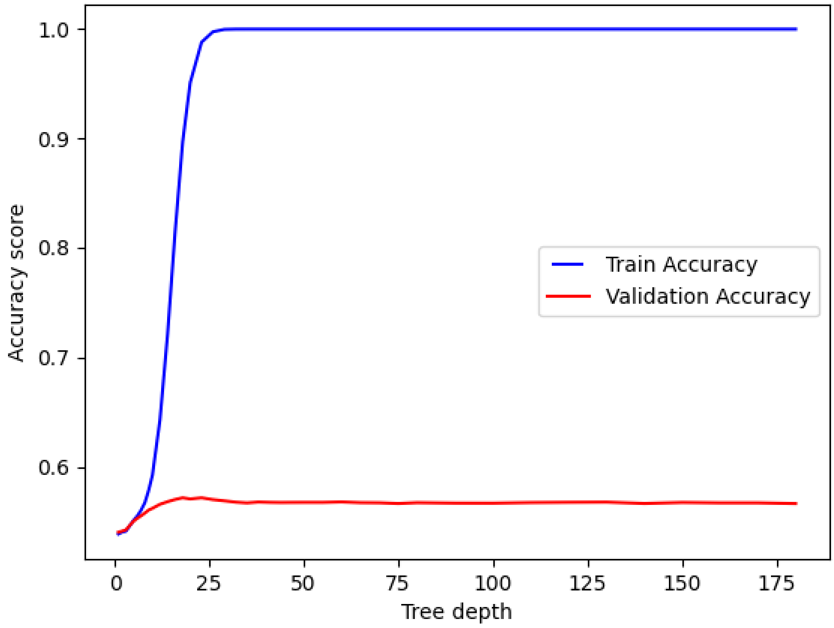

Figure 2: Accuracy on the training and validation sets in relation to tree depth

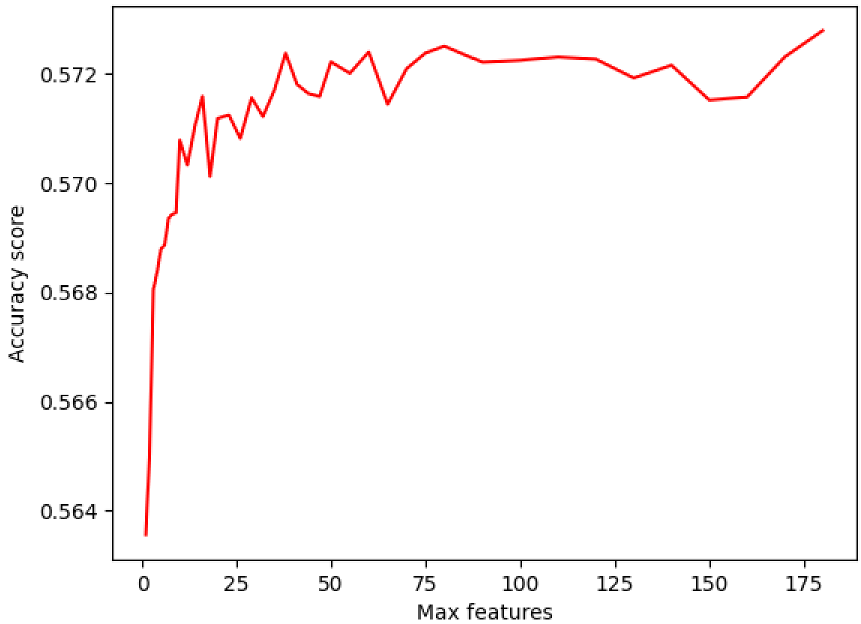

Figure 3: Accuracy for different values of maximum features considered at each node

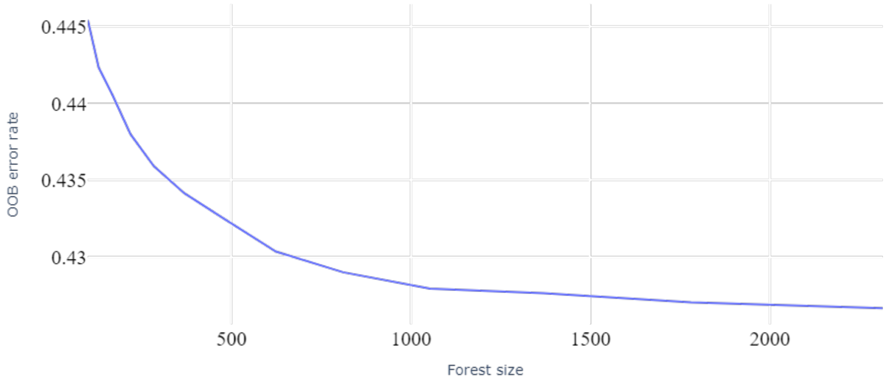

Figure 4: Out-of-Bag error rate for different numbers of estimators

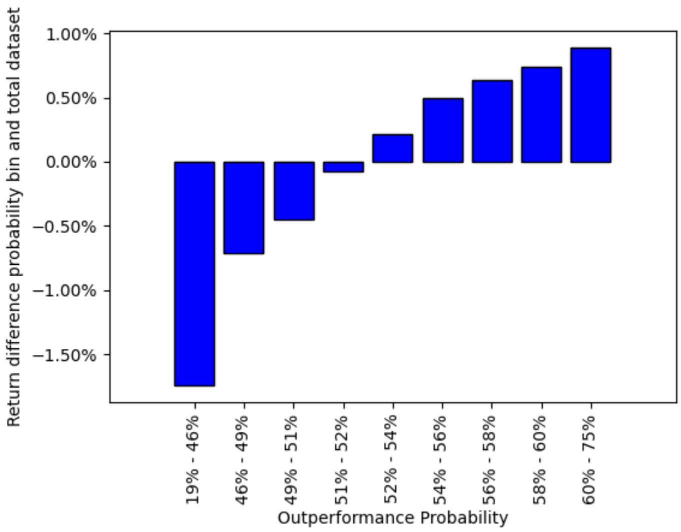

Figure 5: Spread between median return and median return of subgroup

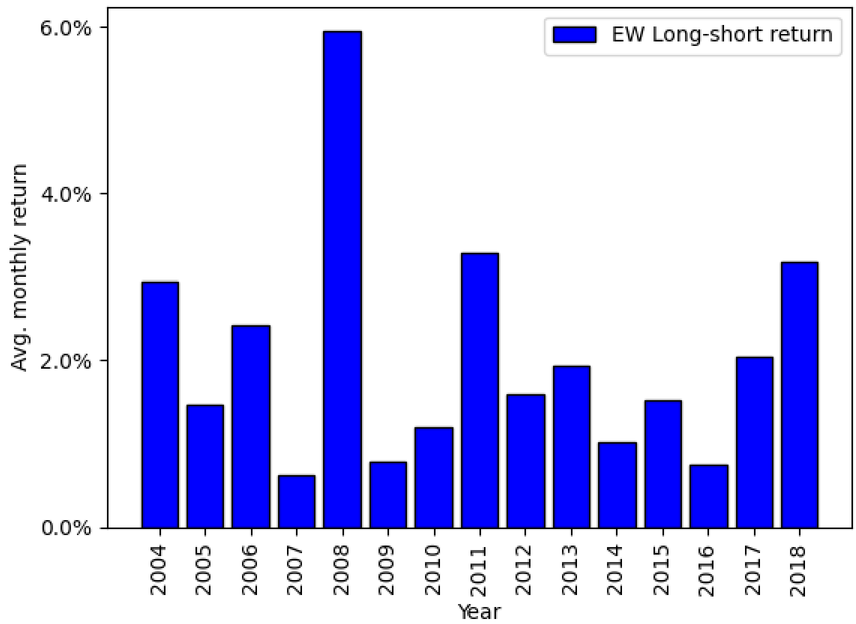

Figure 6: Average monthly return difference top and bottom portfolio
This figure reports the difference between the average monthly return of the top and bottom portfolio within a year.

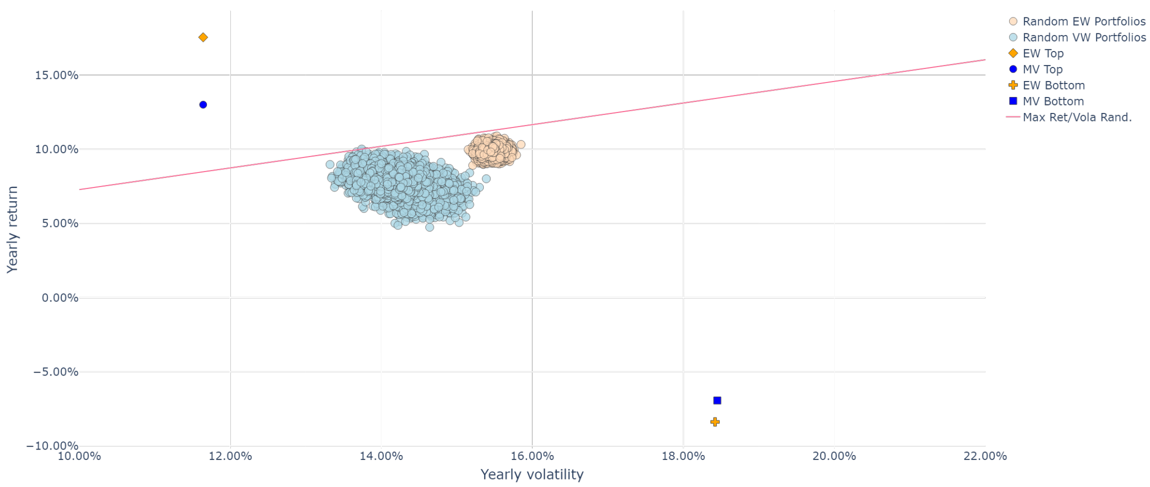

Figure 7: Model-based portfolios vs. random portfolios

Table 1: **Summary Statistics by Country:**

Country	Stocks	MV	Ret.	Country	Stocks	MV	Ret.
Worldwide	18973	3.74	0.64				
Argentina	30	1.51	2.52	Malaysia	203	1.96	0.61
Australia	587	2.56	0.53	Mauritius	11	0.8	0.12
Austria	60	2.81	0.77	Mexico	88	3.98	0.92
Bahrain	6	1.09	-2.83	Morocco	31	2.02	0.64
Bangladesh	40	1.01	0.33	Netherland	87	5.45	0.68
Belgium	74	5.06	0.58	New Zealand	64	1.39	0.97
Brazil	204	3.79	0.77	Nigeria	39	2.04	0.15
Bulgaria	23	0.58	-0.08	Norway	177	4.08	0.67
Canada	896	2.87	0.41	Oman	25	1.11	0.14
Chile	48	3.24	0.87	Pakistan	63	1.24	1.13
China	3205	2.31	0.80	Peru	32	1.4	0.93
Colombia	31	4.86	1.05	Philippines	76	2.33	1.09
Croatia	31	1.43	-0.14	Poland	141	2.09	0.27
Czech Republic	20	5.23	1.24	Portugal	35	3.53	0.37
Denmark	82	2.56	0.86	Qatar	43	4.39	0.7
Egypt	82	1.39	1.05	Romania	22	2.1	0.91
Estonia	8	0.61	-0.16	Russia	148	8.65	0.94
Finland	85	4.80	0.78	Serbia	7	0.73	0.39
France	353	6.19	0.71	Singapore	264	2.08	0.28
Germany	431	7.65	0.75	Slovenia	11	0.69	-0.31
Greece	89	1.93	-0.35	South Africa	156	3.17	1.25
Hong Kong	825	5.42	0.30	Spain	144	7.56	0.33
Hungary	14	3.42	0.86	Sri Lanka	12	0.78	0.77
India	639	3.36	0.97	Sweden	252	2.91	1.1
Indonesia	192	2.64	0.93	Switzerland	163	7.13	0.64
Ireland	30	2.92	0.58	Taiwan	642	1.97	0.3
Italy	215	4.68	0.30	Thailand	203	2.01	0.61
Japan	1237	3.18	0.58	Tunisia	19	0.58	0.81
Jordan	20	1.53	0.12	Turkey	136	2.4	1.18
Kazakhstan	14	1.83	-0.36	USA	4432	5.12	0.68
Kenya	22	1.08	0.47	Ukraine	49	1.78	-1.03
Korea	660	2.97	0.43	United Kingdom	726	4.66	0.61
Kuwait	122	2.03	-0.60	Vietnam	79	1.54	0.67
Lithuania	18	0.59	0.68				

On the country-level, we count the number of stocks (*Stocks*), the average market capitalization in billion USD (MV) and the average monthly return (*Ret.*) within the dataset.

Table 2: **Model Comparison:**

Portfolio	CAGR	Vola	SR	CAGR	Vola	SR	MV
	Equal			Value			
Classification	19.30	8.86	2.18	13.23	8.71	1.52	3.49
Class. refit	14.37	11.43	1.26	8.44	11.24	0.75	3.50
Regression	14.50	10.35	1.4	8.40	10.05	0.84	2.98

This table reports the performance of equally and value-weighted long_short portfolios based on different types of models. We split the dataset into deciles based on the probability of outperformance (Classificaiton, Class. refit) or predicted returns (*regression*). *CAGR* is the compound annual growth rate. *MV* is the average market capitalization in billion USD. *TA* the average daily traded amount in million USD.

Table 3: **Feature importances:**

Category (%)	Rel freq.	World	North America	Europe	Pacifc	Emerging
Momentum	16.757	18.340	18.510	18.100	18.340	18.160
Trend	37.838	36.950	36.400	37.470	36.510	37.150
Volatility	24.865	21.540	22.280	22.020	22.130	21.120
Volume	10.811	13.420	13.510	12.010	13.660	13.770
Other	9.73	9.760	9.300	10.410	9.360	9.790

Feature importances obtained directly from the model. We allocate features to the categories momentum, trend, volatility, volume and other. Then we count the amount of nodes where features from a specific category were used and then relate it to the total amount of nodes. Next to the international model, we further train regional models to test whether certain features are more important in some regions than others. *Rel. freq* is the relative frequency of the features in the category compared to all features. All values are denoted in

Table 4: **Portfolio metrics top, bottom and top bottom portfolios:**

Portfolio (size)	CAGR	Vola	DD_{max}	SR	CAGR	Vola	DD_{max}	SR	MV
		Equal				Value			
MSCI World					5.20	15.52	-22.41	0.33	
T (100)	20.38	10.57	-18.95	1.93	14.25	11.43	-15.18	1.25	4.08
T (decile)	17.54	11.64	-19.33	1.51	12.99	11.65	-15.40	1.12	5.750
T (quintile)	16.65	12.45	-20.26	1.34	11.86	12.48	-16.98	0.95	5.74
B (100)	-20.54	20.85	-30.48	-0.99	-17.81	23.07	-27.50	-0.77	1.22
B (decile)	-8.37	18.42	-26.61	-0.45	-6.93	18.45	-24.77	-0.38	1.700
B (quintile)	-4.22	18.02	-25.30	-0.23	-4.01	17.15	-23.17	-0.23	2.00
TB (100)	49.68	15.37	-9.41	3.23	37.34	19.14	-18.71	1.95	2.65
TB (decile)	26.75	11.31	-8.29	2.37	19.95	12.56	-8.95	1.59	3.725
TB (quintile)	20.33	10.18	-6.97	2.00	15.13	10.23	-6.7	1.48	3.87

We go long into the stocks with the highest calculated probabilities of outperformance (top portfolio) and the lowest ones (bottom portfolio). We present portfolios with investments into fifty stocks as well as investments with on average 600 (decile) and 1200 (quintile) stocks. The *TB* portfolio comprises long investments into the top and short investments into the bottom portfolio. To assess the performance of these portfolios, we calculate compound annual growth rates (*CAGR*), yearly volatilities (*Vola*), the maximum monthly drawdown (DD_{max}) and Sharpe ratios. *MV* is the average market capitalization in billion USD. *TA* the average daily traded amount in million USD.

Table 5: **Six factor model using international factor data:**

Factor	EW Top	VW Top	EW Bottom	VW Bottom	EW TB	VW TB
MKTRF	0.64***	0.7***	0.87***	0.77***	-0.25***	-0.14**
	(16.26)	(19.24)	(16.46)	(13.09)	(-3.48)	(-2.01)
SMB	0.61***	0.08	0.97***	0.35**	-0.71***	-0.5**
	(6.2)	(0.66)	(7.12)	(2.19)	(-3.79)	(-2.33)
HML	0.14	0.02	-0.24*	0.14	0.12	-0.26
	(1.46)	(0.19)	(-1.9)	(0.74)	(0.7)	(-1.23)
RMW	0.05	0.03	-0.07	-0.44**	0.19	0.34*
	(0.75)	(0.51)	(-0.44)	(-2.22)	(1.11)	(1.63)
CMA	-0.26**	-0.18*	0.09	-0.28	-0.21	0.16
	(-2.19)	(-1.65)	(0.46)	(-1.43)	(-0.81)	(0.58)
WML	0.01	0.06	-0.26***	-0.27***	0.25*	0.33***
	(0.08)	(0.93)	(-4.52)	(-5.03)	(1.65)	(2.6)
alpha	**11.36*** **	**7.07*** **	**-9.84*** **	**-7.44*** **	**23.49*** **	**17.51*** **
	(6.05)	**(4.09)**	**(-4.04)**	**(-2.58)**	**(6.82)**	**(5.33)**

This table shows the factor exposure for equally (EW) and value weighted portfolios (VW) constructed based on the highest (lowest) 10% calculated probabilities of outperformance.

Table 6: Factor Loadings Top Portfolio:

Coefficient	(1)	(2)	(3)	(4)	(5)
Constant	0.74***	0.69***	0.61***	0.64***	0.58***
	(4.23)	(4.78)	(4.16)	(3.76)	(3.23)
Factor 1	-0.82***	-0.91***	-1.05***	-1.03***	-1.1***
	(-10.1)	(-12.36)	(-12.78)	(-11.18)	(-10.89)
Factor 2		0.39***	0.44***	0.43***	0.45***
		(7.56)	(9.2)	(8.87)	(8.39)
Factor 3			0.36***	0.33***	0.42***
			(4.17)	(2.97)	(3.1)
Factor 4				0.08	0.04
				(0.56)	(0.24)
Factor 5					0.22*
					(1.85)
R-Squared	0.69	0.79	0.81	0.81	0.82
R-Squared Adj.	0.69	0.79	0.8	0.8	0.81

This table shows the factor exposure for equally (EW) and value weighted portfolios (VW) constructed based on the highest (lowest) 10% calculated probabilities of outperformance.

Table 7: Factor Loadings Bottom Portfolio:

Coefficient	(1)	(2)	(3)	(4)	(5)
Constant	-2.05***	-2.04***	-2.08***	-2.02***	-2.02***
	(-9.12)	(-9.0)	(-8.92)	(-8.17)	(-7.79)
Factor 1	-1.41***	-1.41***	-1.46***	-1.42***	-1.42***
	(-20.39)	(-18.81)	(-14.46)	(-13.14)	(-11.47)
Factor 2		-0.04	-0.02	-0.03	-0.04
		(-0.31)	(-0.16)	(-0.27)	(-0.28)
Factor 3			0.14	0.08	0.08
			(0.68)	(0.41)	(0.36)
Factor 4				0.13	0.13
				(0.74)	(0.69)
Factor 5					-0.01
					(-0.06)
R-Squared	0.73	0.73	0.74	0.74	0.74
R-Squared Adj.	0.73	0.73	0.73	0.73	0.73

This table shows the factor exposure for equally (EW) and value weighted portfolios (VW) constructed based on the highest (lowest) 10% calculated probabilities of outperformance.

Table 8: **Nine factor model using international factor data:**

Factor	EW Top	VW Top	EW Bottom	VW Bottom	EW TB	VW TB
MKTRF	0.45***	0.53***	0.58***	0.55***	-0.33***	-0.26*
	(8.34)	(7.12)	(7.99)	(6.48)	(-2.69)	(-1.8)
SMB	0.43***	-0.08	0.69***	0.16	-0.74***	-0.57**
	(4.88)	(-0.71)	(5.38)	(1.0)	(-3.6)	(-2.3)
HML	0.02	-0.07	-0.2*	0.16	-0.01	-0.43*
	(0.26)	(-0.68)	(-1.66)	(0.86)	(-0.05)	(-1.78)
RMW	0.06	0.01	0.06	-0.3	-0.05	0.11
	(1.27)	(0.21)	(0.38)	(-1.59)	(-0.33)	(0.58)
CMA	-0.19*	-0.12	0.11	-0.23	-0.17	0.25
	(-1.8)	(-0.98)	(0.62)	(-1.22)	(-0.67)	(0.84)
WML	-0.0	0.07	-0.24***	-0.26***	0.25**	0.35***
	(-0.04)	(1.06)	(-4.5)	(-4.56)	(1.93)	(3.2)
Factor 1	-0.51***	-0.4***	-0.66***	-0.61***	-0.12	-0.15
	(-6.57)	(-3.96)	(-5.5)	(-4.26)	(-0.61)	(-0.68)
Factor 2	0.2***	0.22***	-0.04	-0.05	0.49***	0.51***
	(5.27)	(4.81)	(-0.64)	(-0.51)	(4.82)	(4.23)
Factor 3	0.45***	0.33***	0.33**	0.49***	0.06	-0.04
	(6.31)	(4.93)	(2.42)	(3.27)	(0.46)	(-0.25)
alpha	**8.18*** **	**4.67*** **	**-16.62*** **	**-13.71*** **	**25.14*** **	**18.61*** **
	(5.13)	**(3.28)**	**(-6.82)**	**(-4.7)**	**(6.94)**	**(5.22)**

This table shows the factor exposure for equally (EW) and value weighted portfolios (VW) constructed based on the highest (lowest) 10% calculated probabilities of outperformance.

Table 9: Large capitalized firms:

Portfolio (decile)	CAGR	Vola	SR	alpha	MV
MSCI World	5.20	15.52	0.33		
Top EW	13.80	11.69	1.18	6.75***	31.240
Top MVW	12.09	11.95	1.01	5.25***	31.240
Bottom EW	-0.70	18.33	-0.04	-1.34	27.630
Bottom MVW	0.01	17.07	0.00	-1.56	27.630
TB EW	13.23	12.84	1.03	11.94***	29.435
TB MVW	10.73	12.58	0.85	10.1***	29.435

Performance metrics for portfolios of large firm (larger than $10 billion) only.

Table 10: Large capitalized firms:

Portfolio (decile)	CAGR	Vola	SR	alpha	MV
MSCI World	5.20	15.52	0.33		
Top EW	14.91	11.70	1.27	8.23***	13.89
Top MVW	12.93	11.74	1.10	6.27***	13.89
Bottom EW	-3.78	17.94	-0.21	-4.89*	9.71
Bottom MVW	-3.74	17.50	-0.21	-5.38**	9.71
TB EW	17.99	11.63	1.55	16.2***	11.80
TB MVW	15.92	11.78	1.35	14.91***	11.80

Performance metrics for portfolios of large firm based on a relative size threshold. We define large stocks as those that represent at least 0.01% of the overall market capitalization.

Table 11: Optimized randomly drawn portfolios:

Shorting	Portfolio	CAGR	Vola	SR	alpha	NZP
	MSCI World	5.20	15.52	0.33		
No	EW	6.00	13.27	0.45	2.26	50
	MVW	5.88	12.90	0.46	2.16	50
No	MeanVP$_{ret}$	3.38	21.09	0.16	-3.81	12
	MeanVP$_{proba}$	11.34	11.19	1.01	6.38**	12
Yes	MeanVP$_{ret}$	7.35	60.94	0.12	-1.0	49
	MeanVP$_{proba}$	16.73	25.07	0.67	13.7*	49

We randomly select stocks with a market capitalization of more than \$10 billion and compare different portfolio strategies. $MeanVP_{ret}$ is a mean-variance portfolio using past returns as proxy for future returns, $MeanVP_{proba}$ is a mean-variance portfolio using shifted outperformance probabilities as a measure of future returns. *NZP*: is the amount of non-zero weights of fifty investment options.

Table 12: Regional differences:

Region	CAGR	Vola	SR	alpha	MV	Firms
LS Equal Weights						
USA	21.33	13.77	1.55	19.04***	3.775	1956
Europe	22.97	10.50	2.19	20.18***	4.585	1163
Pacific	37.26	15.16	2.46	32.95***	3.245	979
Emerging	26.75	13.17	2.03	23.35***	2.78	2803
LS Value Weights:						
USA	18.27	14.97	1.22	15.06***	3.775	1956
Europe	14.54	13.45	1.08	14.18***	4.585	1163
Pacific	25.90	18.65	1.39	24.12***	3.245	979
Emerging	23.50	15.33	1.53	18.07***	2.78	2803

Equally and Value weighted portfolios based on stocks issued in different regions using the MSCI classifications. We subdivide the dataset into regions and then apply a decile based on the outperformance probability split. We then simulate long-short portfolios and present the results here.*Firms* is the average total amount of investment options.

Table 13: Portfolio performance within different time periods

Group	EW Top	VW Top	EW Bottom	VW Bottom	EW TB	VW TB
Volatility index						
low	8.76***	5.29***	-2.83	-1.33	14.93***	10.89**
	(5.51)	(3.41)	(-0.74)	(-0.29)	(3.23)	(2.27)
high	13.21***	8.54***	-18.65***	-12.55**	31.31***	20.69***
	(4.16)	(2.59)	(-4.15)	(-2.24)	(6.23)	(3.85)
Spread						
low	9.1***	4.8***	-0.81	1.04	13.54***	9.31**
	(4.91)	(3.26)	(-0.21)	(0.21)	(2.91)	(2.07)
high	12.94***	7.91***	-17.74***	-13.67***	31.63***	22.98***
	(4.78)	(2.66)	(-5.27)	(-3.1)	(7.56)	(4.65)
Sentiment						
low	10.47***	6.24***	-10.6***	-8.06**	24.75***	19.1***
	(4.56)	(2.96)	(-3.14)	(-2.0)	(5.77)	(4.6)
high	13.91***	9.2***	-8.59**	-5.29	21.5***	14.75***
	(4.47)	(2.94)	(-2.13)	(-0.95)	(3.78)	(2.44)
Time						
2011-2018	9.87***	5.14***	-4.28	-1.6	16.68***	12.32***
	(5.35)	(2.78)	(-1.1)	(-0.31)	(4.0)	(2.96)
2004-2011	11.65***	7.33**	-14.92***	-12.08***	27.72***	20.12***
	(4.07)	(2.3)	(-5.02)	(-3.12)	(6.74)	(4.18)

We conduct median splits based on variables like volatility, sentiment, spread and time to assess the performance of different portfolios in different periods of time. We consider investments into 10% of the stocks with the largest (lowest) outperformance probabilities.

Table 14: Portfolio strategies vs. Benchmark index, 100 stocks max.

Portfolio	AER	TC	CAGR	Vola	SR	Alpha
Long	83.32	7.3	20.19	11.17	1.81	14.27***
Low AER Long	6.83	0.59	12.20	8.85	1.38	8.85***
Short	86.63	7.59	16.18	20.84	0.78	15.34***
Low AER Short	23.41	2.05	10.2	19.98	0.51	11.42***

We compare the performance of two equally weighted investment strategies with a portfolio size of 100 for both long and short legs We denote the average exit rate of a portfolio in as AER. The yearly transaction costs TC are estimated by multiplying the average bid-ask spread with the monthly AER and then scaling it to yearly estimates by multiplying the result by 12. We thus denote the estimated relative costs of implementing the portfolio strategy. All of these measures are denoted in percent.

Table 15: List of features

	Acronym	Description/Source
1	avg. 50	Return of the last 50 trading days
2	avg. 100	Return of the last 100 trading days
3	avg. 200	Return of the last 200 trading days
4	sharpe_ratio	Yearly return divided by yearly volatility, assuming risk free rate of 0.
5	adj_sharpe_ratio	Yearly return divided by yearly volatility corrected for skewness.
6	skewness	Skewness of daily returns
7	kurtosis	Kurtosis of daily returns
8	max_spread	Maximum difference between largest and smallest daily return
9	avg_return	Average daily return
10	short_vola	Daily volatility during last 50 trading days.
11	long_vola	Daily volatility during last year.
12	difference_vola	Difference between short- and long-term daily volatility.
13	trade_days	Number of trade days within the last year
14	volume_adi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
15	volume_obv	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
16	volume_cmf	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
17	volume_fi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
18	volume_mfi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
19	volume_em	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
20	volume_sma_em	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
21	volume_vpt	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
22	volume_nvi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
23	volume_vwap	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volume-indicators
24	volatility_atr	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
25	volatility_bbm	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
26	volatility_bbh	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
27	volatility_bbl	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
28	volatility_bbw	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
29	volatility_bbp	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
30	volatility_bbhi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
31	volatility_bbli	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
32	volatility_kcc	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
33	volatility_kch	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
34	volatility_kcl	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
35	volatility_kcw	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
36	volatility_kcp	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
37	volatility_kchi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
38	volatility_kcli	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
39	volatility_dcl	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
40	volatility_dch	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
41	volatility_dcm	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
42	volatility_dcw	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
43	volatility_dcp	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
44	volatility_ui	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#volatility-indicators
45	trend_macd	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
46	trend_macd_signal	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
47	trend_macd_diff	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
48	trend_sma_fast	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
49	trend_sma_slow	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
50	trend_ema_fast	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators

Table 16: List of features (continued)

	Acronym	Description/Source
50	trend_ema_fast	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
51	trend_ema_slow	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
52	trend_adx	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
53	trend_adx_pos	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
54	trend_adx_neg	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
55	trend_vortex_ind_pos	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
56	trend_vortex_ind_neg	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
57	trend_vortex_ind_diff	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
58	trend_trix	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
59	trend_mass_index	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
60	trend_cci	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
61	trend_dpo	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
62	trend_kst	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
63	trend_kst_sig	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
64	trend_kst_diff	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
65	trend_ichimoku_conv	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
66	trend_ichimoku_base	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
67	trend_ichimoku_a	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
68	trend_ichimoku_b	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
69	trend_visual_ichimoku_a	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
70	trend_visual_ichimoku_b	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
71	trend_aroon_up	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
72	trend_aroon_down	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
73	trend_aroon_ind	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
74	trend_psar_up	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
75	trend_psar_down	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
76	trend_psar_up_indicator	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
77	trend_psar_down_indicator	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
78	trend_stc	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#trend-indicators
79	momentum_rsi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
80	momentum_stoch_rsi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
81	momentum_stoch_rsi_k	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
82	momentum_stoch_rsi_d	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
83	momentum_tsi	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
84	momentum_uo	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
85	momentum_stoch	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
86	momentum_stoch_signal	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
87	momentum_wr	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
88	momentum_ao	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
89	momentum_kama	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
90	momentum_roc	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
91	momentum_ppo	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
92	momentum_ppo_signal	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
93	momentum_ppo_hist	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#momentum-indicators
94	others_dr	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#others-indicators
95	others_dlr	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#others-indicators
96	others_cr	https://technical-analysis-library-in-python.readthedocs.io/en/latest/ta.html#others-indicators