UCLA Anderson School of Management

2020 Applied Finance Project: Machine Learning for Equity Factor Rotation Modeling

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1. Introduction

The goal is to use comprehensive indicator systems, such as macroeconomic and fundamental indicators in multiple machine learning models to forecast the future performance of (6-12 month) equity factors and form a factor rotation investment strategy. The project is a classification problem where the dependent variables are the performance of various equity style strategies, and the independent variables are the macroeconomic and fundamental indicators. The model developed in the project would provide an investment direction for each equity style and the level of confidence in the predictions. Using these predictions, asset managers can dynamically adjust their portfolio allocations in regards to equity style strategies, size factor or Value factor (B/M).

1.1 Executive summary

Using our forecast, we form a factor rotation portfolio strategy, and we found evidence that factor timing strategies can add significant values as compared to a simple static strategy.

After reviewing the literature, we gathered many pertinent features and models needed to perform the main objectives. Then, we process the features and implement feature engineering to reduce the dimensionality of the features in hope to reduce noise. Afterwards, we input the subsetted features into the models and was able to provide robust signals for each of the factors. We present our findings below.

Our primary findings in the mid-point analysis include:

1. Size rotation strategy: 8.8% annual excess return and 0.54 Sharpe ratio.
    a. Higher than static strategy: 6.8% return and 0.41 Sharpe ratio.
2. Value rotation strategy: 8.6% annual excess return and a 0.57 Sharpe ratio.
    a. Higher than static strategy: 6.8% return and 0.46 Sharpe ratio.
3. Linear models tend to generate the best overall prediction.

2. Literature Review

Tactical Style Allocation— A New Form of Market Neutral Strategy -- by NOËL AMENC, PHILIPPEMALAISE, LIONELMARTELLINI, AND DAPHNE SFEIR

The belief in "style timing or tactical style allocation strategies aimed at exploiting evidence of predictability in style factor". Noel et al. confirmed value outperforms growth if the interest rate is steepening, and small outperforms big if big performed extremely well last month. Based on these observations, Noel et al. confirmed the presence of predictability in growth/value and size style differentials leveraging anticipating market reactions to known economic variables. Rather than using 400 and more economic variables, they short-listed 30 intuitive variables that are related to interest rate, volatility, liquidity, and more. They used a multi-factor modeling approach and updated the model with Kalman filter, comparing with logit regression to forecast bets recommendation with probability rather than absolute values, with Bet 1 being a bet on the Growth minus Value ETF strategy and Bet 2 is a bet on the Small minus Big ETF strategy. If no satisfactory is available, 100% of the portfolio is invested in cash. The idea to combine leverage constraint, the possibility of investing in cash, and using Kalman filters will be important in the model selection phase of this project.

How Can "Smart Beta" Go Horribly Wrong? -- by Arnott, R., Beck, N., Kalesnik, V., and West, J.

This is the first of a series on the future of smart beta by Arnott et al. To predict the relative factor-return of value vs growth, they find the P/B valuation ratio, the average P/B ratio for the value portfolio divided by the average P/B ratio for the growth portfolio, are useful. Also, this valuation measure can be exploited to other factors, like size, liquidity, and profit. The correlations between subsequent 5-year excess returns of predictive factors and the P/B valuation ratio are strongly negative. Since it presents that a high valuation ratio implies that the portfolio is expensive (the long portfolio has higher P/B than the short one does), the 5-year future returns tend to below. This fact gives a concrete interpretation, and it enables us to incorporate this variable in our project.

To win with "Smart Beta" Ask If the Price is Right— by Arnott, R., Beck, N., Kalesnik, V., and West, J.

This is the second of a series on the future of smart beta by Arnott et al. Related to "How Can "Smart Beta" Go Horribly Wrong?", they enhance the analysis of predicting the factor returns by adding new explanatory variables. In addition to the P/B valuation ratio, they broaden the forecast horizon from 1 predictor to 4 predictors. New variables are Price to Earnings ratio, Price to Dividend ratio, and Price to Sales ratio. They also use these financial indicators as a valuation ratio, creating aggregate valuation in a similar way to P/B valuation in Arnot et al (2016). The aggregate score makes it easier to create these valuations as it helps us comfortably to treat the missing value of those financial indicators. Using these variables, they sharpen the prediction for the factor returns. Prediction for factor returns can improve their t-stat significantly in many factors.

The Promises and Pitfalls of Factor Timing -- by J. Bender, X. Sun, R. Thomas, V. Zdorovtsov

Factor timing is defined as the time-varying factor performance, and it has been an area of academic and practitioner research for decades. In the paper, dividing the 47 predictors into specific categories, Financial condition, Economic Cycle, Risk Sentiment, Valuation, and Trend/Momentum, examine a statistical relationship with factor returns and those predictors. The test for predictability of indicators is univariate regressions of non-overlapped 3-month factor excess returns against the predictors. Depending on the horizons, the number of statistically significant predictors changes. Since this observation implies that the predictability is not stable over time, we should be careful to choose the predictors depending on our investment horizon. In addition, to test the validity of the model, they divide the data periods into 1970-1990 and 1990-2010. Although multiple predictors can be statistically significant from 1970 to 1990, they cannot confirm that many predictors work in the out-sample period. This result may deny that those predictors do not have the predictability of factor timing, but we do not have to conclude that the machine learning methods will reach a similar result. Therefore, we plan to include the data used in this paper as a candidate for predictors in our project.

Share Issuance and Factor Timing -- by Robin M. Greenwood and Samuel Gregory Hanson

It is well known that firms that issue stock subsequently earn low returns relative to other firms. In this paper, Greenwood and Hanson show that corporate equity issuance, specifically the issuer–repurchaser spreads can be used to forecast characteristic-based factor returns. The results are significant in seven characteristics including book-to-market, size, nominal share price, distress, payout policy, profitability, and industry. The "strongest and most robust results, however, are for book-to-market and size—that is, the issuer–repurchaser spreads are useful for forecasting the SMB and HML factors, therefore factor timing for these two factors ... While the relationship between expected returns and individual firm issuance and repurchase decisions will be noisy, the full cross-section of net stock issuance may contain valuable information about characteristic-level expected returns." For example, if the characteristic in question is B/M, then it is simply the return on the Fama and French HML portfolio. For the size (ME) characteristic, the return is negative one times SMB. Greenwoods and Hanson's main prediction is that the long-short portfolio for a given characteristic will underperform the following periods when the issuer–repurchaser spread is high. One concern with the results is that the paper might simply be repackaging the net issuance anomaly in characteristic space, instead of time-varying characteristic expected returns. To address this concern, Greenwood then forecasts the returns to "issuer-purged" characteristic portfolios computed using only the set of non-issuing firms.

Factor Timing -- by Valentin Haddad, Serhiy Kozak, Shrihari Santosh

This paper empirically shows that an optimal factor timing is equivalent to the stochastic discount factor. Thus, to estimate the stochastic discount factor, this paper uses Principal Component Analysis (PCAs) in the largest explained variation. They found the first 5 components from their 50 anomaly portfolio accurately represent the returns, leading to a large dimension reduction from the 50 anomalies.

3. Data Description

3.1 Data Description

Based on our goals, targets are future factor returns of SMB and HML. We can use these factor returns from Kenneth R. French website, however, we prefer to use Russell indices as a proxy variable because they have a couple of advantages. First advantage is that compared to the portfolio that is introduced in Fama and French (1988), it is much less complicated to invest in ETFs underlying such indices. Thus, it is directly investable. To replicate the returns French's website, we would also need to invest in a wide range of stocks to build the theirl HML and SMB portfolios. We also know that Russell indices are a large part of the major indices in the US market, and so they cover a wide array of ETFs strategies that relate to Russell indices. These ETFs correlate highly with the actual factor. Secondly, the time series data of those indices can be downloaded directly from Bloomberg, so it is much easier to process data. We can also pull many other predictors from bloomberg. Below illustrates the indices below to calculate HML and SMB factor returns.

Table 3.1 Our targets

Facto: Index	**Description**
Small: Russell 2000 Index (RTY)	Smallest 2000 companies in Russell 3000 Index
Big: Russell 1000 Index (RIY)	Largest 1000 companies in Russell 3000 Index
Value: Russell Value Index (RAV)	Value-weighted by P/B ratio
Growth: Russell Growth Index (RAG)	Value-weighted by P/E ratio

In this section, we will discuss the types of predictors available and the rationality of those variables. Based on the literature reviews, we prepare more than 70 time-series data that belong to the four categorical groups. The papers in our literature reviews confirmed the predictability of data for future factor returns, and most of the data could be easily found in Bloomberg. Table 3.2 summarizes the four main categories of predictors, and we will state how those categories can make our analysis valuable.

Table 3.2 Categories of Dataset

Category	Examples of Predictors
Market	S&P 500, US Term Spread (10year – 2 year), Credit Spread
Valuation Indicator	P/E, Dividend Payout Ratio, Price to Sales Ratio
Economic Indicator	ISM PMI, CPI, Consumer Confidence
Financial Condition	M2 Index, FF rate, US Total Debt Outstanding

First of all, the variables in the Market and Valuation Indicator Category have information about various assets' historical returns and the states of firms. Those categories can capture the momentum, seasonality, or trend of the market that represents investor sentiment or what is happening in the market. In a sense, we will include those variables to grasp the relationship with past market movements and future factor returns. Secondly, Economic Indicators have an impact on future economic cycles in the long term. For example, ISM PMI describes the sentiment of firms, and it positively relates to business activities ahead. Next, although the Financial Condition and Economic Indicator are closely related to each other, we treat those categories separately. This is because a financial condition is becoming a more valuable clue in the recent market, especially, after the Lehman shock, the central banks actively have implemented their monetary policies, including quantity easing, negative interest rate, etc., to deal with a potential economic recession. Therefore, it is necessary to separate the category of the Financial Condition from Economic Indicator.

3.2 Data Processing

To draw valuable information properly, we will transform the data to stationary and the scales through several ways before running the model. Unless the data are already appropriately stationary, the distributions of time-series data can be inconsistent. This situation implies that the quality of information can vary in their time-series. In other words, expectations and variances can change depending on periods.

1. The form (Seasonality) of data: Based on the convention of the data treatment, we will apply an appropriate form of data, like month to month, or year over year.
2. Smoothing data: Since we have several noisy data, use moving average to create a smooth data series.

3. Demean and Detrend: Some data has an obvious trend or mean, like down-trend capacity utilization, or ISM PMI that has a neutral level at 50. In the detrending, we use the linear trend and the Hodrick-Prescott (HP) Filter.
4. Winsorization: We observe several significant outliers in our dataset due to an abnormal market event. Since those outliers will make the value of other normal movements of data smaller, they should be eliminated to preserve the features of the data. After implementing all those data processing, we will standardize data to select key features of the dataset. This is because some methods of key feature selection require standardized data. For example, in the principal component analysis, we will measure the euclidean distance between every variable. If the data has different scales, it is hard to obtain valuable results from such an analysis.

3.2.1 Summary of original features

Table 3.3 Common Predictors

Symbol	Ticker / Field	Data Resource	Category	Data Description	Data Treatment 1	Data Treatment 2	Data Treatment 3
SMB_MA3	RTY Index, RIY Index	Bloomberg	Market	SMB Monthly Return MA	3 months MA	raw	winsorize
SMB_MA6	RTY Index, RIY Index	Bloomberg	Market	SMB Monthly Return MA	6 months MA	raw	winsorize
HML_MA3	RAG Index, RAV index	Bloomberg	Market	HML Monthly Return MA	3 months MA	raw	winsorize
HML_MA6	RAG Index, RAV index	Bloomberg	Market	HML Monthly Return MA	6 months MA	raw	winsorize
M1	M1 Index	Bloomberg	Financial Condition	Money Supply M1	Year over Year	raw	raw
M2	M2 Index	Bloomberg	Financial Condition	Money Supply M2	Year over Year	raw	raw
BankAsset	ALCBC&IL Index	Bloomberg	Financial Condition	Commercial Bank Assets Loans & Lease	Year over Year	raw	raw
PCE	PCE CYOY Index	Bloomberg	Economic Indicator	Personal Consumption Expenditure	Year over Year	raw	raw
CapacityUtilization	CPTICHNG Index	Bloomberg	Economic Indicator	US Capacity Utilization	HP Filter	raw	winsorize
DebtOutstanding	DEBPINNT Index	Bloomberg	Financial Condition	US Total Debt Outstanding	Year over Year	raw	raw
ConsumerCredit	CCOSTOT Index	Bloomberg	Economic Indicator	Fed Consumer Credit Outstanding	Year over Year	raw	raw
SavingRate	PIDSDPS Index	Bloomberg	Economic Indicator	US Personal Saving Rate	Year over Year	raw	winsorize
ConsumerConfidence	CONCCONF Index	Bloomberg	Economic Indicator	Conference Board Consumer Confidence	raw	Demean by 100	raw
PersonalIncome	PITLYOY Index	Bloomberg	Economic Indicator	US Personal Income	raw	raw	raw
CPIYOY	CPI YOY Index	Bloomberg	Economic Indicator	US CPI	raw	raw	raw
PPIYOY	PPI YOY Index	Bloomberg	Economic Indicator	US PPI	raw	raw	raw
Unemployment	USRTOT Index	Bloomberg	Economic Indicator	US Unemployment Rate	raw	raw	winsorize
EmploymentTrend	ETI INDX Index	Bloomberg	Economic Indicator	US Employment Trend Index	HP Filter	raw	winsorize
NewHomes	NHSLTOT Index	Bloomberg	Economic Indicator	US New Home Sales	Year over Year	raw	raw
SPX_MA3	SPX Index	Bloomberg	Market	S&P500 Monthly Return MA	3 months MA	raw	raw
SPX_MA6	SPX Index	Bloomberg	Market	S&P500 Monthly Return MA	6 months MA	raw	raw
LeadingIndicatorUS	LEI TOTL Index	Bloomberg	Economic Indicator	Conference Board Economic Leading Index	HP Filter	raw	winsorize
ISMPMI	NAPMPMI Index	Bloomberg	Economic Indicator	ISM PMI	raw	Demean by 50	raw
Coincident	COI TOTL Index	Bloomberg	Economic Indicator	Conference Board Economic Coincidence Indicator	HP Filter	raw	winsorize
LeadingIndicatorOECD	OEUSKLAC Index	Bloomberg	Economic Indicator	OECD Economic Leading Indicator	raw	Demean by 100	raw
IP	IP Index	Bloomberg	Economic Indicator	US Industorial Product	HP Filter	raw	winsorize
Commodity_MA3	BCOMTR Index	Bloomberg	Market	BBG Commodity Index MA	3 months MA	raw	raw
Commodity_MA6	BCOMTR Index	Bloomberg	Market	BBG Commodity Index MA	6 months MA	raw	raw
Michigan	CONSSENT Index	Bloomberg	Economic Indicator	University of Michigan Consumer Sentiment	raw	Demean	raw
FFRate	FEDL01 Index	Bloomberg	Financial Condition	Fed Funds Rate	raw	raw	raw
DXY_MA3	DXY Index	Bloomberg	Market	DXY Index Monthly Return MA	3 months MA	raw	raw
DXY_MA6	DXY Index	Bloomberg	Market	DXY Index Monthly Return MA	6 months MA	raw	raw
LeadingSpread	LEI IRTE Index	Bloomberg	Economic Indicator	LEI - 10Y yield spread	raw	raw	raw
TwoYTenYSpread	USYC2Y10 Index	Bloomberg	Market	US 2y-10y spread	raw	raw	raw
TenRealYield	RR10CUS Index	Bloomberg	Market	US 10y real yield	raw	raw	raw
LeadingCredit	LEI LCI Index	Bloomberg	Economic Indicator	Conference Board Leading Credit Index	raw	Demean	winsorize
RecessionProb	NYFYPROB Index	Bloomberg	Economic Indicator	NY Fed Recession Probability	raw	raw	raw
CAPE		Shiller's web	Financial Condition	CAPE Ratio	raw	raw	raw
IGSpread	LUACOAS Index	Bloomberg	Market	Investment Grade credit spread	raw	raw	winsorize
HYSpread	LF98OAS Index	Bloomberg	Market	High Yield Spread	raw	raw	winsorize
UnitHousing	NHSPSTOT Index	Bloomberg	Economic Indicator	US New Housing Unit Started	Year over Year	raw	raw
US2YR	USGG2YR Index	Bloomberg	Financial Condition	US 2 year yield	raw	raw	raw
Libor3M	US0003M Index	Bloomberg	Financial Condition	US Libor 3 month rate	raw	raw	raw
TedSpread	.TED G Index	Bloomberg	Financial Condition	Ted Spread	raw	raw	winsorize

Table 3.4 SMB Valuation Predictors

Symbol	Ticker / Field	Data Resource	Category	Data Description	Data Treatment 1	Data Treatment 2	Data Treatment 3
PE_RIY	RIY index / indx general pe ratio	Bloomberg	Valuation Indicator	P/E on RIY	raw	raw	raw
FwdPE_RIY	RIY index / indx general est pe	Bloomberg	Valuation Indicator	forward P/E on RIY	raw	raw	raw
EstPE_RIY	RIY index / est pe next yr aggte	Bloomberg	Valuation Indicator	P/E Estimate on RIY	raw	raw	raw
DVD_RIY	RIY index / dvd payout ratio	Bloomberg	Valuation Indicator	dividend payout ratio on RIY	raw	raw	winsorize
PB_RIY	RIY index / indx px book	Bloomberg	Valuation Indicator	price to book on RIY	raw	raw	winsorize
PS_RIY	RIY index / indx px sales	Bloomberg	Valuation Indicator	price to sales on RIY	raw	raw	raw
EV_RIY	RIY index / ev to t12m ebit	Bloomberg	Valuation Indicator	ev to trailing 12 month ebit on RIY	raw	raw	raw
ROE_RIY	RIY index / return com eqy	Bloomberg	Valuation Indicator	return on equity on RIY	raw	raw	raw
ROA_RIY	RIY index / return on asset	Bloomberg	Valuation Indicator	ROA on RIY	raw	raw	raw
Sales_RIY	RIY index / trail 12m sales per sh	Bloomberg	Valuation Indicator	trailing 12month sales on RIY	HP Filter	raw	raw
EPS_RIY	RIY index / T12 eps aggte	Bloomberg	Valuation Indicator	eps on RIY	HP Filter	raw	raw
EstEPS_RIY	RIY index / best eps	Bloomberg	Valuation Indicator	estimated eps on RIY	Year over Year	raw	raw
DebtToEV_RIY	RIY index / net debt to ev	Bloomberg	Valuation Indicator	net debt to ebitda on RIY	raw	raw	winsorize
DebtToAsset_RIY	RIY index / tot debt to tot asset	Bloomberg	Valuation Indicator	total debt to total asset on RIY	raw	raw	raw
Beta_RIY	RIY index / beta raw overridable	Bloomberg	Valuation Indicator	beta on RIY	raw	raw	raw
PE_RTY	RTY index / indx general pe ratio	Bloomberg	Valuation Indicator	P/E on RTY	raw	raw	winsorize
FwdPE_RTY	RTY index / indx general est pe	Bloomberg	Valuation Indicator	forward P/E on RTY	raw	raw	winsorize
EstPE_RTY	RTY index / est pe next yr aggte	Bloomberg	Valuation Indicator	P/E Estimate on RTY	raw	raw	raw
DVD_RTY	RTY index / dvd payout ratio	Bloomberg	Valuation Indicator	dividend payout ratio on RTY	raw	raw	winsorize
PB_RTY	RTY index / indx px book	Bloomberg	Valuation Indicator	price to book on RTY	raw	raw	raw
PS_RTY	RTY index / indx px sales	Bloomberg	Valuation Indicator	price to sales on RTY	raw	raw	raw
EV_RTY	RTY index / ev to t12m ebit	Bloomberg	Valuation Indicator	ev to trailing 12 month ebit on RTY	raw	raw	winsorize
ROE_RTY	RTY index / return com eqy	Bloomberg	Valuation Indicator	return on equity on RTY	raw	raw	raw
ROA_RTY	RTY index / return on asset	Bloomberg	Valuation Indicator	ROA on RTY	raw	raw	raw
Sales_RTY	RTY index / trail 12m sales per sh	Bloomberg	Valuation Indicator	trailing 12month sales on RTY	HP Filter	raw	raw
EPS_RTY	RTY index / T12 eps aggte	Bloomberg	Valuation Indicator	eps on RTY	HP Filter	raw	raw
EstEPS_RTY	RTY index / best eps	Bloomberg	Valuation Indicator	estimated eps on RTY	Year over Year	raw	raw
DebtToEV_RTY	RTY index / net debt to ev	Bloomberg	Valuation Indicator	net debt to ebitda on RTY	raw	raw	winsorize
DebtToAsset_RTY	RTY index / tot debt to tot asset	Bloomberg	Valuation Indicator	total debt to total asset on RTY	raw	raw	raw
Beta_RTY	RTY index / beta raw overridable	Bloomberg	Valuation Indicator	beta on RTY	raw	raw	raw

Table 3.5 HML Valuation Predictors

Symbol	Ticker / Field	Data Resource	Category	Data Description	Data Treatment 1	Data Treatment 2	Data Treatment 3
PE_RAG	RAG index / indx general pe ratio	Bloomberg	Valuation Indicator	P/E on RAG	raw	raw	raw
FwdPE_RAG	RAG index / indx general est pe	Bloomberg	Valuation Indicator	forward P/E on RAG	raw	raw	raw
EstPE_RAG	RAG index / est pe next yr aggte	Bloomberg	Valuation Indicator	P/E Estimate on RAG	raw	raw	raw
DVD_RAG	RAG index / dvd payout ratio	Bloomberg	Valuation Indicator	dividend payout ratio on RAG	raw	raw	winsorize
PB_RAG	RAG index / indx px book	Bloomberg	Valuation Indicator	price to book on RAG	raw	raw	raw
PS_RAG	RAG index / indx px sales	Bloomberg	Valuation Indicator	price to sales on RAG	raw	raw	raw
EV_RAG	RAG index / ev to t12m ebit	Bloomberg	Valuation Indicator	ev to trailing 12 month ebit on RAG	raw	raw	raw
ROE_RAG	RAG index / return com eqy	Bloomberg	Valuation Indicator	return on equity on RAG	raw	raw	raw
ROA_RAG	RAG index / return on asset	Bloomberg	Valuation Indicator	ROA on RAG	raw	raw	raw
Sales_RAG	RAG index / trail 12m sales per sh	Bloomberg	Valuation Indicator	trailing 12month sales on RAG	HP Filter	raw	raw
EPS_RAG	RAG index / T12 eps aggte	Bloomberg	Valuation Indicator	eps on RAG	HP Filter	raw	raw
EstEPS_RAG	RAG index / best eps	Bloomberg	Valuation Indicator	estimated eps on RAG	Year over Year	raw	raw
DebtToEV_RAG	RAG index / net debt to ev	Bloomberg	Valuation Indicator	net debt to ebitda on RAG	raw	raw	raw
DebtToAsset_RAG	RAG index / tot debt to tot asset	Bloomberg	Valuation Indicator	total debt to total asset on RAG	raw	raw	raw
Beta_RAG	RAG index / beta raw overridable	Bloomberg	Valuation Indicator	beta on RAG	raw	raw	raw
PE_RAV	RAV index / indx general pe ratio	Bloomberg	Valuation Indicator	P/E on RAV	raw	raw	raw
FwdPE_RAV	RAV index / indx general est pe	Bloomberg	Valuation Indicator	forward P/E on RAV	raw	raw	raw
EstPE_RAV	RAV index / est pe next yr aggte	Bloomberg	Valuation Indicator	P/E Estimate on RAV	raw	raw	raw
DVD_RAV	RAV index / dvd payout ratio	Bloomberg	Valuation Indicator	dividend payout ratio on RAV	raw	raw	winsorize
PB_RAV	RAV index / indx px book	Bloomberg	Valuation Indicator	price to book on RAV	raw	raw	raw
PS_RAV	RAV index / indx px sales	Bloomberg	Valuation Indicator	price to sales on RAV	raw	raw	raw
EV_RAV	RAV index / ev to t12m ebit	Bloomberg	Valuation Indicator	ev to trailing 12 month ebit on RAV	raw	raw	raw
ROE_RAV	RAV index / return com eqy	Bloomberg	Valuation Indicator	return on equity on RAV	raw	raw	raw
ROA_RAV	RAV index / return on asset	Bloomberg	Valuation Indicator	ROA on RAV	raw	raw	raw
Sales_RAV	RAV index / trail 12m sales per sh	Bloomberg	Valuation Indicator	trailing 12month sales on RAV	HP Filter	raw	raw
EPS_RAV	RAV index / T12 eps aggte	Bloomberg	Valuation Indicator	eps on RAV	HP Filter	raw	raw
EstEPS_RAV	RAV index / best eps	Bloomberg	Valuation Indicator	estimated eps on RAV	Year over Year	raw	raw
DebtToEV_RAV	RAV index / net debt to ev	Bloomberg	Valuation Indicator	net debt to ebitda on RAV	raw	raw	winsorize
DebtToAsset_RAV	RAV index / tot debt to tot asset	Bloomberg	Valuation Indicator	total debt to total asset on RAV	raw	raw	raw
Beta_RAV	RAV index / beta raw overridable	Bloomberg	Valuation Indicator	beta on RAV	raw	raw	raw

4. Methodology

4.1 Variable Selection

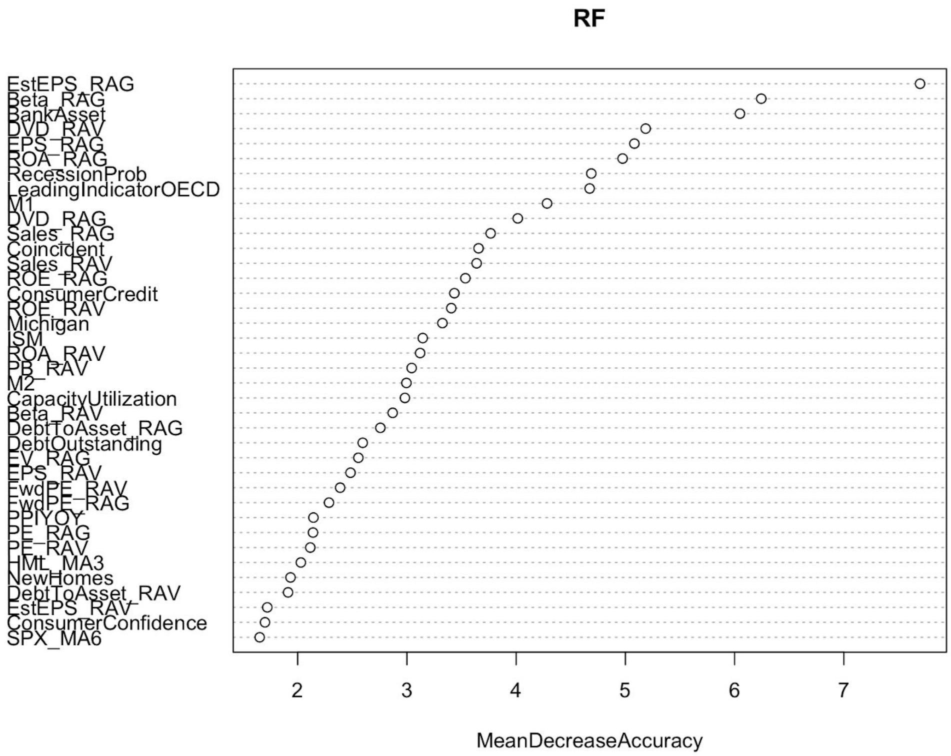
Variable selection is important for our projects because by supplying all variables into a model at once, we face the curse of dimensionality. Issues such as overfitting and less meaningful clusters could arise from high dimensionality. Therefore, our objective is to reduce the number of ineffective, irrelevant, and noisy variables now to increase model prediction accuracy later.

We used 10 methods to generate scores for each feature. These methods are widely used in the industry to perform feature selection. The methods include Random Forest, XGBoost with Logistic Regression with default parameters, XGBoost with Logistic Regression Tuned, PCA, Sparse PCA, Two-Sample T-Test, and Step-wise with Logistic, Elastic Net, Lasso, Gradient Boosting with Bernoulli for classification, and Gradient Boosting with ADA Boosting. The targets that features are aiming to predict in the 10 methods are 6-month, 9-month, and 12-month indicators of small versus big Russell indices, and 6-month, 9-month, and 12-month indicators of growth versus value Russell indices. If a feature is selected or ranked high by a model, it receives a score of 1. The sum of scores from all methods and targets are the final score of a feature. A higher final score indicates higher importance of a feature. The plots are examples from feature selection with regards to the 6-month Russell Value vs Growth target.

Non-linear methods are weighted more because of accuracy, bias, and variance trade-off. Gradient Boosting with ADA, Gradient Boosting with Bernoulli, Random Forest, and XGBoost methods are given a score of 3 when they recommend a feature. Step-wise, Lasso, Elastic Net are given a score of 2. PCA, Sparse PCA, and Two Sample T-Test are given a score of 1. The highest score possible is 21. Feature above score 5 (4 for value factor in 12 months) would be recognized as a recommendation from the 10 models. We chose score 5 to ensure the recommended variables are selected by both linear and non-linear models.

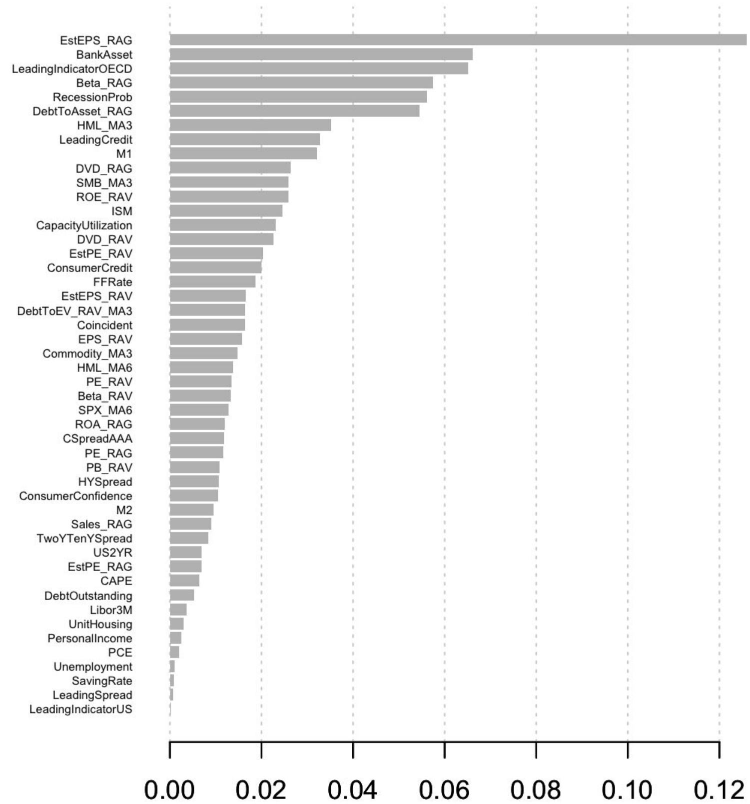
We proceed with a general introduction to each method below. Random Forest is a method of bootstrapping that follows a decision tree. Random Forest has a random selection of m of the p predictors for each bootstrapped sample -- a way to de-correlated the samples. A mean decrease accuracy plot helps us determine a group of predictors that the method recommends. Mean decrease accuracy is the measure of the performance of the model without each predictor. A higher value indicates the importance of that feature in predicting. In our particular case, the threshold value is 3.5. The figure 4.1 shows a significant decline in accuracy at score 4. Variables above score of 4 would be recommended.

Figure 4.1 Example of Random Forest Mean Decrease Accuracy



XGBoost, also called eXtreme Gradient Boosting is a boosting algorithm that has high speed and high accuracy. In XGBoost, we use its importance plot to help us determine a group of predictors. Afterward, we tuned the model using random grid search. The importance provides a score that indicates how useful a feature is in the construction of the boosted decision trees. In our particular case, the threshold value is 0.025. The figure 4.2 shows a significant decline in importance at value 0.03. Variables above importance of 0.03 would be recommended.

Figure 4.2 Example of XGBoost Importance



In PCA, we chose the top 10% features in the first few principal components that explains 20% cumulative variances in all features. We apply the same decision rules for Sparse PCA. PCA usually are linear combinations of all predictors, while Sparse PCA overcomes this disadvantage by finding linear combinations that contain just a few input variables.

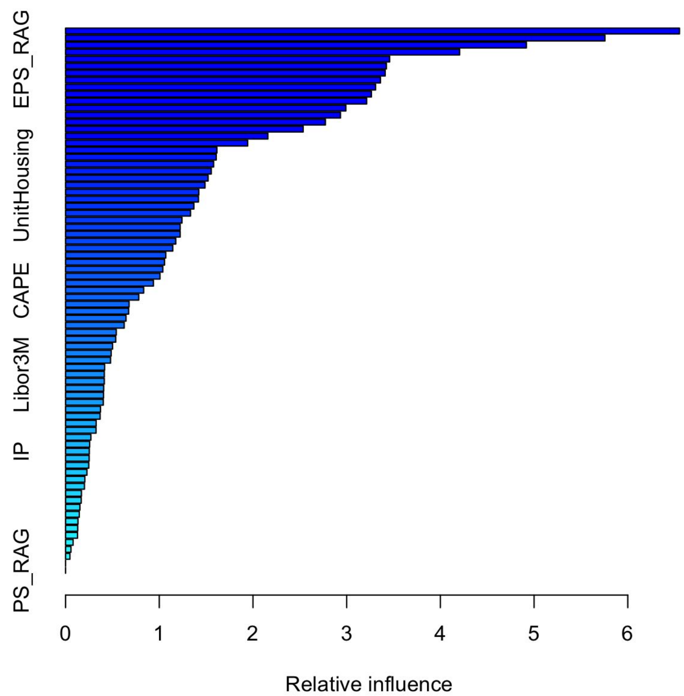
We apply the Two Sample T-Test between our binary classified group for each feature. A high t values for one feature indicates that the respective feature is different for the compared classes. Therefore, the feature may be an appropriate choice for our classification problem. By industrial standard, a p-value of less than 0.05 is our preferred threshold.

Step-wise with Logistic Regression is a way to compare models with different selection of features. The algorithm goes back and forth, hence the name of Step-wise, to decide the optimal number of predictors and the optimal selection of predictors. The optimal model would have the lowest mean square error during cross validation.

Elastic Net and Lasso Regularization are a regularized linear regression by adding a penalized variable to the objective function. Some predictors may be set to zeros in such a process, which helps select predictors.

Gradient Boosting with Bernoulli for classification and ADA are all boosting methods that create stronger tree learners based on previous weaker trees. Bernoulli distribution is commonly used for classification problems. ADA algorithms first train a decision tree with equal weight on all observations. The algorithms then increase weights on observation that are difficult to classify to build on subsequent trees.

Figure 4.3 Example of Relative Influence Importance



4.2 Feature Selection Results

Based on our current data and feature selection methods, we selected approximately 25 variables for Value versus Growth factor rotation, and 25 variables for Small versus Big factor rotation on average for 6-month, 9-month, and 12-month-forward return targets on average. The variables are in the table below based on their score from the highest to the lowest. While the score is one important factor in our current decision, the industry application of these features is also insightful in our selections. To summarize our results, we can group features into 6 categories: Inflation, Technical, Valuation, Consumer Spending, Saving & Sentiments, Producer Output, Spending & Sentiments, Economic Environment, and Currency.

Variables that may reflect inflation levels such as M2, M1, CPI, and more are related to stock returns. It is well-known from Fisher's hypothesis that expected nominal returns should be the sum of expected real returns plus expected inflation, therefore, nominal returns should move as inflation moves if real returns are constant. Inflation also presents a risk in cross sectional return: “stocks whose returns are negatively correlated to inflation shocks command a risk premium” (Duarte,2010). Hence, equity factors are likely to be impacted by inflation and monetary condition variables.

Technical variables such as beta and sales of our indices. Technical variables have long been considered by financial institutions and tested by many researchers. Along with macroeconomic variables, technical variables “provide complementary information over the business cycle: technical indicators better detect the typical decline in the equity risk premium near business-cycle peaks, whereas macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical troughs” (Neely, David E. Rapach, Jun Tu, Guofu Zhou, 2014).

Valuation variables such as return on equity, return on asset, price-to-learning, and more also have impact on style factors. Valuation variables reflect the health of companies that made up an index, therefore reflect the health of the index relative to others.

Producer Spending, Output & Sentiments including ISM, Commodity, and PPI are a reflection of the overall economy. These variables could tell us the price of goods after production, which reflect inflation pressure faced by producers and have impact ripples to final demand in the economy. Consumer Spending, Saving & Sentiments include variables such as personal income, consumer credit outstanding, and University of Michigan consumer sentiment.

Economic environment variables include unemployment, recession probability, two and ten-year spread, and more. The economic environment is linked to financial markets, while not perfectly. Some of these variables are leading indicators that help understand the future state of the markets.

Last but not least, US Dollar strength impacts the import and export level of the economy, which translates to producer spending and output. The number in the bracket under each variable is the score of the variable from the 10 models in table 4.4.

Table 4.4 Variable Selection Result

	6 Month		12 Month	
	Value	Size	Value	Size
1	PCE (17)	PB_RTY (19)	EV_RAG (18)	PB_RTY (17)
2	ConsumerCredit (17)	Commodity_MA6 (18)	M2 (14)	DebtToEV_RTY (14)
3	SavingRate (16)	ROA_RIY (16)	CPIYOY (14)	DebtToAsset_RIY (13)
4	EstEPS_RAG (13)	DXY_MA6 (15)	EstEPS_RAG (13)	PCE (11)
5	SMB_MA3 (13)	DebtToAsset_RIY (12)	DebtToAsset_RAV (12)	ROA_RIY (11)
6	M2 (12)	Commodity_MA3 (11)	TedSpread (11)	Commodity_MA3 (11)
7	DebtToEV_RAV (12)	DXY_MA3 (11)	PE_RAV (10)	DebtOutstanding (10)
8	TenRealYield (11)	LeadingIndicatorUS (10)	SMB_MA3 (10)	ROA_RTY (10)
9	EV_RAG (11)	M1 (9)	Libor3M (9)	PersonalIncome (8)
10	SMB_MA6 (11)	BankAsset (7)	HML_MA3 (6)	PS_RTY (8)
11	CapacityUtilization (9)	PCE (7)	SPX_MA6 (6)	DebtToAsset_RTY (8)
12	ConsumerConfidence (8)	ROA_RTY (7)	CapacityUtilization (5)	IGSpread (7)
13	EstPE_RAG (8)	Coincident (6)	SMB_MA6 (5)	RecessionProb (6)
14	SPX_MA3 (8)	PS_RTY (6)	SPX_MA3 (5)	SMB_MA6 (6)
15	M1 (7)	IGSpread (5)	ConsumerCredit (4)	SavingRate (5)
16	LeadingSpread (7)	DVD_RTY (5)	SavingRate (4)	ConsumerConfidence (5)
17	ROA_RAG (7)	DVD_RIY (5)	Coincident (4)	DVD_RTY (5)

18	DebtToAsset_RAG (7)	DebtToEV_RIY (5)	PE_RAG (4)	DebtToEV_RIY (5)
19	DVD_RAV (7)	UnitHousing (5)	DVD_RAG (4)	Commodity_MA6 (5)
20	DebtToAsset_RAV (7)		Sales_RAG (4)	
21	TedSpread (7)		EstPE_RAV (4)	
22	SPX_MA6 (7)		PB_RAV (4)	
23	RecessionProb (6)		EPS_RAV (4)	
24	Sales_RAG (6)			
25	HML_MA6 (6)			
26	LeadingIndicatorUS (5)			
27	TwoYTenYSpread (5)			
28	PE_RAV (5)			
29	EPS_RAV (5)			
30	EstEPS_RAV (5)			
31	IGSpread (5)			
32	CAPE (5)			
33	Commodity_MA3 (5)			
34	DXY_MA6 (5)			

4.3 Validation and Metric

In utilizing the data above, we apply a cross-validation approach in training and splitting the models to capture the accuracies in each model. Our dependent variable is the lagged 6-month factor returns, and our independent variables are used from the feature selection. We first split the data into 3 different training and testing splits. The first training split uses the first 5 years, the second uses 10 years, and the third uses 15 years. The first test split uses the 18 years after the first training split, the second test split uses the 13 years after the second training split, and the third test split uses the 8 years after the third training split. This will allow us to validate each machine learning method and at the same time avoid the look ahead biases in testing the data. We call this rolling forward cross-validation. There are obvious main advantages in choosing these splits. The most common is that we have the model learn about the dot-com meltdown in the 90s. Then we also learn it right before the financial crisis. The testing period should provide a more robust indication of the market based off of these splits. We visualize the training and test split in the table below. The data starts in June 1996 and stops on June 30, 2020. Note: we lose 1 years of data due to data treatment. Afterward, we evaluate the out-of-sample accuracy based on the mean of the methods' 3 test splits. We call this the hit ratio.

Table 4.5 Training and Testing Splits

Splits	Training	Test
1	1996-2001	2001-2019
2	1996-2006	2006-2019
3	1996-2011	2011-2019

In this section we define a few metrics to evaluate the model. We used 4 metrics to evaluate the models:

- **Hit Ratio**: the prediction accuracy of factor outperformance over the actual total factor outperformance.
- **Evaluation Score (ES):** The average hit ratio minus benchmark (typically 80% for in-sample, 60% for OOS) divided by standard deviation of the 3 hit ratio. A higher score is preferred and it's analogous to the Sharpe Ratio.
- **In-Sample Metric:** The average of the 3 training splits hit ratio.
- **Out-of-Sample (OOS) Metric:** The average of the 3 test splits hit ratio.

In recommending the model, we look at ES score to rank the models.

4.4 Model Selections

We used various classification models to predict whether Small or Big and High or Low Book-to-Market value outperforms the other. We first start off by using discriminant analysis: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Regularized Discriminant Analysis (rDA). Then we apply Support Vector Machines (SVM) with different kernels: SVM Polynomial, SVM Sigmoid, SVM Linear, SVM Radial. Lastly, we used multiple non-parametric methods: KNN, Random Forest (RF), XGBoost Linear, XGBoost Logistic, Catboost. The linear methods tend to outperform the non-linear methods. All of this was done in R, using packages MASS (LDA, QDA), klaR (rDA), e1071 (SVM), caret, randomForest (RF), xgboost, and catboost. We validate the model based on the following few reasons.

Reasonings for the Model Selections:

1. *Small sample size, many features*

   Since we are dealing with monthly financial data, with small sample size and many features, it is not optimal to use methods like Neural Network because it requires a large sample size in order to be effective. Logistic regression, on the other hand, is proven to be effective and widely used in finance in classification problems with a small dataset and many predictors. Therefore, this would be our base model. We will also examine the LDA model and its variants because they use prior probabilities to classify each dependent variable. Indications that discriminate analysis outperforms suggests that physical probability measures could be accurate and classify the factors.

2. *Non-linear relationships in financial data*

   In finance, trees classification models such as Random Forest and Boosted Trees are widely used because of their ability to capture the non-linear relationships in financial data, while avoiding the issues of overfitting. We will examine the popular Random Forest model, and compare it with the more advanced models in XGBoost and CatBoost. Although these advanced models are quite new, they have already earned a high reputation in the Machine Learning community, with a proven record of delivering high predicting accuracy with a small or large sample size and many predictors.

3. *Ideas from Literature*

   Support Vector Machines(SVM) has been used in the literature (Nalbantov et al.) and empirically, it is shown that this model is highly effective in predicting equity factor timing. It is considered one of the best general-purpose algorithms for classification because it can be applied to both linear and non-linear problems. Therefore, we will include SVM in our model selections.

Hyperparameter Tuning Methods:

For XGBoost and Catboost, we will use the Randomized Search method to tune the hyperparameters, because the number of hyperparameters is large. For all other models, we will use the Grid Search method.

4.5 Model Results

Using a rolling forward cross-validation method and then taking the average of in-sample and out-of-sample hit rates, we obtained the below results for our models.

4.5.1 Size

For the size factor, we predict 6 month ahead because the results are much more robust in predicting 6 month than the further time spans. We found SVM with a linear kernel to perform the best by the ES metric. However, logistic regression tends to have the best OOS hit ratio. This means SVM is more stable throughout time. We use cutoff 16 of the feature score because all the best performing models agree on these 3 features: PB_RTY, Commodit_MA6, and ROA_RIY. In the evaluation score, we used 80% for in sample as a benchmark and 65% for OOS benchmark. We can find all of the best model results in the appendix for both 9 months and 12 months.

Table 4.6 Size factor 6 months results

Factor	Models	In-sample Hit Ratio	OOS Hit Ratio	In-sample ES	OOS ES
Size - 6 mo	SVM-Linear	82%	69%	0.41	2.31
Size - 6 mo	SVM-Radial	89%	68%	2.95	1.44
Size - 6 mo	Logistic	79%	70%	-0.50	1.25

4.5.2 Value

For the HML factor, we predict the 12 month ahead because the results are much more robust in predicting 12 month ahead than in the nearer future. We found Logistic regression to perform the best. We also found the other shrinkage methods perform similarly. Then we found KNN to perform the second best in this data set, but there is no direct intuition for this. Thus, report SVM-Linear since it performs almost as well as KNN. In the evaluations core, we used 80% In sample as a benchmark and 69% for the OOS benchmark. We used a high OOS benchmark here because the prediction accuracy tends to be better for HML. It is also interesting to note as the training sample increases for the value factor, the accuracy of the model tends to increase. The top models agree on these 6 inputs: EV_RAG, M2, CPIYOY, EstEPS_RAG, DebtToAsset_RAV, and TedSpread. We can find all of the best model results in the appendix for both 6 months and 9 months.

Table: 4.7 Value factor 12 month results

Factor	Models	In-sample Hit Ratio	OOS Hit Ratio	In-sample ES	OOS ES
Value - 12 mo	Logistic Lasso	88%	72%	1.60	0.60
Value - 12 mo	SVM-Linear	88%	71%	1.75	0.23

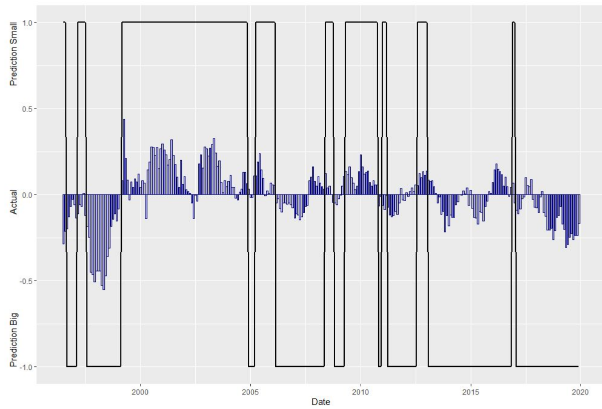
Overall, we see that HML has a more robust hit ratio. The comparison of ES is only valid if they have the same benchmark. We recommend using SVM and Logistic regression because linear models tend to perform better, and they are simpler to understand. SVM also came from literature. We also find that all the top models agree on the same amount of cutoff scores or features to use. Next, we will use the model to generate the signals.

5. Results

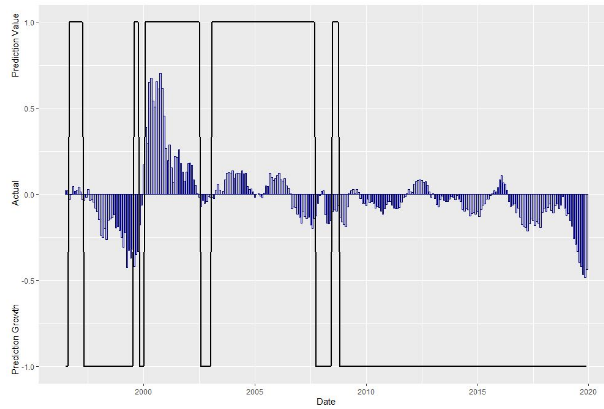
5.1 Portfolio Strategies

For this project, we focus on 2 strategies, size rotation and value rotation. For our size strategy, we will rotate our investments between Russell 2000 and Russell 1000 ETF. For our value strategy, we will rotate between Russell 3000 Value and Russell 3000 Growth, according to our signals. For both cases, we switch strategies only if we see two consecutive signals in the opposite direction. This is for abundance of caution. Because we know changes in regime are long-term in nature, and we want to make sure we switch strategies really at the right time. We want to be cautious since every time we switch a strategy, we commit 100 percent. That's the reason why we choose to construct the portfolios this way. For both strategies, the benchmark is a 50/50 buy and hold portfolio.

Size (1= Small, -1 = Big)



Value (1=Value, -1=growth)



The graphs above show how well our models fit with the actual targets. The black line across the top and the bottom is our prediction, and the blue bars in the middle are the actual 1-year forward size and value premiums. As we can see for size strategies, the changes in signals is between every 12 to 16 months, and that is also consistently with the actual frequency of changes in regime. On the right, we can see our value models also fit well in both training and testing. For both graphs, the hit ratios are around 90% in sample and 70% out of sample.

5.2 Portfolio Evaluation (Split #2, 10 year training/ 15 year testing):

- Portfolios are adjusted with a 5 bps transaction costs
- Benchmark for Size strategy is a 50/50 buy and hold portfolio on Russell 1000 and Russell 2000 ETF. The benchmark for Value is a 50/50 buy and hold portfolio on Russell 3000 Growth, and Russell 3000 Value.

Table 5.1 Portfolio statistics for Size strategy

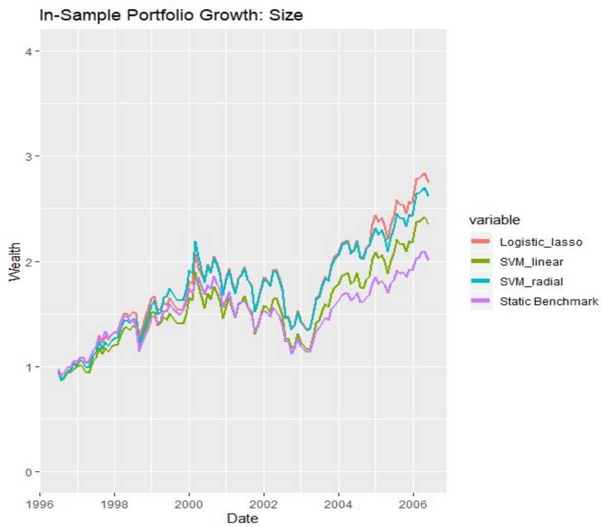
2006-2019	Static Benchmark	SVM_radial	SVM_linear	Logit_Lasso
Mean Excess Returns	6.8%	8.8%	8.8%	8.5%
Standard Deviation	16.5%	16.3%	16.7%	16.7%
Sharpe Ratio	0.41	0.54	0.53	0.50
Tracking Error		3.8%	3.8%	3.9%
Information Ratio		0.53	0.53	0.41
Max Drawdown	53.1%	47.0%	49.3%	49.3%
Max 1m Loss	19.3%	17.6%	19.8%	19.8%
%negative months	36%	33%	32%	32%
Average Turnover		0.48	0.37	0.37
Average Holding Period		12m	16m	16m

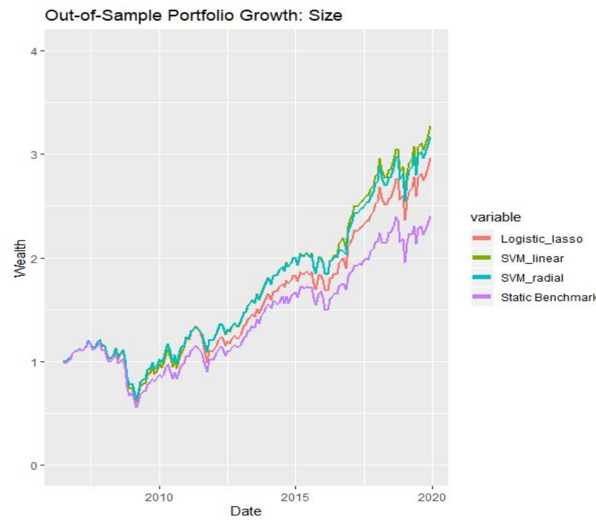
Table 5.2 Portfolio statistics for Value strategy

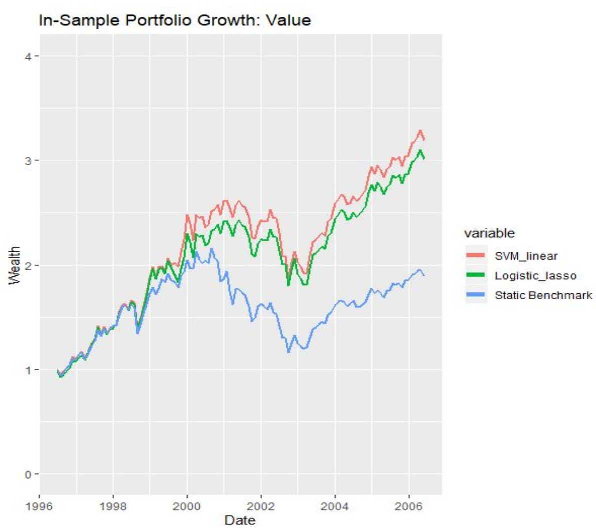
2006-2019	Static Benchmark	SVM_linear	Logit_Lasso
Mean Excess Returns	6.8%	8.7%	8.6%
Standard Deviation	15.0%	15.0%	14.9%
Sharpe Ratio	0.46	0.58	0.57
Tracking Error		3.0%	3.0%
Information Ratio		0.61	0.60
Max Drawdown	53.1%	49.3%	47.0%
Max 1m Loss	19.3%	17.9%	17.9%
%negative months	36%	35%	35%
Average Turnover		0.35	0.22
Average Holding Period		16m	27m

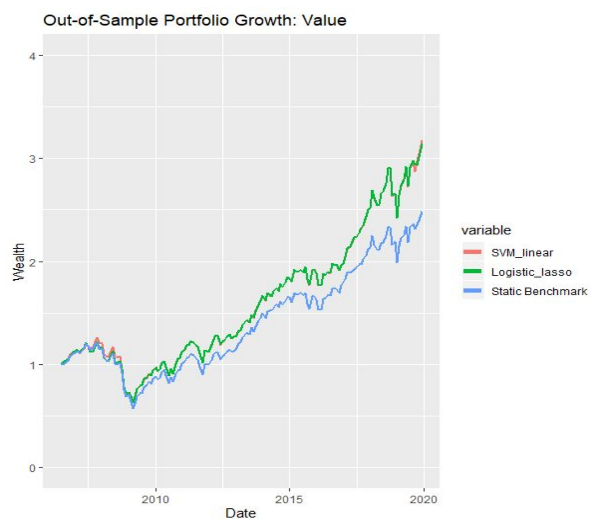
Compared to the static benchmark, not only do our models deliver higher excess returns, they also have higher Sharpe ratios, meaning the extra returns generated by our models are justified with lower marginal risks. The lower risks of our dynamic portfolios are also shown in the lower drawdowns as compared to the benchmark. The information ratios for our value strategies are around 0.60, which is on the higher end if we compare them to the industry average. Overall, all the models selected exhibit strong portfolio performance, all with better statistics across the board than the benchmark portfolios. To visualize how much value those strategies add to our investments, we illustrate the results in figure 5.1.

Figure 5.1 Backtest Results









As we can see in the above plots for portfolio growth, all our strategies outperform the benchmark in both training and testing periods, and the values added are quite significant, even though we use more data to test than we use to train. The value models perform much better in training, and they perform almost the same in testing. That is because in the testing period, growth has consistently outperformed value, and both models are able to pick that up. Our size models perform equally well in both training and testing, meaning that the performance will likely be consistent moving forward.

Next, we will use rolling returns to show how robust the results really are. What we are doing is comparing the compound returns of our dynamic portfolios against those of the benchmarks in the testing period. For example, rolling 6m means, for each month, we compute the forward 6m returns of our portfolios and the benchmark, then we compare them. The first table shows how frequently our models outperform or underperform. As we can see, as the time horizon goes longer to 5 year, our models are able to beat the benchmark 95% of the time. The second table shows the average return differences. As we can see, not only do our models outperform more frequently, they outperform with a larger magnitude than they underperform.

Table 5.3 Average Percent Instances

	Rolling 6M	Rolling 1Y	Rolling 3Y	Rolling 5Y
%Dynamic > Static	64%	73%	86%	95%
%Dynamic ≤ Static	36%	27%	14%	5%

Table 5.4 Average Annual Differences

	Rolling 6M	Rolling 1Y	Rolling 3Y	Rolling 5Y
%Dynamic > Static	64%	73%	86%	95%
%Dynamic ≤ Static	36%	27%	14%	5%

6. Conclusion

Proper data processing as well as features selection are crucial for model performance. Therefore, we start off this process from building 74 stationary processes from the data to predict the target indices. After processing the data we implement common dimension reduction techniques to reduce the amount of features our model will only see. In total, we picked up roughly 20 features for SMB and 25-30 features for HML. Then we pass the subset list of features to the model and run them for each different cutoff. The linear models tend to outperform; and for size factor 6 month ahead were the most accurate and for value factor 12 month were the most accurate. On average, we were able to score roughly 85% in-sample accuracy and 70% out-of-sample accuracy, where the evaluation score tells there consistency throughout time. Lastly, we back tested these models and showed that they outperform the static benchmark in almost all statistical categories. With that, we show using Machine Learning to predict direction of equity factors returns are definitely feasible and could have strong profit potential in practice.

6.1 Possible Future Extensions

1. Expand research on other popular factors: Volatility, Momentum, Liquidity.
2. 3-Level Signal Predictions (i.e. Small, Big, and Neutral) in addition to binary classification.
3. Backtest on Long-Short Portfolios: long signal, short the opposite.
4. Global Markets Expansion: predict which markets (US, EU, UK, Japan, or EM) will outperform in certain periods the future

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6.3 Appendix

6.1 Variable Selection

6M Value

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	PCE	17	NA	3	2	2	2	3	3	1	NA	1
2	ConsumerCredit	17	3	3	NA	2	2	3	3	NA	NA	1
3	SavingRate	16	NA	3	2	2	2	3	3	NA	NA	1
4	EstEPS_RAG	13	3	3	NA	NA	NA	3	3	1	NA	NA
5	SMB_MA3	13	3	3	NA	NA	NA	3	3	1	NA	NA
6	M2	12	NA	3	NA	2	NA	3	3	NA	NA	1
7	DebtToEV_RAV	12	3	NA	2	NA	NA	3	3	1	NA	NA
8	TenRealYield	11	NA	3	NA	2	NA	3	3	NA	NA	NA
9	EV_RAG	11	3	NA	2	2	2	NA	NA	1	1	NA
10	SMB_MA6	11	NA	NA	2	2	2	3	NA	1	1	NA
11	CapacityUtilization	9	NA	NA	2	2	NA	3	NA	1	NA	1
12	ConsumerConfidence	8	NA	NA	2	2	2	NA	NA	NA	1	1
13	EstPE_RAG	8	NA	3	NA	2	NA	NA	3	NA	NA	NA
14	SPX_MA3	8	NA	NA	NA	2	2	3	NA	NA	1	NA
15	M1	7	NA	NA	2	2	2	NA	NA	NA	NA	1
16	LeadingSpread	7	3	NA	NA	2	2	NA	NA	NA	NA	NA
17	ROA_RAG	7	3	NA	NA	2	NA	NA	NA	1	1	NA
18	DebtToAsset_RAG	7	NA	3	NA	2	2	NA	NA	NA	NA	NA
19	DVD_RAV	7	NA	NA	2	2	2	NA	NA	NA	1	NA
20	DebtToAsset_RAV	7	NA	NA	NA	NA	NA	3	3	1	NA	NA
21	TedSpread	7	NA	NA	NA	2	NA	3	NA	1	1	NA
22	SPX_MA6	7	NA	NA	2	2	2	NA	NA	NA	1	NA
23	RecessionProb	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
24	Sales_RAG	6	3	3	NA	NA	NA	NA	NA	NA	NA	NA
25	HML_MA6	6	NA	NA	NA	2	2	NA	NA	1	1	NA
26	LeadingIndicatorUS	5	NA	NA	NA	2	2	NA	NA	NA	NA	1
27	TwoYTenYSpread	5	NA	NA	NA	2	2	NA	NA	NA	1	NA
28	PE_RAV	5	NA	NA	NA	2	2	NA	NA	NA	1	NA
29	EPS_RAV	5	NA	NA	NA	2	2	NA	NA	1	NA	NA
30	EstEPS_RAV	5	NA	NA	NA	2	2	NA	NA	NA	1	NA
31	IGSpread	5	NA	NA	2	NA	NA	3	NA	NA	NA	NA
32	CAPE	5	NA	NA	NA	2	2	NA	NA	NA	1	NA
33	Commodity_MA3	5	NA	NA	NA	2	2	NA	NA	1	NA	NA
34	DXY_MA6	5	NA	3	2	NA	NA	NA	NA	NA	NA	NA

6M Size

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	PB_RTY	19	3	3	2	2	2	3	3	1	NA	NA
2	Commodity_MA6	18	3	3	2	2	2	3	3	NA	NA	NA
3	ROA_RIY	16	3	3	2	NA	NA	3	3	1	1	NA
4	DXY_MA6	15	NA	3	2	2	2	3	3	NA	NA	NA
5	DebtToAsset_RIY	12	3	3	2	2	2	NA	NA	NA	NA	NA
6	Commodity_MA3	11	NA	3	2	NA	NA	3	3	NA	NA	NA
7	DXY_MA3	11	NA	3	2	NA	NA	3	3	NA	NA	NA
8	LeadingIndicatorUS	10	NA	NA	2	2	2	3	NA	NA	NA	1
9	M1	9	NA	NA	2	NA	NA	3	3	NA	NA	1
10	BankAsset	7	3	NA	2	NA	NA	NA	NA	1	NA	1
11	PCE	7	NA	3	NA	NA	NA	3	NA	NA	NA	1
12	ROA_RTY	7	3	3	NA	NA	NA	NA	NA	1	NA	NA
13	Coincident	6	NA	NA	2	NA	NA	3	NA	NA	NA	1
14	PS_RTY	6	3	NA	2	NA	NA	NA	NA	1	NA	NA
15	IGSpread	6	3	NA	2	NA	NA	NA	NA	1	NA	NA
16	DVD_RTY	5	3	NA	NA	NA	NA	NA	NA	1	1	NA
17	DVD_RIY	5	3	NA	2	NA	NA	NA	NA	NA	NA	NA
18	DebtToEV_RIY	5	3	NA	2	NA	NA	NA	NA	NA	NA	NA
19	UnitHousing	5	NA	3	2	NA	NA	NA	NA	NA	NA	NA

9M Value

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	SMB_MA6	18	3	3	NA	2	2	3	3	1	1	NA
2	EstEPS_RAG	17	3	3	NA	2	2	3	3	1	NA	NA
3	SavingRate	16	NA	3	2	2	2	3	3	NA	NA	1
4	TedSpread	14	3	3	NA	NA	NA	3	3	1	1	NA
5	EV_RAG	12	3	3	NA	2	2	NA	NA	1	1	NA
6	HML_MA3	12	NA	3	NA	2	2	NA	3	1	1	NA
7	M1	11	NA	3	2	2	NA	3	NA	NA	NA	1
8	DebtToAsset_RAV	11	3	NA	2	2	NA	NA	3	1	NA	NA
9	DebtToEV_RAV	9	NA	NA	2	NA	NA	3	3	1	NA	NA
10	NewHomes	7	NA	NA	2	NA	2	NA	NA	1	1	1
11	LeadingIndicatorUS	7	NA	NA	2	2	2	NA	NA	NA	NA	1
12	SPX_MA6	7	NA	NA	2	2	2	NA	NA	NA	1	NA
13	Coincident	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
14	IP	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
15	LeadingSpread	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
16	PE_RAV	6	NA	NA	NA	2	NA	3	NA	NA	1	NA
17	PB_RAV	6	3	NA	2	NA	NA	NA	NA	NA	1	NA
18	EstPE_RAG	5	3	NA	2	NA	NA	NA	NA	NA	NA	NA
19	ROA_RAG	5	3	NA	NA	NA	NA	NA	NA	1	1	NA

9M Size

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	ROA_RIY	16	3	3	2	NA	NA	3	3	1	1	NA
2	Commodity_MA6	16	NA	3	2	2	2	3	3	1	NA	NA
3	ROA_RTY	15	3	3	2	NA	NA	3	3	1	NA	NA
4	ConsumerConfidence	14	NA	NA	2	2	2	3	3	1	NA	1
5	PersonalIncome	13	3	3	2	NA	NA	NA	3	1	NA	1
6	LeadingIndicatorUS	13	NA	NA	2	2	2	3	3	NA	NA	1
7	DXY_MA3	13	NA	3	NA	2	2	3	3	NA	NA	NA
8	PS_RTY	12	NA	3	2	NA	NA	3	3	1	NA	NA
9	SavingRate	11	NA	NA	NA	2	2	3	3	NA	NA	1
10	Commodity_MA3	11	NA	NA	NA	2	2	3	3	1	NA	NA
11	PCE	10	NA	3	NA	NA	NA	3	3	NA	NA	1
12	DebtToEV_RTY	9	3	NA	NA	NA	NA	3	3	NA	NA	NA
13	HML_MA6	9	NA	NA	2	NA	NA	3	3	NA	1	NA
14	SMB_MA6	8	NA	NA	NA	NA	NA	3	3	1	1	NA
15	NewHomes	7	NA	NA	2	2	2	NA	NA	NA	NA	1
16	DebtToAsset_RTY	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
17	EstPE_RIY	6	NA	NA	2	2	2	NA	NA	NA	NA	NA
18	M2	5	NA	NA	NA	2	2	NA	NA	NA	NA	1

12M Value

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	EV_RAG	18	3	3	NA	2	2	3	3	1	1	NA
2	M2	14	3	3	NA	NA	NA	3	3	1	NA	1
3	CPIYOY	14	3	3	NA	NA	NA	3	3	1	NA	1
4	EstEPS_RAG	13	3	3	NA	NA	NA	3	3	1	NA	NA
5	DebtToAsset_RAV	12	3	NA	NA	2	NA	3	3	1	NA	NA
6	TedSpread	11	3	3	NA	NA	NA	3	NA	1	1	NA
7	PE_RAV	10	NA	NA	NA	2	NA	3	3	1	1	NA
8	SMB_MA3	10	NA	3	NA	NA	NA	3	3	1	NA	NA
9	Libor3M	9	3	3	NA	NA	NA	3	NA	NA	NA	NA
10	HML_MA3	6	NA	NA	NA	2	2	NA	NA	1	1	NA
11	SPX_MA6	6	NA	NA	NA	2	NA	NA	3	NA	1	NA
12	CapacityUtilization	5	NA	3	NA	NA	NA	NA	NA	1	NA	1
13	SMB_MA6	5	NA	NA	NA	NA	NA	3	NA	1	1	NA
14	SPX_MA3	5	NA	NA	NA	2	2	NA	NA	NA	1	NA

12M Size

	Feature	Score	RandomForest	XGBoost	StepLogitBoth	ElasticNet	Lasso	GBM_Ada	GBM_Bernoulli	TwoSampleTTest	PCA	Sparse_PCA
1	PB_RTY	17	3	3	NA	2	2	3	3	1	NA	NA
2	DebtToEV_RTY	14	3	3	NA	2	NA	3	3	NA	NA	NA
3	DebtToAsset_RIY	13	3	3	NA	NA	NA	3	3	1	NA	NA
4	PCE	11	NA	3	NA	NA	NA	3	3	1	NA	1
5	ROA_RIY	11	3	NA	NA	NA	NA	3	3	1	1	NA
6	Commodity_MA3	11	NA	NA	NA	2	2	3	3	1	NA	NA
7	DebtOutstanding	10	NA	3	NA	NA	NA	3	3	NA	NA	1
8	ROA_RTY	10	3	3	NA	NA	NA	3	NA	1	NA	NA
9	PersonalIncome	8	3	3	NA	NA	NA	NA	NA	1	NA	1
10	PS_RTY	8	NA	NA	NA	2	2	NA	3	1	NA	NA
11	DebtToAsset_RTY	8	3	NA	NA	2	2	NA	NA	1	NA	NA
12	IGSpread	7	3	NA	NA	NA	NA	3	NA	1	NA	NA
13	RecessionProb	6	NA	3	NA	NA	NA	NA	3	NA	NA	NA
14	SMB_MA6	6	NA	NA	NA	2	2	NA	NA	1	1	NA
15	SavingRate	5	NA	NA	NA	2	2	NA	NA	NA	NA	1
16	ConsumerConfidence	5	NA	NA	NA	NA	NA	NA	3	1	NA	1
17	DVD_RTY	5	3	NA	NA	NA	NA	NA	NA	1	1	NA
18	DebtToEV_RIY	5	3	NA	NA	2	NA	NA	NA	NA	NA	NA
19	Commodity_MA6	5	NA	NA	NA	2	2	NA	NA	1	NA	NA

6.2 Model Result

The last number in the model refers to the cutoff score in the feature score.

Factor	Models	In-sample Hit Ratio	OOS Hit Ratio	In-sample ES	OOS ES
SMB - 6mo	SVM - Radial 16	89%	68%	2.95	1.44
SMB - 6mo	SVM - Linear 16	82%	69%	0.41	2.31
SMB - 6mo	Logistic 16	79%	70%	-0.50	1.25
SMB - 9mo	KNN 10	87%	70%	2.65	1.89
SMB - 9mo	KNN 11	88%	67%	3.84	2.00
SMB - 9mo	Catboost 11	100%	64%	Inf	-0.40
SMB - 9mo	SVM - Radial 11	90%	63%	6.55	-0.65

SMB - 12mo	Catboost 11	100%	67%	34.64	4.58
SMB - 12mo	KNN 5	91%	68%	2.91	3.46
SMB - 12mo	RDA 13	85%	66%	0.57	3.93
SMB - 12mo	XGB - Logistic 11	98%	67%	6.24	2.29

Factor	Models	In-sample Hit Ratio	OOS Hit Ratio	In-sample ES	OOS ES
HML - 6mo	QDA 11	89%	61%	1.49	1.73
HML - 6mo	RDA 11	89%	61%	1.49	1.73
HML - 6mo	KNN 8	87%	64%	4.58	0.92
HML - 6mo	QDA 13	82%	63%	0.25	0.69
HML - 6mo	RDA 8	89%	62%	0.81	0.67
HML - 6mo	SVM - Sigmoid 11	71%	63%	-1.54	0.54
HML - 9mo	SVM - Linear 11	80%	69%	0.00	0.92
HML - 9mo	Logistic 11	82%	68%	0.79	0.53
HML - 9mo	LDA 11	81%	68%	0.33	0.50
HML - 9mo	LDA 9	82%	68%	0.62	0.50
HML - 12mo	Logistic Lasso 11	88%	72%	1.60	0.60
HML - 12mo	Logistic Ridge 11	87%	72%	1.16	0.54
HML - 12mo	Logistic Elastic 11	87%	72%	1.16	0.54
HML - 12mo	KNN 12	90%	71%	17.32	0.35

HML - 12mo	KNN 11	90%	71%	8.66	0.36
HML - 12mo	LDA 11	87%	71%	1.26	0.26
HML - 12mo	SVM - Linear 11	88%	71%	1.75	0.23
HML - 12mo	Catboost 12	100%	70%	34.64	0.22