Portfolio Rotation via Machine Learning

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Highlights:

- Machine learning models are suitable in portfolio return prediction under the circumstance of high dimensionality and muti-collinearity
- The best portfolio rotation strategy comes from PLS model, which has an average return of 0.93% and risk adjusted return of 0.74% per month.
- Macro variables and portfolio lag returns are able to predict portfolio returns

Abstract

We propose a novel method to rotate portfolios dynamically via machine learning. Our empirical results show that portfolio rotation strategies via machine learning can generate significant economic value. The best portfolio rotation strategy comes from PLS model, which has an average return of 0.93% and risk adjusted return of 0.74% per month. We find that machine learning models are suitable in portfolio return prediction under the circumstance of high dimensionality and muti-collinearity. All machine learning models generate positive out of sample R^2. Elastic Net model has the highest average out of sample $R^2$of 3.18 for all portfolios among all machine learning models. We also find that lag returns capture more than 70% of total predictive power in PCA, PLS, RIDGE, RF and GBRT model. Furthermore, we show that our extra return come from both portfolio selection and portfolio timing.

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1. Introduction

Sophisticated investors tend to invest portfolios to diversity risk of individual since Markowitz proposed Mean-Variance theory. Academic research has shown that some style and sector portfolios generate positive returns across time. However, portfolios returns also exhibit highly volatile pattern and suffer from significant drawback during bad times. As a result, investors need to diversify investment portfolios across periods, raising the question of how to allocate assets across portfolios dynamically. Portfolio returns are very hard to predict for three reasons. First, there are many predictors in the existing literature and all these predictors are highly correlated. Variance of Ordinary Least Square (OLS) estimation increase tremendously when variables are highly correlated, making the estimators insignificant and unstable. Second, the interaction effect between predictors may also be able to predict portfolio returns, which are hard to capture in OLS models. Third, the relation between portfolios return and predictors are not necessarily linear. We cannot capture the non-linearity with linear models. Due to above problems, we try to use machine learning models to predict portfolio returns.

Traditional prediction methods break down when the predictor count approaches the observation count or predictors are highly correlated. With an emphasis on variable selection and dimension reduction techniques, machine learning is well suited for such challenging prediction problems by reducing degrees of freedom and condensing redundant variation among predictors. Principle Component Analysis (PCA) and Partial Least Square (PLS) can reduce the dimensionality and Penalized linear models can shrink the variance of estimators. Regression Tree models are suitable for incorporating muti-way predictor interactions and capture the nonlinear relationship between portfolio returns and predictors.

In this paper, we use the highest and lowest decile portfolios of 14 style portfolios and 30 sector portfolios from French Data Library as our underlying assets and reconstruct long-short portfolios based on machine learning algorithms predictions dynamically. These style portfolios are the most representative and well-studied portfolios in the anomaly literature. We want to show that our methodology succeed in predicting portfolio returns even if we consider the least predictable portfolios. We want to extend the dimensionality of portfolio constructions, so we add 30 sectors portfolios in our sample set. To keep the number of stocks within each sector relative stable and comparable, we choose the 30 sector portfolios rather than 49 sector portfolios. Our sample period covers July 1964 to December 2017. We choose this period because we want to compare with SP500 index, and the index started from 1964. We construct lag returns of each portfolios by calculating its past performance for 1, 3, 6 and 12 month exclude last month. Then we construct macro variables combined with lag returns as our predictors. At the end of each month, we predict portfolio returns and sort all 58 portfolios into deciles based on our predictions. Then we construct long short portfolios based on our monthly rebalancing.

We find that machine learning models are suitable in portfolio return prediction under the circumstance of high dimensionality and muti-collinearity. We compare seven models in total, including PCR, PLS, Least Absolute Shrinkage and Selection Operator (LASSO), RIDGE, Elastic Net (ENET), random forest (RF), gradient boosted regression tree (GBRT). All machine learning models generate positive R^2_{oos}. ENET has the highest average R^2_{oos} of 3.18% among all models. For individual portfolio, the lowest group of variance of daily returns (RESVAR-Lo) the easiest to predict. Our empirical results show that portfolio rotation strategies via machine learning can generate significant economic value. The best portfolio rotation strategy comes from PLS model, which has an average return of 0.93% and risk adjusted return of 0.74% per month.

We find that macro variables and lag factor returns can predict portfolio returns. We calculate the variable importance for each predictors and normalized to 100%. Lag returns captures more than 70% of predictive power in PCA, PLS, RIDGE, RF and GBRT model. For some particular portfolio return prediction, LASSO and Elastic Net tend to penalize all predictors to zero, so the sum of predictor is not 100%. In these case, the LASSO and Elastic Net models are fitting the portfolio returns with only the intercept.

To better understand the source of our strategies' extra return, we further test whether portfolio selection or portfolio timing contributes to the extra return. We find that our strategies select top ranking portfolios in terms of sharp ratio in our sample period, which proves that portfolio selection contributes to the overall extra return. In addition, we compare the turnover rate of our strategies with that of a benchmark model, prevailing mean model, to test whether portfolio timing also contributes to extra returns. Our dynamically rotate portfolios generates alpha by selecting better performed portfolios during both good times and bad times. To summarize, the sources of our strategy's alpha come from both portfolio selection and portfolio timing.

There is a recent debate about whether portfolio rotation is possible. Some research proves that portfolio rotation is possible (Arnott et al. 2016; Bender et al. 2018, and Gupta & Kelly 2019). However, Asness et al. (2017) compare the impact of value timing to that of strategic exposure to value itself and find that strategic diversification turns out to be a tough benchmark to beat. The expected return of one factor may relate to other factor returns and macro variables (Hodges et al., 2017; Lee, 2017). In terms of sector rotation, Hong et al. (2007) introduce information frictions into an economy with multiple linked industries. The second literature is machine learning in finance. Gu et al. (2018) find that machine learning offers an improved description of expected return behavior relative to traditional forecasting methods. Some researchers apply LASSO model to deal with sparse signals in financial markets and to select variables to predict sector returns (Rapach et al 2019; Chinco et al. 2018). In this paper, we try to apply a bunch of machine learning techniques to predict portfolio returns and build up portfolio rotation strategies based on predicted returns. Compared to earlier literature on portfolio rotation, we propose a novel method to allocate assets across style and sector portfolios dynamically.

The rest of the paper is organized as follows. We describe the data in Section 2. Section 3 presents our empirical methodology. We report our empirical results in

Section 4. Finally, Section 5 concludes the paper

2. Data

Our sample period covers July 1964 to December 2017. We construct eight macroeconomic predictors following the variable definitions detailed in Welch and Goyal (2008), including dividend-price ratio (dp), earnings-price ratio (ep), book-to-market ratio (bm), net equity expansion (ntis), Treasury-bill rate (tbl), term spread (tms), default spread (dfy), and stock variance (svar). Investor sentiments index is from Baker and Wurgler (2006). New investor sentiment index is from Huang, Jiang, Tu & Zhou (2015). Difference between the risk-neutral and objective expectations of realized variance is from Zhou et al (2018). Policy-related economic uncertainty is from Baker, Bloom, and Davis (2016). Stock market's expectation of volatility implied by S&P 500 index options is from CBOE. We provide the details of these macro variables in Appendix Table I.

// Insert Table 1 about here//

We collect factor and sector portfolios from Ken French Data Library. For factor portfolios, we include Accruals (AC), Book-to-Market (BE-ME), Market beta (BETA), Cashflow-to-Price (CF-P), Dividend Yield (D-P), Earnings-to-Price (E-P), Investment (INV), Long-Term Reversal (LR), Size (ME), Momentum (MOM), Net Share Issues (NI), Operating Profitability (OP), Variance of daily returns (RESVAR) and Short-Term Reversal (SR). These style portfolios are the most representative and well-studied portfolios in the anomaly literature. We want to show that our methodology succeed in predicting portfolio returns even if we consider the least predictable portfolios. Table 1 Panel A presents summary statistics of macro variables. We compute the mean, standard deviation.

We consider monthly data on the 30 industries indexes coming again from the website of Kenneth R. French. We want to extend the dimensionality of portfolio constructions, so we add 30 sectors portfolios in our sample set. To keep the number of stocks within each sector relative stable and comparable, we choose the 30 sector portfolios rather than 49 sector portfolios. Details about sector portfolios are in the Appendix. For all factor and sector portfolios, we construct lag returns for past 1, 3, 6, 12 month exclude last month. We provide the details of these factor portfolios in Appendix Table II.

3. Methodology

This section describes the collection of machine learning methods that we use in our analysis. All of our estimates share the basic objective of minimizing mean squared predictions error (MSE). Following Gu, Kelly, and Xiu (2018) setups, we describe a portfolio returns as an additive prediction error model:

$$\mathrm{r}_{i,t+1} = \quad g_i^*\left(r_{-i,t-\tau}, macro_t\right) + \epsilon_{i,t+1} \tag{1}$$

where factors are indexed as i = 1,. . . , N and months by t = 1,. . . , T. $\mathrm{r}_{i,t+1}$ is factor i realized return in time t+1. $r_{-i,t-\tau}$ are lag returns of other factors over 2-3, 2-6, 2-12 periods. $macro_t$ are the macro variables at time t. g*(·) is flexible function of these predictors.

3.1 Sample Splitting

The data sample starts from 1964 July to 2017 December, 654 months in total. We divide the 40 years of data into 13 years of training sample (1964 - 1980), 10 years of validation sample (1980 - 1990), and the remaining 27 years (1990 - 2017) for out-of-sample testing. We fill in missing variables in lag returns with zero. In our empirical exercise, we adopt a hybrid of these schemes by recursively increasing the training sample, periodically refitting the entire model once per year, and making out-of-sample predictions using the same fitted model over the subsequent year. Each time we refit, we increase the training sample by a year, while maintaining a fixed size rolling sample for validation. We choose to not cross-validate in order to maintain the temporal ordering of the data for prediction.

3.2 Machine Learning Methodologies

3.2.1 Dimension Reduction: PCR and PLS

Two classic dimension reduction techniques are principal components regression (PCR) and partial least squares (PLS). The weights used to construct j^{th} PCR component solve

$$\mathrm{w_j} = argmax_w \ Var(Xw), \ s.t. w'w = 1, w'X'Xw_l = 0, l = 1,2,\dots,j-1 \tag{2}$$

Intuitively, PCR seeks the K linear combinations of X, Ω_{K}, that most faithfully mimic the full predictor set. The objective illustrates that the choice of components is not based on the forecasting objective at all. Instead, the emphasis of PCR is on finding components that retain the most possible common variation within the predictor set. The well-known solution for (3) computes K via singular value decomposition of X, and therefore the PCR algorithm is extremely efficient from a computational standpoint. In contrast to PCR, the PLS objective seeks K linear combinations of X that have maximal predictive association with the forecast target.

The weights used to construct j^{th} PLS component solve

$$\mathrm{w_j} = argmax_w \ corr^2(Y, Xw)Var(Xw), \ s.t. w'w = 1, w'X'Xw_l = 0, l = 1,2,\dots,j-1 \tag{3}$$

This objective highlights the main distinction between OLS, PCR and PLS. PLS is willing to sacrifice how accurately $X\Omega_{\mathrm{K}}$ approximates X in order to find components with more potent return predictability. Compared with OLS, PLS not only maximize correlation coefficient of Y and Xw, but also take $Var(Xw)$ in to consideration. In general, PLS combine both advantages of OLS and PCA methods. Finally, given a solution for Ω_{K}, $\beta_{\mathrm{K}}$is estimated in both PCR and PLS via OLS regression of R on $\mathrm{X}\Omega_{\mathrm{K}}$. For both models, K is a hyperparameter that can be determined adaptively from the validation sample.

3.2.2 Penalized Liner: Ridge, LASSO and Elastic Net

The most common machine learning device for imposing parameter parsimony is to append a penalty to the objective function in order to favor more parsimonious specifications. This "regularization" of the estimation problem mechanically deteriorates a model's in-sample performance in hopes that it improves its stability out-of-sample. This will be the case when penalization manages to reduce the model's fit of noise while preserving its fit of the signal. Penalized methods differ by incorporating a new term in the loss function:

$$\mathrm{L}(\beta;\cdot) = L(\beta) + \phi(\beta;\cdot) \tag{4}$$

There are several choices for the penalty function$\phi(\beta;\cdot)$. Generally, Ridge penalty takes the form:

$$\min_{\beta} \left|\left|Y - X\beta\right|\right|^2 + \lambda\left|\left|\beta\right|\right|^2 \tag{5}$$

Ridge uses a l_2 parameter penalization that draws all coefficient estimates closer to zero but does not impose exact zeros anywhere. LASSO use l_1 parameter penalization. LASSO takes the form:

$$\min_{\beta} \left|\left|Y - X\beta\right|\right|^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{6}$$

The fortunate geometry of the LASSO sets coefficients on a subset of covariates to exactly zero. In this sense, the LASSO imposes sparsity on the specification and can thus be thought of as a variable selection method. The last penalty model is Elastic Net model, which takes the form:

$$\min_{\beta} \left|\left|Y - X\beta\right|\right|^2 + \lambda \sum_{j=1}^{p} (\alpha\beta^2 + (1-\alpha)|\beta_j|) \tag{7}$$

The elastic net involves two non-negative hyperparameters, λ andα, and includes two well-known regularizers as special cases. The α = 0 case corresponds to the LASSO penalty and the α = 1 case corresponds to Ridge penalty. We adaptively optimize the tuning parameters, λ and α, using the validation sample. Our implementation of penalized regression uses the accelerated proximal gradient algorithm and accommodates both least squares and Huber objective functions as Kelly et al (2019).

3.2.3 Regression Tree Models: Random Forest and GBRT

Penalized models does not account for interactions among predictors. One way to add interactions is to expand the penalized linear model to include interaction among predictors. However, this method will increase the dimensionality of predictors tremendously, making the estimators unstable. As an alternative, regression trees have become a popular machine learning approach for incorporating multi-way predictor interactions. Unlike linear models, trees are fully nonparametric and possess a logic that departs markedly from traditional regressions. A tree “grows” in a sequence of steps. At each step, a new “branch” sorts the data leftover from the preceding step into bins based on one of the predictor variables. This sequential branching slices the space of predictors into rectangular partitions, and approximates the unknown function $g_i^*(\cdot)$ with the average value of the outcome variable within each partition. Single tree model suffer from overfitting problem, so we further introduce ensemble and boosting method to improve the tree model prediction.

Random Forest is a special ensemble method. It generate m training set by bootstrapping. For each train set, it creates a decision tree. The tree model randomly choose some features to find the optimal solution. Through randomly selecting features, random forest can avoid overfitting problem. GBRT is iteration decision tree mode. The key of this method is each tree need to learn the residual of previous trees and build up new trees on the gradient of residual reduction.

3.3 Performance Evaluation

Following Gu et al (2019), we calculate the out of- sample R^2as

$$R^2_{oos} = 1 - \frac{\Sigma(r_{i,t+1-}\hat{r}_{i,t+1})}{\Sigma r^2_{i,t+1}} \tag{8}$$

The R^2_{oos} pools prediction errors across portfolios and over time into a grand cross section level assessment of each model. A subtle but important aspect of our R^2 metric is that the denominator is the sum of squared excess returns without demeaning. In many out-of-sample forecasting applications, predictions are compared against historical mean returns. While this approach is sensible for the aggregate index or long-short portfolios, for example, it is flawed when it comes to analyzing individual stock returns. Predicting future excess stock returns with historical averages typically underperforms a naive forecast of zero by a large margin. That is, the historical mean stock return is so noisy that it artificially lowers the bar for "good" forecasting performance. We avoid this pitfall by benchmarking our R^2 against a forecast value of zero. To give an indication of the importance of this choice, when we benchmark model predictions against historical mean stock returns, the out-of-sample monthly R^2 of all methods rises by roughly three percentage points.

3.4 Variable Importance

We aim to identify covariates that have an important influence on the cross-section of expected returns while simultaneously controlling for the many other predictors in the system. We discover influential covariates by ranking them according to a notion of variable importance. We denote the importance of a given input variable j as VI_j , and define it as the reduction in predictive R^2 from setting all values of predictor j to zero, while holding the remaining model estimates fixed (see Kelly et al., 2017).

4 Empirical Results

4.1 Performance of Portfolio Rotation Strategy

At the end of each month, we calculate one-month-ahead out-of-sample portfolio return predictions for each method. We then sort stocks into deciles based on each model's forecasts. We reconstitute portfolios each month using equal weights. Since we only have the portfolio level data, so we are not able to calculate the market value of each portfolio. The most straightforward way is to use equal weighted scheme. Finally, we construct a zero-net-investment portfolio that buys the highest expected return stocks (decile 10) and sells the lowest (decile 1).

4.1.1 Decile Sorting of Portfolio Rotation Strategy

Table 2 reports the results. We construct Prevailing Mean (PM) as our benchmark model, which has no significant positive returns in terms of Fama French five factor models. In panel A, the best 10-1 strategy comes from PLS model, which has an average return of 0.93% and risk adjusted return of 0.74% per month. All portfolio rotation strategies achieve significant positive returns. We also report risk adjusted performance of machine learning portfolios based on Fama French five factor pricing models on the last column. Almost all machine learning models generates positive and significant alphas except PCA model with a t stats smaller than 1.96. We also reports the risk adjust performance for benchmark portfolios. Figure 1 plots the cumulative return for each machine learning portfolio. The long portfolios performance better than the market (SP500), but for some tree models, the short portfolios are not significantly worse than the market.

// Insert Table 2 about here//

4.1.2 Comparison of Predictive R^2 for Portfolio Returns

Table 3 reports the comparison of machine learning techniques in terms of their in sample and out-of-sample predictive R^2. We compare seven models in total, including PCR, PLS, LASSO, RIDGE, Elastic Net (ENET), random forest (RF), gradient boosted regression tree (GBRT). ENET has the average R^2_{oos} of 3.18, which are the highest among all models. All machine learning models have positive OOS scores.

// Insert Table 3 about here//

4.1.3 Which Covariates Matter?

We now investigate the relative importance of predictors for the performance of each model. Table 4 reports the results. Variable importance within a given model are normalized to sum to one, giving them the interpretation of relative importance for that particular model. Compared with macro variables, lag returns capture more than 70% of total predictive power in PCA, PLS, RIDGE, RF and GBRT model. Lag returns contains more predictive power than macro variables in portfolio return predictions. For some particular portfolio returns, LASSO and Elastic Net tend to penalize all variables to zero, so the sum of predictor contribution are not 100%. In these case, the LASSO and Elastic Net models are fitting the data with only the intercept.

// Insert Table 4 about here//

4.2 Source of Portfolio Rotation Alpha

In this part, we want to discuss where does our portfolio rotation alpha comes from. There are two typical sources of our portfolio rotation strategies, i.e. portfolio selection and portfolio timing. In Table 5 Panel A, we reports the average return of each portfolios. We want to find whether our portfolio rotation strategies are selecting the best performance strategies in the sample period. We also report portfolio performance during recession and nonrecession periods. We want to know whether our strategies could select high return portfolios during recession.

// Insert Table 5 about here//

4.2.1 Portfolio Selection

Table 5 Panel A reports best 10 and worst 10 portfolios in the whole sample period. We want to show that our portfolio rotation strategies can select best performed portfolios in the long position and worst performed portfolios in the short position. In addition, we separate the whole sample into recession and nonrecession periods to prove that our strategies are relative stable over business cycle.

Table 5 Panel B reports out of sample portfolio rotation strategies holding positions. All our portfolio rotation strategies select the best performed portfolio in terms of average return in our sample set, which is MOM-Hi 10. In general, our portfolio selections in long position lies in the top one thirds of all portfolios ranking by average return. This confirms that part of our portfolio rotation alpha comes from portfolio selection.

In Table 5 Panel C, we compare the portfolio rotation strategies performance during recession and nonrecession periods. First, we want to know whether our strategies select different portfolios during recession. Compared with Panel A, our strategies select less momentum portfolios in both long and short positions. Instead, we frequently select Coals and Smoke sector portfolios during recession. Second, we want to find whether our strategies could select better performed portfolios during the bad times. Both Coals and Smoke sectors perform relative better during recession period, which proves that our strategies could select better performed portfolios during recession.

4.2.2 Portfolio Timing

We want to know whether out strategies returns come from portfolio timing. In Table 5, we reports the performance of prevailing mean strategy as a benchmark strategy. The benchmark strategy also selects the best performed portfolios in history. However, the risk adjusted return is only 0.18 per month. Prevailing mean strategy is quite stable because the historical mean does not vary too much. The turnover rate of prevailing mean strategy should be very small. We define the strategy's average monthly turnover as

$$\text{Turnover} = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N}\left(\mathrm{w}_{\mathrm{j,t+1}} - \mathrm{w}_{\mathrm{j,t}}\right) \tag{9}$$

Where $\mathrm{w}_{\mathrm{j,t}}$ is the strategy weight of portfolio j before rebalancing at t+1. $\mathrm{w}_{\mathrm{j,t+1}}$ is the strategy weight after rebalancing. In Table 6, we report the turnover rate for each strategy. For each model, we report the mean and standard deviation of long, short and overall turnover in the whole out of sample period, recession and non-recession. All our machine learning has a higher turnover ratio than prevailing mean model. Linear models have higher turnover rates in Nonrecession period than in Recession period. In contrast, tree models have higher turnover rates in Recession period.

// Insert Table 6 about here//

4.3 Robustness Check

To approximate the net performance of a strategy, we assume that each portfolio incurs a monthly transaction cost of 2×turnover×transaction cost. That is, each unit of turnover incurs a double units cost, paid as one unit cost upon entry and another unit cost upon exit of a position. We set up two kinds of cost fees to measure the transaction costs, 5bp and 10 bp per transaction. We choose unit cost of transaction approximates the average trading cost experienced by large asset managers, as reported in Frazzini et al. (2018). Table 7 reports the performance of portfolio rotation strategies after accounting for transaction costs. Linear models have the highest turnover rate so the transaction cost is influential to strategy returns. For regression tree models, the influence of transaction cost is relative small compared with linear models. Our portfolio rotation strategies still get significant positive returns even after accounting for transactions cost. For prevailing mean model, the turnover rate is very limited, so the transaction cost has almost no influence on it. In sum, Table 7 demonstrates the attractive risk-return tradeoff to investing portfolio rotation strategies even after accounting for transactions cost.

// Insert Table 7 about here//

5 Conclusion

In this paper, we try to find out whether machine learning methods could help dynamically allocate portfolios. Our empirical results show that portfolio rotation strategies via machine learning can generate significant economic value. The best portfolio rotation strategy comes from PLS model, with an average monthly return of 0.93 and risk adjusted return of 0.74 per month. We find that machine learning models are suitable in portfolio return prediction under the circumstance of high dimensionality and muti-collinearity. All machine learning models generate positive R^2_{oos}. ENET has the average R^2_{oos} of 3.18, which are the highest among all models. We also prove that macro variables and portfolio lag returns are able to predict portfolio returns. Compared with macro variables, lag returns capture more than 70% of total predictive power in PCA, PLS, RIDGE, RF and GBRT model. Furthermore, we show that our extra return come from both portfolio selection and portfolio timing. Our portfolio rotation strategies can hedge the down side risk during economic recession. We also calculate the turnover rate and transaction as robustness check. Almost all machine learning models generates positive and significant alphas after considering transaction cost.

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Table 1. Summary Statistics

Panel A. Summary Statistics of Predictors

Variable	Mean	Std	Variable	Mean	Std
b/m	0.49	0.27	Ntis	0.01	0.02
d_e	-0.77	0.32	RPCE_diff	0.26	0.51
d_p	-3.61	0.41	RPI_diff	0.26	0.57
d_y	-3.6	0.41	SI	0.01	1.01
Dfr	0.02	1.48	SI1	0	1.01
Dfy	1.04	0.45	Svar	0.22	0.45
e_p	-2.84	0.44	Tbl	4.77	3.26
ep_D	0.4	4.29	Ted	0.58	0.42
Epu	107.9	31.7	ted_diff	0.02	0.22
epu_diff	0.01	0.18	Tms	1.87	1.49
hjtz_invs	0	1	UNRATE_diff	0.01	2.87
INDPRO_diff	0.2	0.74	Vix	19.41	7.6
Infl	0.33	0.36	vix_diff	0.01	0.16
INVEST_diff	0.57	0.93	VRP	16.02	20.59
Ltr	0.63	3	VRP_diff	-0.98	22.05
Lty	6.65	2.71			

Note: This table reports summary statistics of macro variables and factor returns. We build up 31 macro predictors from existing literatures (Panel A). Our sample period covers July 1964 to December 2017. We provide the details of these macro variables in Appendix Table I. Across all macro variables, we report the pooled sample mean and standard deviation. Panel B reports summary statistics of factor returns from 1964 to 2017. All our factors and industry portfolio are from French Data Library. For all factor portfolios, we report min, max, mean, median and sharp ratio. For each factor portfolio, "Hi" stands for the highest decile portfolio and "Lo" stands for the lowest decile portfolio. We provide the details of these factor portfolios in Appendix Table II. The industry abbreviations are in footnotes.

Panel B. Summary Statistics of Portfolios

Style Portfolio						Sector Portfolio[1]					
Portfolio	**Mean**	**Std**	**Portfolio**	**Mean**	**Std**	**Portfolio**	**Mean**	**Std**	**Portfolio**	**Mean**	**Std**
AC-Lo 10	0.75	5.6	**AC-Hi 10**	0.31	5.91	**Food**	0.66	4.28	**Carry**	0.8	6.32
BE-ME-Lo 10	0.45	5.02	**BE-ME-Hi 10**	0.9	6.09	**Beer**	0.76	5.12	**Mines**	0.56	7.58
BETA-Lo 10	0.55	3.43	**BETA-Hi 10**	0.63	7.84	**Smoke**	1.01	6.04	**Coal**	0.73	10.4
CF-P-Lo 10	0.46	5.48	**CF-P-Hi 10**	0.88	5.19	**Games**	0.77	7.1	**Oil**	0.62	5.4
D-P-Lo 10	0.52	5.62	**D-P-Hi 10**	0.59	4.42	**Books**	0.53	5.76	**Util**	0.45	3.99
E-P-Lo 10	0.48	5.59	**E-P-Hi 10**	0.88	5.24	**Hshld**	0.52	4.63	**Telcm**	0.48	4.6
INV-Lo 10	0.76	5.3	**INV-Hi 10**	0.34	6.03	**Clths**	0.71	6.44	**Servs**	0.73	6.52
LR-Lo 10	0.88	6.64	**LR-Hi 10**	0.5	5.84	**Hlth**	0.69	4.82	**BusEq**	0.62	6.72
ME-Lo 10	0.77	6.28	**ME-Hi 10**	0.47	4.18	**Chems**	0.59	5.53	**Paper**	0.57	5.02
MOM-Lo 10	-0.16	8.02	**MOM-Hi 10**	1.11	6.1	**Txtls**	0.71	7.11	**Trans**	0.59	5.78
NI-Lo 10	0.56	4.37	**NI-Hi 10**	0.14	5.57	**Cnstr**	0.6	6.03	**Whlsl**	0.65	5.59
OP-Lo 10	0.35	6.46	**OP-Hi 10**	0.61	4.56	**Steel**	0.38	7.36	**Rtail**	0.68	5.36
RESVAR-Lo 10	0.56	3.53	**RESVAR-Hi 10**	-0.03	8.49	**FabPr**	0.62	6.16	**Meals**	0.81	6.1
SR-Lo 10	0.62	7.21	**SR-Hi 10**	0.28	5.43	**ElcEq**	0.78	6.2	**Fin**	0.61	5.4
						Autos	0.46	6.75	**Other**	0.33	5.79

[1] Food = Food Products; Beer = Beer and Liquor; Smoke = Tobacco Products; Games = Recreation; Books = Printing and Publishing; Hshld = Consumer Goods; Clths = Apparel; Hlth = Healthcare, Medical Equipment, and Pharmaceutical Products; Chems = Chemicals; Txtls = Textiles; Cnstr = Construction and Construction Materials; Steel = Steel Works, Etc.; FabPr = Fabricated Products and Machinery; ElcEq = Electrical Equipment; Autos = Automobiles and Trucks; Carry = Aircraft, Ships, and Railroad Equipment; Mines = Precious Metals, Non-Metallic, and Industrial Metal Mining; Coal = Coal; Oil = Petroleum and Natural Gas; Util = Utilities; Telcm = Communication; Servs = Personal and Business Services; BusEq = Business Equipment; Paper = Business Supplies and Shipping Containers; Trans = Transportation; Whlsl = Wholesale; Rtail = Retail; Meals = Restaurants, Hotels, and Motels; Fin = Banking, Insurance, Real Estate, and Trading; Other = Everything Else.

Table 2. Performance of Machine Learning Portfolios

		Low(L)	2	3	4	5	6	7	8	9	High(H)	H-L	FF5_α
PM	**Pred**	0.30	0.72	0.84	0.90	0.95	1.00	1.07	1.14	1.22	1.39	1.09	
	Realized	0.49	0.78	0.96	0.98	0.92	0.85	0.91	1.05	1.01	1.10	0.62	0.18
	t-stat	1.87	5.70	7.65	7.57	7.44	6.74	6.67	8.04	7.67	8.10	7.36	0.92
PCA	**Pred**	0.21	0.50	0.62	0.72	0.83	0.97	1.11	1.25	1.40	1.71	1.51	
	Realized	0.56	0.70	0.72	0.85	0.75	1.03	1.12	1.11	1.19	1.30	0.73	0.31
	t-stat	3.66	5.01	5.50	5.99	5.79	7.72	7.86	8.12	9.24	9.27	4.94	1.71
PLS	**Pred**	-0.28	0.38	0.65	0.83	0.97	1.12	1.27	1.46	1.74	2.34	2.62	
	Realized	0.42	0.57	0.89	0.90	1.07	1.01	1.07	1.04	1.00	1.35	0.93	0.74
	t-stat	2.90	4.18	6.70	5.94	8.44	7.91	7.55	8.29	7.13	8.96	6.02	3.58
LASSO	**Pred**	-0.13	0.38	0.61	0.77	0.90	1.05	1.19	1.35	1.58	2.14	2.27	
	Realized	0.43	0.66	0.82	0.93	1.01	1.04	0.97	1.02	1.21	1.22	0.79	0.44
	t-stat	2.81	4.72	6.38	6.70	7.82	8.38	7.27	7.80	8.93	7.73	5.03	2.24
RIDGE	**Pred**	0.23	0.61	0.77	0.88	0.97	1.07	1.17	1.28	1.43	1.77	1.54	
	Realized	0.46	0.51	0.85	0.83	0.96	1.16	0.98	1.08	1.15	1.31	0.85	0.70
	t-stat	3.02	3.78	6.45	5.65	7.50	9.31	7.06	8.37	8.69	8.45	5.22	3.18
ENET	**Pred**	0.38	0.71	0.81	0.88	0.95	1.01	1.08	1.17	1.29	1.54	1.16	
	Realized	0.43	0.75	0.76	0.97	1.03	1.01	0.92	1.16	0.95	1.33	0.90	0.62
	t-stat	2.73	5.36	5.96	7.20	8.12	7.98	6.68	9.03	7.05	8.47	5.90	3.72
RF	**Pred**	0.26	0.65	0.79	0.89	0.97	1.06	1.15	1.26	1.41	1.80	1.54	
	Realized	0.62	0.69	0.89	0.82	0.87	0.91	1.13	0.98	1.14	1.27	0.65	0.57
	t-stat	4.02	5.06	6.77	5.99	7.05	7.34	7.89	7.46	8.37	8.13	4.07	3.61
GBRT	**Pred**	0.42	0.74	0.85	0.92	0.98	1.05	1.12	1.21	1.35	1.64	1.22	
	Realized	0.54	0.86	0.78	0.88	1.04	0.95	1.00	1.04	1.05	1.16	0.62	0.41
	t-stat	3.09	6.22	5.79	6.27	8.32	7.45	7.38	8.08	8.14	8.63	4.10	2.35

Note: This table reports the performance of equal-weighted decile portfolios sorted on out-of-sample machine learning return forecasts. "Pred", "Avg" and "t-stat" report the predicted monthly returns for each decile, the average realized monthly returns and t statistics, respectively. For all machine learning High minus Low strategies, we report the risk adjusted returns. "FF5" respect to the Fama-French five-factor model. We also compares machine learning strategies with benchmark strategies. PM stands for Prevailing Mean strategy, which is based on the historical mean returns from the beginning of the sample through the month of forecast formation.

Table 3: Out of Sample R^2 for each model

	IS		OOS	
	Mean	**Std**	**Mean**	**Std**
PCA	3.99	1.81	2.91	2.05
PLS	1.34	2.81	0.58	3.7
LASSO	6.22	2.25	2.77	1.93
RIDGE	7.93	2.15	3.02	1.91
ENET	4.54	1.86	3.18	1.85
RF	7.25	1.92	3.16	1.74
GBRT	7.05	1.73	3.05	1.7

Note: In this table, we report the summary statistics of in-sample (IS) and out-of-sample (OOS) R^2s for machine learning models of PCA, Ridge, Lasso, Elastic Net (ENet), random forest (RF) and gradient boosted regression trees (GBRT), respectively. Our In sample period covers July 1964 to July 1990 and our out of sample period covers August 1990 to December 2017. All our style and industry portfolio are from French Data Library.

Table 4: Variable Importance by Machine Learning Model

	Macro		Lag returns	
	Mean	**Std**	**Mean**	**Std**
PCA	2.24	0.45	97.76	0.45
PLS	24.24	8.38	75.76	8.38
LASSO	18.38	28.14	35.07	39.61
RIDGE	28.11	4.38	71.89	4.38
ENET	16.67	21.84	54.02	39.65
RF	10.34	1.41	89.66	1.41
GBRT	14.44	2.15	85.56	2.15

Note: This table repots variable importance for all factor and sector portfolios using different machine learning models. All predictors are divided into two groups, macro variables and lag returns. Predictor contribution are normalized to 100%. In general, lag returns captures more than 70% of machine learning models predictive power in PCA, PLS, RIDGE, RF and GBRT model. For some particular y variable, LASSO and Elastic Net tend to penalize all variables to zero, so the sum of predictor contribution are not 100%. In these case, the LASSO and Elastic Net models are fitting the data with only the intercept.

Table 5. Holding Information

Panel A. Average Return of Portfolios

	ALL						Recession						Nonrecession					
	Best 10	**Mean**	**Std**	**Worest 10**	**Mean**	**Std**	**Best 10**	**Mean**	**Std**	**Worest 10**	**Mean**	**Std**	**Best 10**	**Mean**	**Std**	**Worest 10**	**Mean**	**Std**
1	**MOM-Hi 10**	1.49	6.13	**MOM-Lo 10**	0.23	8.06	**Smoke**	1.35	5.98	**RESVAR-Hi 10**	-1.49	12.14	**MOM-Hi 10**	1.74	5.88	**MOM-Lo 10**	0.36	6.83
2	**Smoke**	1.40	6.06	**RESVAR-Hi 10**	0.35	8.53	**LR-Lo 10**	1.17	9.15	**Other**	-0.89	8.53	**Carry**	1.49	5.83	**RESVAR-Hi 10**	0.63	7.82
3	**BE-ME-Hi 10**	1.28	6.12	**NI-Hi 10**	0.52	5.60	**Rtail**	1.12	7.77	**FabPr**	-0.89	9.03	**BE-ME-Hi 10**	1.46	5.41	**NI-Hi 10**	0.70	5.02
4	**LR-Lo 10**	1.27	6.67	**SR-Hi 10**	0.67	5.45	**Clths**	0.89	9.46	**Steel**	-0.85	10.19	**CF-P-Hi 10**	1.45	4.73	**AC-Hi 10**	0.83	5.39
5	**E-P-Hi 10**	1.26	5.26	**AC-Hi 10**	0.68	5.93	**Food**	0.75	6.00	**Carry**	-0.82	8.77	**E-P-Hi 10**	1.42	4.83	**OP-Lo 10**	0.88	6.04
6	**CF-P-Hi 10**	1.25	5.21	**INV-Hi 10**	0.71	6.06	**Beer**	0.61	6.84	**SR-Hi 10**	-0.78	7.42	**Smoke**	1.40	6.07	**SR-Hi 10**	0.88	5.06
7	**Meals**	1.21	6.12	**OP-Lo 10**	0.73	6.49	**Hlth**	0.55	6.57	**LR-Hi 10**	-0.73	8.92	**ElcEq**	1.40	5.72	**INV-Hi 10**	0.90	5.44
8	**ElcEq**	1.19	6.22	**Other**	0.74	5.81	**Meals**	0.45	9.03	**Mines**	-0.73	9.84	**ME-Lo 10**	1.37	5.88	**Util**	0.94	3.69
9	**Carry**	1.19	6.33	**Steel**	0.74	7.40	**Txtls**	0.31	12.29	**NI-Hi 10**	-0.70	8.45	**Games**	1.35	6.39	**Telcm**	0.97	4.44
10	**Games**	1.18	7.12	**BE-ME-Lo 10**	0.83	5.04	**Coal**	0.24	13.93	**D-P-Lo 10**	-0.65	8.36	**Meals**	1.32	5.55	**Autos**	0.98	5.98

Note: This table reports the holding information of each machine learning model. The out of sample period is from 1990-7 to 2017-12. For each model, we report the most frequent selected portfolios in long decile and short decile group. In Panel A, we reports the average return of top 10 portfolios in the period from 1964-07 to 2017-12 in both recession and non-recession period.

Panel B. Portfolio Rotation Strategy Holding Information

		Long	**%**	**Short**	**%**			**Long**	**%**	**Short**	**%**
	1	**MOM-Hi 10**	70.91	**MOM-Lo 10**	74.24		**1**	**MOM-Hi 10**	93.33	**MOM-Lo 10**	93.64
	2	ME-Lo 10	61.52	**RESVAR-Hi 10**	61.82		**2**	**BE-ME-Hi 10**	56.67	**NI-Hi 10**	86.36
PCA	**3**	Meals	44.85	**AC-Hi 10**	51.82	ENET	**3**	**Smoke**	55.15	**RESVAR-Hi 10**	76.97
	4	**BE-ME-Hi 10**	38.48	**NI-Hi 10**	37.27		**4**	ME-Lo 10	46.97	**AC-Hi 10**	74.55
	5	Oil	33.94	Util	37.27		**5**	**LR-Lo 10**	45.45	**SR-Hi 10**	53.94
	1	**MOM-Hi 10**	46.67	**MOM-Lo 10**	66.97		**1**	**MOM-Hi 10**	89.09	**MOM-Lo 10**	92.12
	2	**LR-Lo 10**	31.52	**RESVAR-Hi 10**	52.12		**2**	**Smoke**	63.94	**RESVAR-Hi 10**	89.39

PLS	**3**	**Smoke**	30.91	Util	34.55	RF	**3**	**BE-ME-Hi 10**	63.64	**NI-Hi 10**	81.82
	4	ME-Lo 10	30	Other	29.09		**4**	**CF-P-Hi 10**	55.45	**AC-Hi 10**	62.73
	5	Oil	30	ME-Lo 10	23.94		**5**	ME-Lo 10	50	**SR-Hi 10**	47.88
	1	**MOM-Hi 10**	53.64	**MOM-Lo 10**	54.24		**1**	**MOM-Hi 10**	96.97	**RESVAR-Hi 10**	97.27
	2	Coal	39.09	**AC-Hi 10**	42.42		**2**	**BE-ME-Hi 10**	76.06	**MOM-Lo 10**	97.27
LASSO	**3**	Smoke	33.33	**RESVAR-Hi 10**	42.12	GBRT	**3**	**Smoke**	75.45	**NI-Hi 10**	94.85
	4	**ME-Lo 10**	33.03	**NI-Hi 10**	26.97		**4**	**CF-P-Hi 10**	64.55	**AC-Hi 10**	79.39
	5	Beer	25.15	Other	26.06		**5**	**E-P-Hi 10**	49.39	**SR-Hi 10**	77.58
	1	**MOM-Hi 10**	73.03	**MOM-Lo 10**	81.82		**1**	**MOM-Hi 10**	100	**NI-Hi 10**	100
	2	ME-Lo 10	43.33	**RESVAR-Hi 10**	63.03		**2**	**Smoke**	91.52	**MOM-Lo 10**	100
RIDGE	**3**	**LR-Lo 10**	40.91	**AC-Hi 10**	44.24	PM	**3**	**BE-ME-Hi 10**	88.79	**RESVAR-Hi 10**	100
	4	Coal	35.76	**NI-Hi 10**	38.79		**4**	**CF-P-Hi 10**	76.97	**SR-Hi 10**	99.39
	5	**Smoke**	35.45	Util	35.45		**5**	**LR-Lo 10**	76.36	**AC-Hi 10**	96.36

Note: In Panel B, we report the percentage of the most frequently selected portfolios for each group. For example, PCA model select MOM-Hi 10 in its long decile group for 70.91%. All machine portfolios select momentum long short strategy, which proves that machine learning models are able to select high performance portfolios. For sector portfolios, our machine learning model select consumption sector such as Smoke, Beer and Meals.

Panel C. Portfolio Rotation Strategy Holding Information in Business Cycle.

		Recession				**Nonrecession**			
		Long	**%**	**Short**	**%**	**Long**	**%**	**Short**	**%**
	1	**Smoke**	100	MOM-Lo 10	100	**MOM-Hi 10**	100	**RESVAR-Hi 10**	100
	2	MOM-Hi 10	100	**NI-Hi 10**	100	**Smoke**	90.54	**MOM-Lo 10**	100
PM	**3**	BE-ME-Hi 10	94.12	**RESVAR-Hi 10**	100	**BE-ME-Hi 10**	88.18	**NI-Hi 10**	100
	4	CF-P-Hi 10	91.18	**SR-Hi 10**	100	LR-Lo 10	81.08	**SR-Hi 10**	99.32
	5	E-P-Hi 10	73.53	AC-Hi 10	94.12	**CF-P-Hi 10**	75.34	**AC-Hi 10**	96.62
	1	ME-Lo 10	67.65	Util	58.82	**MOM-Hi 10**	73.31	**MOM-Lo 10**	77.7

	2	Whlsl	52.94	AC-Hi 10	55.88	**ME-Lo 10**	60.81	**RESVAR-Hi 10**	64.19
PCA	**3**	MOM-Hi 10	50	**NI-Hi 10**	50	**Meals**	46.28	**AC-Hi 10**	51.35
	4	**LR-Lo 10**	47.06	**LR-Hi 10**	44.12	**BE-ME-Hi 10**	41.55	NI-Hi 10	35.81
	5	BETA-Hi 10	41.18	MOM-Lo 10	44.12	Oil	34.8	**Util**	34.8
	1	Coal	70.59	**Other**	50	**MOM-Hi 10**	50	**MOM-Lo 10**	70.61
	2	SR-Lo 10	44.12	**D-P-Hi 10**	50	Oil	33.11	**RESVAR-Hi 10**	54.39
PLS	**3**	**Smoke**	44.12	Oil	44.12	**ME-Lo 10**	32.09	**Util**	34.46
	4	**LR-Lo 10**	38.24	MOM-Lo 10	35.29	LR-Lo 10	30.74	Other	26.69
	5	Chems	38.24	Util	35.29	**Smoke**	29.39	Coal	25.68
	1	Coal	76.47	**RESVAR-Hi 10**	67.65	**MOM-Hi 10**	54.73	**MOM-Lo 10**	53.38
	2	MOM-Hi 10	44.12	MOM-Lo 10	61.76	**ME-Lo 10**	34.8	**AC-Hi 10**	42.23
LASSO	**3**	**Smoke**	41.18	ME-Lo 10	47.06	Coal	34.8	**RESVAR-Hi 10**	39.19
	4	Beer	26.47	AC-Hi 10	44.12	**Smoke**	32.43	Other	28.38
	5	**LR-Lo 10**	23.53	**NI-Hi 10**	38.24	**CF-P-Hi 10**	26.01	**NI-Hi 10**	25.68
	1	Coal	79.41	MOM-Lo 10	64.71	**MOM-Hi 10**	75.34	**MOM-Lo 10**	83.78
	2	**Smoke**	61.76	**RESVAR-Hi 10**	61.76	**ME-Lo 10**	45.61	**RESVAR-Hi 10**	63.18
RIDGE	**3**	MOM-Hi 10	52.94	**Mines**	47.06	LR-Lo 10	40.88	**AC-Hi 10**	47.3
	4	SR-Lo 10	41.18	ME-Lo 10	47.06	Beer	34.46	**NI-Hi 10**	38.85
	5	ElcEq	41.18	**NI-Hi 10**	38.24	**Smoke**	32.43	**Util**	35.14
	1	MOM-Hi 10	91.18	MOM-Lo 10	94.12	**MOM-Hi 10**	93.58	**MOM-Lo 10**	93.58
	2	Coal	73.53	**RESVAR-Hi 10**	70.59	**BE-ME-Hi 10**	60.81	**NI-Hi 10**	88.85
ENET	**3**	**Smoke**	67.65	AC-Hi 10	67.65	**Smoke**	53.72	**RESVAR-Hi 10**	77.7
	4	**LR-Lo 10**	64.71	**NI-Hi 10**	64.71	**ME-Lo 10**	48.31	**AC-Hi 10**	75.34
	5	SR-Lo 10	47.06	**SR-Hi 10**	55.88	**CF-P-Hi 10**	46.28	**SR-Hi 10**	53.72
	1	Coal	85.29	**SR-Hi 10**	67.65	**MOM-Hi 10**	92.91	**MOM-Lo 10**	96.28
	2	**Smoke**	67.65	**RESVAR-Hi 10**	61.76	**BE-ME-Hi 10**	67.23	**RESVAR-Hi 10**	92.57

RF	**3**	SR-Lo 10	64.71	MOM-Lo 10	55.88	**Smoke**	63.51	**NI-Hi 10**	87.84
	4	MOM-Hi 10	55.88	ME-Lo 10	50	**CF-P-Hi 10**	61.15	**AC-Hi 10**	66.89
	5	**Hlth**	41.18	Autos	38.24	**ME-Lo 10**	53.38	**SR-Hi 10**	45.61
	1	MOM-Hi 10	79.41	**SR-Hi 10**	85.29	**MOM-Hi 10**	98.99	**MOM-Lo 10**	99.66
	2	Coal	70.59	**RESVAR-Hi 10**	79.41	**BE-ME-Hi 10**	80.07	**RESVAR-Hi 10**	99.32
GBRT	**3**	**Smoke**	58.82	MOM-Lo 10	76.47	**Smoke**	77.36	**NI-Hi 10**	98.65
	4	**LR-Lo 10**	58.82	**NI-Hi 10**	61.76	**CF-P-Hi 10**	68.58	**AC-Hi 10**	82.43
	5	SR-Lo 10	50	AC-Hi 10	52.94	**E-P-Hi 10**	53.04	**SR-Hi 10**	76.69

Note: In Panel C, we compare the holding position of machine learning models in recession and non-recession period. We want to know if machine learning models could hedge the risk during the bad times. Our machine learning models select less momentum strategy in recession period. Our selections coincide with the best performance portfolios in both periods.

Table 6: Turnover Rate of Machine Learning Portfolios

	All				Recession				Nonrecession			
	Long		**Short**		**Long**		**Short**		**Long**		**Short**	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
PM	0.03	0.06	0.02	0.05	0.02	0.06	0.02	0.05	0.03	0.07	0.02	0.05
PCA	0.55	0.32	0.52	0.32	0.55	0.31	0.52	0.32	0.51	0.38	0.45	0.38
PLS	0.55	0.26	0.52	0.25	0.57	0.26	0.53	0.25	0.43	0.24	0.45	0.27
LASSO	0.58	0.22	0.61	0.24	0.59	0.22	0.63	0.24	0.52	0.20	0.50	0.22
RIDGE	0.53	0.26	0.52	0.26	0.54	0.26	0.52	0.25	0.44	0.25	0.43	0.28
ENET	0.42	0.25	0.36	0.24	0.43	0.25	0.37	0.23	0.32	0.23	0.29	0.26
RF	0.38	0.20	0.31	0.20	0.38	0.20	0.30	0.20	0.34	0.16	0.44	0.17
GBRT	0.27	0.18	0.19	0.16	0.26	0.17	0.17	0.14	0.37	0.19	0.34	0.20

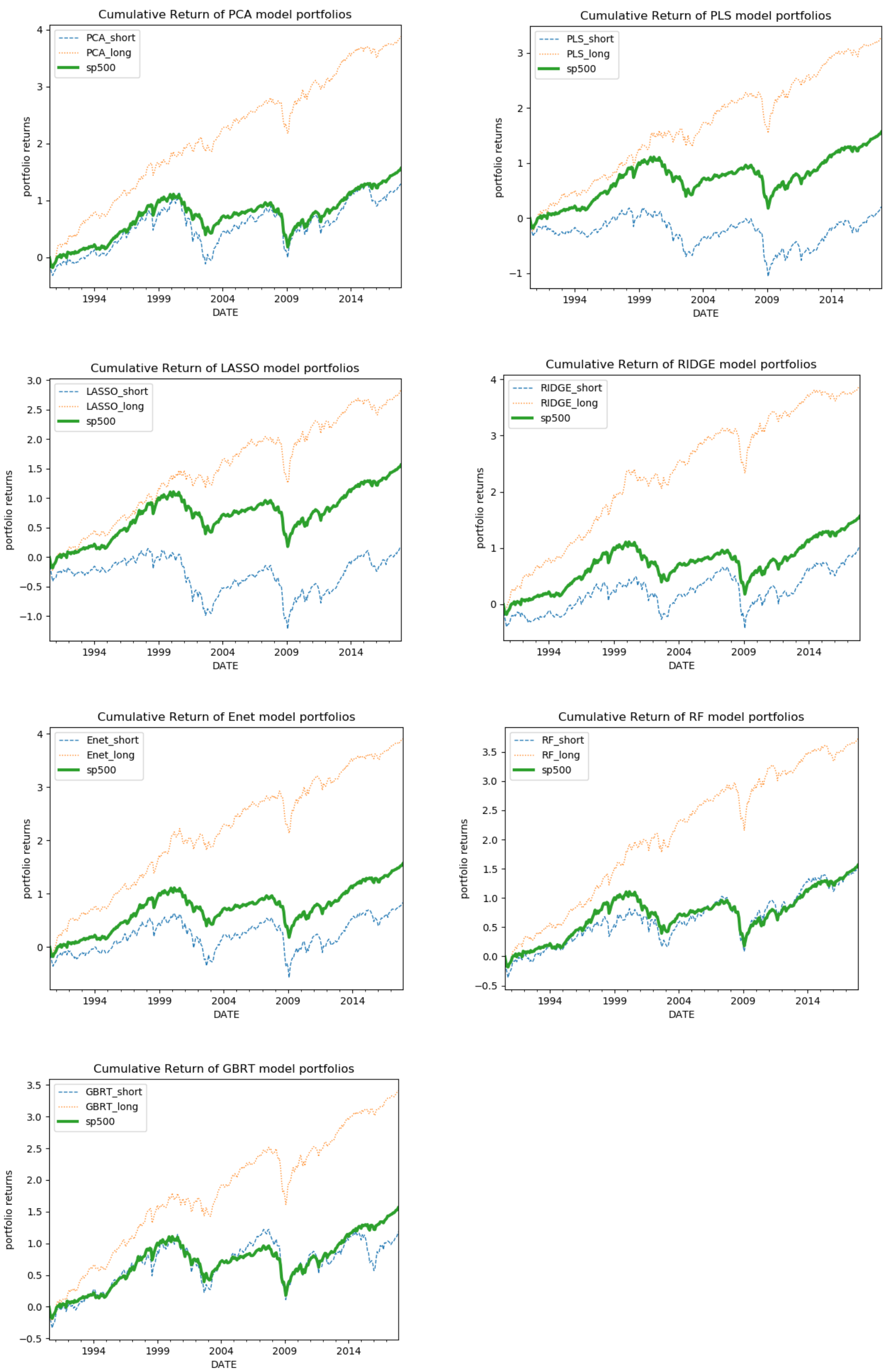
Note: This table reports the turnover rate of machine learning models. For each model, we report the mean and standard deviation of long, short and overall turnover in the whole out of sample period, non-recession and recession period. All our machine learning has a higher turnover ratio than prevailing mean model. Linear models have higher turnover rates in Nonrecession period than in Recession period. In contrast, tree models have higher turnover rates in Recession period.

Table 7: Transaction Cost

		Gross		Net(ts = 5bp)		Net(ts = 10bp)	
		Return	**t-stat**	**Return**	**t-stat**	**Return**	**t-stat**
PM	H-L	0.62	2.52	0.61	2.51	0.61	2.5
	Alpha	0.18	0.92	0.18	0.91	0.18	0.9
PCA	H-L	0.73	3.61	0.63	3.09	0.52	2.56
	Alpha	0.31	1.71	0.2	1.12	0.09	0.53
PLS	H-L	0.93	4.64	0.82	4.11	0.71	3.57
	Alpha	0.74	3.58	0.63	3.06	0.52	2.53
LASSO	H-L	0.79	3.86	0.67	3.28	0.55	2.7
	Alpha	0.44	2.24	0.32	1.62	0.2	1.01
RIDGE	H-L	0.85	4.06	0.75	3.57	0.65	3.07
	Alpha	0.7	3.18	0.59	2.7	0.49	2.23
ENET	H-L	0.9	5.37	0.83	4.91	0.75	4.45
	Alpha	0.62	3.72	0.54	3.26	0.47	2.8
RF	H-L	0.65	3.88	0.55	3.29	0.45	2.7
	Alpha	0.57	3.61	0.47	3	0.38	2.39
GBRT	H-L	0.62	3.69	0.57	3.38	0.51	3.06
	Alpha	0.41	2.35	0.36	2.05	0.31	1.76

Note: This table reports transaction costs for portfolio rotation strategies. We reports transaction cost adjust returns for two situations, 5bp and 10bp. For each strategy, we report the average return and risk adjust return based on Fama French 5 factor model. Compared with benchmark model (PM), portfolio rotation has much higher turnover rate, but the risk adjust returns are still significant when we consider the transaction cost.

Figure 1: Model Trading Strategy Cumulative Returns



Note: This figure plots the cumulative log returns of portfolios sorted on out of sample machine learning return forecasts. The dot line represent the long (10%) positions and the dash line represent the short (10%) position, respectively. The solid line represent the sp500. All portfolios are equal weighted.

Appendix

Table I: Detailed Description for Predictors

Predictors	Detailed Description
	Panel A. Market Conditions Predictors
Dividend Price (d_p)	log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices
Dividend yield (d_y)	difference between the log of dividends and log of lagged prices
Earnings Price (e_p)	difference between the log of earnings on the S&P 500 index and log of prices, where earnings are measured using a one-year moving sum
Dividend Payout (d_e)	difference between the log of dividends and log of earnings on the S&P 500 index
Book-to-Market (b_m)	ratio of book value to market value for the Dow Jones Industrial Average
Stock Variance (svar)	sum of squared daily returns on the S&P 500 index
Net Equity Expansion (ntis)	ratio of twelve-month moving sums of net issues by NYSE listed stocks to total end-of-year market capitalization of NYSE stocks
Long Term Yield (lty)	long-term government bond yield
Treasury bill rate (TBL)	interest rate on a 3-month Treasury bill
Term Spread (tms)	difference between the long-term yield and Treasury bill rate
Default Yield Spread (dfy)	difference between BAA- and AAA-rated corporate bond yields
Default Return Spread (dfr)	difference between long-term corporate bond and long-term government bond returns
Long Term Returns (ltr)	return on long-term government bonds
Ted spread (Ted)	difference between three-month Treasury bill and three-month LIBOR
Inflation (infl)	calculated from the CPI (all urban consumers); following Goyal and Welch (2008), inflation are lagged for two months relative to stock market return to account for the delay in CPI releases
Investor sentiments index (hjtz_invs)	investor sentiments index from Baker and Wurgler (2006)
New investor sentiments index (hjtz_invs)	new investor sentiment index from Huang, Jiang, Tu & Zhou (2015)
variance risk premium (VRP)	difference between the risk-neutral and objective expectations of realized variance from Zhou (2018)
Economic Policy Uncertainty (epu)	policy-related economic uncertainty from Baker, Bloom, and Davis (2016)
The CBOE Volatility Index (VIX)	stock market's expectation of volatility implied by S&P 500 index options

Panel B. Lag Returns	
Lag Factor Returns 1	Past performance for 1 month
Lag Factor Returns 3	Past performance for 3 month exclude last month
Lag Factor Returns 6	Past performance for 6 month exclude last month
Factor Momentum 12	Past performance for 12 month exclude last month

Notes: This table reports the detailed description four main categories of signals most commonly proposed and analyzed in the extant literature. These are Market Conditions Predictors, Economic Conditions Predictors, Uncertainty/Risk sentiment variables and factor momentums.

Table II: Factor Returns Construction Details

Factors	Detail for Portfolios Construction in French Library
30 Industry Portfolios	We assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time
Accruals (AC)	The portfolios are formed on Accruals (AC) at the end of each June using NYSE breakpoints. AC for June of year t is the change in operating working capital per split-adjusted share from the fiscal yearend t-2 to t-1 divided by book equity per share in t-1.
Book-to-Market (BE-ME)	Portfolios are formed on BE/ME at the end of each June using NYSE breakpoints. The BE used in June of year t is the book equity for the last fiscal year end in t-1. ME is price times shares outstanding at the end of December of t-1.
Market beta (BETA)	The portfolios are formed on univariate market beta (β) at the end of each June using NYSE breakpoints. β for June of year t is estimated using the preceding five years (two minimum) of past monthly returns.
Cashflow-to-Price (CF-P)	Portfolios are formed on CF/P at the end of each June using NYSE breakpoints. The cashflow used in June of year t is total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in t-1. P (actually ME) is price times shares outstanding at the end of December of t-1.
Dividend Yield (D-P)	Portfolios are formed on D/P at the end of each June using NYSE breakpoints. The dividend yield use to form portfolios in June of year t is the total dividends paid from July of t-1 to June of t per dollar of equity in June of t.
Earnings-to-Price (E-P)	Portfolios are formed on E/P at the end of each June using NYSE breakpoints. The earnings used in June of year t are total earnings before extraordinary items for the last fiscal year

	end in t-1. P (actually ME) is price times shares outstanding at the end of December of t-1.
Investment (INV)	The portfolios are formed on the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets at the end of each June using NYSE breakpoints.
Long-Term Reversal (LR)	The portfolios are constructed monthly using NYSE prior (13-60) return decile breakpoints.
Size (ME)	The portfolios are constructed at the end of each June using the June market equity and NYSE breakpoints.
Momentum (MOM)	The portfolios are constructed monthly using NYSE prior (2-12) return decile breakpoints.
Net Share Issues (NI)	The portfolios are formed on Net Share Issues (NI) at the end of each June using NYSE breakpoints. NI for June of year t is the change in the natural log of split-adjusted shares outstanding from the fiscal yearend in t-2 to the fiscal yearend in t-1.
Operating Profitability (OP)	The portfolios are formed on profitability (OP) at the end of each June using NYSE breakpoints. OP for June of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1.
Variance of daily returns (RESVAR)	The portfolios are formed monthly on the variance of the residuals from the FF three-factor model (RVar) using NYSE breakpoints. RVar is estimated using 60 days (minimum 20) of lagged returns.
Short-Term Reversal (SR)	The portfolios are constructed monthly using NYSE prior (1-1) return decile breakpoints.

Notes: Detail for portfolios construction is from French Library. (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)