Applying Machine Learning to SEC 13F Investment Manager Filings for Portfolio Construction and Rebalancing

Yinan Chen
Rutgers University
Newark, NJ
yc1127@scarletmail.rutgers.edu

Samson Qian
Massachusetts Institute of Technology
Cambridge, MA
samsonq@mit.edu

Yiwen Song
Imperial College London
London, United Kingdom
yiwen.song22@imperial.ac.uk

Alexander Fleiss
Rebellion Research
New York, NY
alex@rebellionresearch.com

Abstract

In this study, we examine machine learning methods applied to SEC 13F forms filed by investment managers to report their quarterly holdings. Machine learning algorithms can be applied to predict investment manager performances by analyzing their specific holdings across different market sectors and industries. We explore the performances of various trading strategies by extracting factors and signals from 13F data and using machine learning models to make predictions. We try to find some alpha from the 13F data that could be used to construct portfolios with better performances. We use the original 13F pool and 13F S&P500 stock pool to validate the strategies.

1 Introduction

SEC Form 13F is a quarterly report filed by investment managers with over $100 million AUM to report their current holdings and positions, as required by the U.S. Securities and Exchange Commission (SEC). These filings are available to the public and allow investors to see which stocks many funds have picked and what their greatest holdings are. This enables investors to identify the top holdings of high-performing investment managers, which are often the stocks that are the "best picks" [1] and carry the most significant weight in the investment managers' portfolios because they understand those stocks the most. Since there is a large amount of historical 13F filings data available provided by the SEC, we can explore machine learning methods to learn from historical investment manager holdings and resulting performances and to develop alpha trading strategies based on these insights.

1.1 Objectives

Investment manager holdings are potentially a significant indicator of performance [2] and can be used to predict future performance. We leverage machine learning algorithms to learn from historical 13F data and predict future investment manager performances based on their holdings across multiple economic sectors and industries. To begin, we identify and build important factors and indicators about investment manager holdings. Then, we develop and test various factor models and strategies based on the insights learned from the historical data of investment manager holdings and performances.

2 Data

2.1 Raw Data

The data used for this research consists of historical SEC 13F filings and historical stock price data from 2013 to 2020. The SEC 13F data presents quarterly holdings by investment managers that are scraped directly off of 13F forms found on the SEC website (Table 1). The price data includes daily-frequency fundamental stock open-high-low-close (OHLC) data (Table 2).

2.2 Preprocessing

Stock Price

To ensure the validity and accuracy of the data set, we first preprocess the stock price data by cleaning up abnormal and missing values. We fix inconsistent measurement unit issues and impute missing prices in the 13F data using Yahoo Finance and Bloomberg.

SEC Form 13F

Similar to cleaning stock price data, we first dropped duplicates and missing values in the 13F data. Subsequently, we filtered out records that may result in bias of our models and strategy with the following criteria:

1) Records with low market value (<100K) or outstanding shares (<10K)
2) Records filled before 2013/06/30 [1]
3) Using Yahoo Finance, we aggregate and join the corresponding industry of each stock to the data

After cleaning the data with the above steps, we merge these two tables based on the keys (iCUSIP and iPERIOD_END) and then construct the factors.

2.3 Feature Extraction

However, the raw 13F data does not provide insight into top-performing investment managers for constructing a strategy. To capture the behavioral patterns of the smart money, we created the following factors based on 13F and stock price data that represent trading signals:

Factors (Original 13F and S&P500 Stock Pool)

- Return: Current quarter's return of the individual security, starting from iPERIOD_END
- Return2: Subsequent quarter's return of the individual security
- iFRACTION: Percentage weight of a security held by a particular institution of the total value of securities held by that institution
- iFRACTION_CHANGE: Current iFRACTION minus last quarter's iFRACTION
- iFRACTION_CHANGE_RATIO: Rate of change of iFRACTION
- security_ratio: Percentage weight of a security held by a particular institution in the total value of that security held by all institutions
- security_hold_ratio: Percentage of institutions holding security out of the total number of institution
- sharpe_rolling: Rolling Sharpe ratio of portfolio for the last four quarters
- excess_return: Portfolio return minus this quarter's S&P500 return

To avoid look-ahead bias, we use **Return2** as the label to train the model because before the 13F form is filed for each quarter, the exact positions held by various institutions are unknown. The historical data shows that the maximum period for institutions to file the form is nearly a full quarter. This implies that following and copying the 13F filings to rebalance our portfolio can only be done so after the filing date. Therefore, to avoid look-ahead bias, we use Return2 instead of Return to evaluate the portfolio and strategy's performance.

[1]Companies were not required by the SEC to file 13Fs before this date.

Factors (Only 13F S&P500 Stock Pool)

- hold_float_ratio: Percentage weight of a security held by a particular institution of the total floating value of that security
- iFRACTION_sp500: Percentage weight of security in the 13F S&P500 stock pool held by a particular institution of the total value of securities held by that institution
- security_ratio_sp500: Percentage weight of security in the 13F S&P500 stock pool held by a particular institution in the total value of that security held by all institutions

3 Model Performance

With the data and factors constructed above, we use the prediction result of different models to create 10 separate portfolios by quantile to evaluate the strategy and compare them with the average performance of the institutions and the S&P500 performance. For simplicity, we will disregard transaction costs, although this may be an important factor for trading in real-world markets. For each model, the tables for net value change and portfolio weighting change are shown in the appendix, which can be useful for inspecting and quantifying results.

3.1 Random Forest

To prevent overfitting on the training data, we start with using random forests to reduce model variance. Random forest is a bootstrap aggregating algorithm that fits multiple decision trees using bootstrapped training data and aggregates the trees to make predictions. The resulting portfolio performance for the original 13F and S&P500 pool using random forest is displayed below.

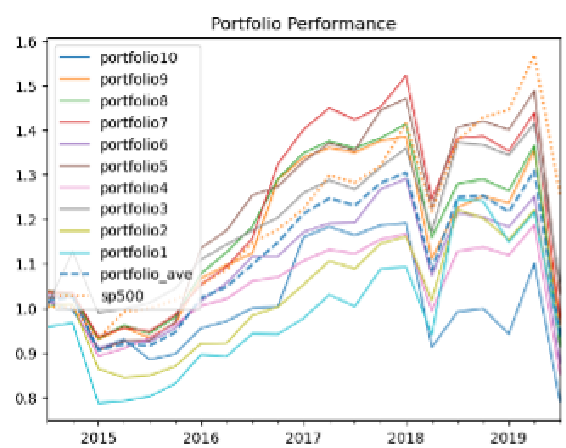

Figure 1: Portfolio Performance for Random Forest (Original Pool)

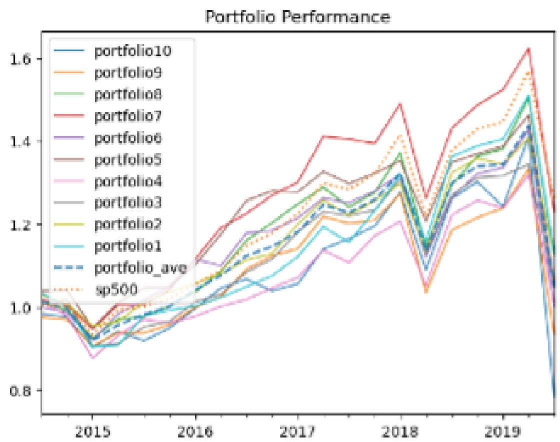

Figure 2: Portfolio Performances for Random Forest (S&P500 Pool)

Observing the plots above, only a few of the ten portfolios constructed using the factors is beating the market, as measured by the S&P500 performance. However, it seems that most of the constructed portfolios by the strategy, along with the average of the ten portfolios, fall short of beating the market and perform consistently worse than the S&P500 over the years from 2014 to 2020. Nevertheless, it appears that the model is learning from the 13F factors and rebalancing weights according to the holdings of other top-performing investment managers.

3.2 XGBoost

Gradient boosting has performed significantly well for prediction tasks on limited data. XGBoost is a state-of-the-art implementation of gradient boosting that has consistently outperformed bagging methods. The resulting portfolio performance for the original 13F and S&P500 pool using XGBoost is displayed below.

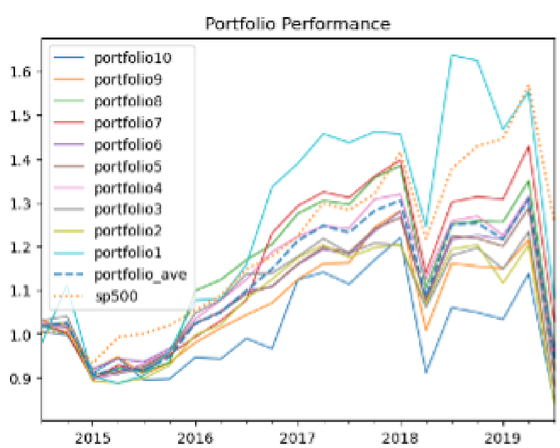

Figure 3: Portfolio Performance for XGBoost (Original Pool)

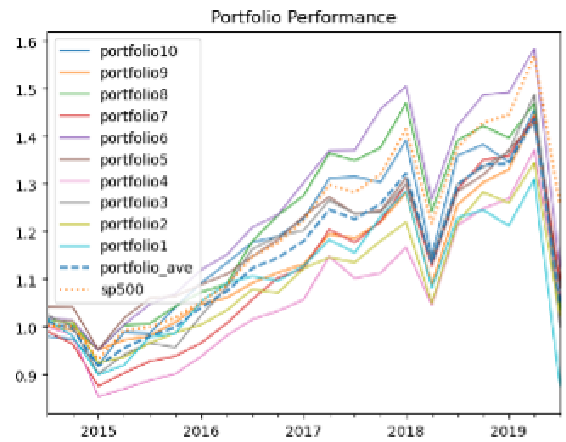

Figure 4: Portfolio Performance for XGBoost (S&P500 Pool)

XGBoost seems to yield a similar result to random forests but has a higher overall average portfolio performance across the ten constructed portfolios. We can see that the majority of the portfolios constructed from the factors still cannot consistently beat the market. However, it is interesting to see that the portfolios perform consistently better than the average of other investment managers' portfolios from 2014 to 2020.

3.3 CatBoost

Extending from XGBoost, CatBoost is another implementation of gradient boosting that is optimized for speed and the use of categorical data. As CatBoost can better handle categorical features, we add a new categorical feature "industry", representing a stock's industry, into the data. The resulting portfolio performance for the original 13F and S&P500 pool using CatBoost is displayed below.

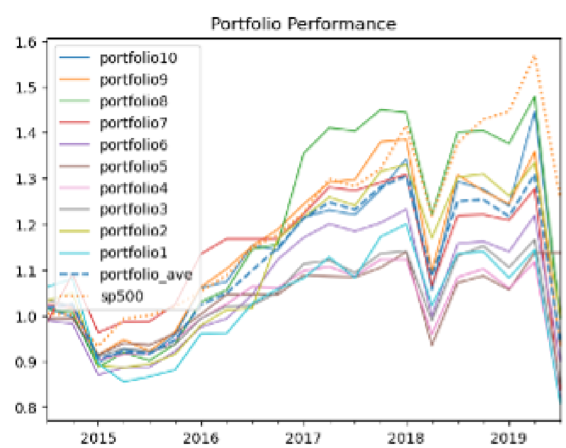

Figure 5: Portfolio Performance for CatBoost (Original Pool)

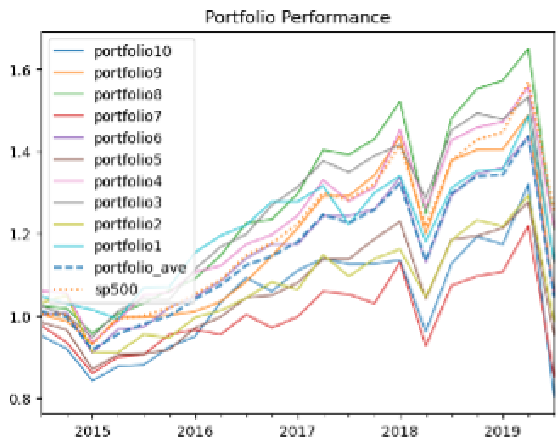

Figure 6: Portfolio Performance for CatBoost (S&P500 Pool)

Adding the industry factor in addition to the other categorical factors in the data seems to have had a positive effect for constructing the portfolios. Compared to the results from XGBoost, the portfolios built from CatBoost seem to perform better on average and converge closer to the S&P500 performance. However, similar to before, most of the portfolios underperform the market while performing consistently better than the average of other institutional investors' portfolios in the data.

4 Portfolio Strategy Evaluation

According to the results above, it's difficult to construct a strategy to create a portfolio consistently better than the S&P500 market benchmark. However, it appears that the models and strategies are able to consistently construct better portfolios than average institutional investment managers. One possible reason could be due to survivorship bias in which there are some S&P500 component stocks not included in the limited 13F data.

Comparing the three models, we can see that Random Forest and CatBoost used on the S&P500 stock pool have significantly better performance. Among the three models, CatBoost turns out to be the best performing, resulting in the highest net value in the top portfolios and the most number of portfolios that outperform the S&P500 benchmark. The charts above show that the returns are spread more widely, which implies the efficiency of the model's prediction ability and efficacy to construct the portfolio.

In the charts, the portfolios constructed by low quantiles of prediction have weaker performance as our basic assumption, but most of the charts show that the top-performing portfolios are the ones between the middle to third top quantiles. A possible explanation of why the top quantiles don't perform as well could be due to good historical performances in the 13F filings which attract investors to follow and take positions, which may dilute the strategy's PnL.

This strategy is not market neutral, as shown in the results over the years from 2014-2020. It's noticeable that in a bullish market, following "the smart money" [3] can generate alpha and result in an excess return on the market. However, it is difficult for the model and strategy to perform consistently in a bearish market and the strategy may have large drawdowns. This can be seen around March 2020 when the COVID-19 pandemic first started, resulting in a market crash. Therefore, it is important to have hedging strategies that complement the 13F strategies to mitigate this risk.

5 Conclusion

5.1 Considerations

In our simulation, we do not consider market transaction costs when executing trades and rebalancing portfolios. However, executing these trades and constantly rebalancing in real-world markets can be expensive and affect the PnL of the strategy. This must be considered when devising a strategy to optimize the cost of the strategy.

Furthermore, the regulations and guidelines for filing 13F do not require investment managers to report short positions, which may make the information in the 13F misleading. Investors could hold a significant long position in a stock to hedge against a short position, which does not necessarily make the stock a "best pick". It is impossible to distinguish which of these long positions hold genuine value and which only serve as hedges.

5.2 Results

Overall, the objective of this study was to find alpha in public SEC 13F filings by constructing relevant factors and building a model to construct portfolios.[2] The models and strategies explored above show that 13F filings can provide some alpha in bullish markets but are inconsistent in bearish markets. Following the smart money and best picks of top-performing investment managers can work well long-term under normal market conditions but can also perform badly in short-term market shocks.

References

[1] Quantpedia. Alpha Cloning – Following 13F Fillings.

[2] Miguel Anton, Randolph B. Cohen, and Christopher Polk. Best Ideas.

[3] Russ Wermers. Is Money Really 'Smart'? New Evidence on the Relation between Mutual Fund Flows, Manager Behavior, and Performance Persistence.

[2] **Disclaimer**: This information is only intended for educational purposes and is not intended as investment advice or solicitation for the sale or purchase of any specific securities, products, services, or investment strategy.

A Appendix

Field	Type	Description
RECORD_ID	Integer(11)	Unique identifier for each record
CIK	Char(10)	Unique identifier for each asset manager
CUSIP	Char(9)	Unique identifier for each security
PERIOD_END	Date	Quarter to which filing corresponds (YYYY-MM-DD)
FILING_DATE	Date	Actual filing date (YYYY-MM-DD)
QTY	Integer	Number of shares held
MARKET_VALUE	Float	Total amount of capital invested in this security

Table 1: SEC Form 13F Data Schema

Field	Type	Description
CUSIP	Char(9)	Unique identifier for each security
EXCHANGE	Char	Exchange on which the security is traded
TICKER	Char(9)	Unique identifier for each security
DATE	Date	Date to which the price data corresponds (YYYY-MM-DD)
VOLUME	Integer	Volume of the security on the specified date
OPEN	Float	Opening price of the security on the specified date
HIGH	Float	High price of the security on the specified date
LOW	Float	Low price of the security on the specified date
CLOSE	Float	Closing price of the security on the specified date

Table 2: Stock Price Data Schema

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	678	678	678	678	678	678	678	678	678	678	6780
12/31/2014	687	687	687	687	688	687	687	687	687	688	6872
3/31/2015	685	685	685	685	686	685	685	685	685	686	6852
6/30/2015	686	686	686	687	686	686	687	686	686	687	6863
9/30/2015	682	683	683	683	683	682	683	683	683	683	6828
12/31/2015	677	678	677	678	678	677	678	677	678	678	6776
3/31/2016	673	673	674	673	674	673	673	674	673	674	6734
6/30/2016	669	669	669	669	670	669	669	669	669	670	6692
9/30/2016	652	653	652	653	652	653	652	653	652	653	6525
12/31/2016	663	663	663	663	664	663	663	663	663	664	6632
3/31/2017	654	654	654	654	655	654	654	654	654	655	6542
6/30/2017	640	641	640	641	641	640	641	640	641	641	6406
9/30/2017	652	653	653	653	653	652	653	653	653	653	6528
12/31/2017	660	660	660	660	660	660	660	660	660	660	6600
3/31/2018	653	653	653	654	653	653	654	653	653	654	6533
6/30/2018	659	660	660	660	660	660	660	660	660	660	6599
9/30/2018	639	639	639	640	639	639	640	639	639	640	6393
12/31/2018	626	627	627	627	627	626	627	627	627	627	6268
3/31/2019	636	636	636	637	636	636	637	636	636	637	6363
6/30/2019	628	629	628	629	629	628	629	628	629	629	6286
9/30/2019	621	622	622	622	622	621	622	622	622	622	6218

Figure 7: Number of Securities for Portfolios Over Time (Random Forest)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	0.958451	1.004658	1.00425	1.014913	1.024254	1.030681	1.038021	1.041097	1.037423	1.014235	1.016798	1.004366
12/31/2014	0.967819	1.010331	1.127831	1.008042	1.026805	1.027616	1.035559	1.028844	1.025072	0.995897	1.02565	1.002045
3/31/2015	0.787807	0.864965	0.989927	0.893527	0.906393	0.910914	0.936842	0.932788	0.930879	0.909415	0.906268	0.932551
6/30/2015	0.792605	0.845351	0.999343	0.910456	0.927021	0.92689	0.956895	0.962244	0.95714	0.931001	0.920508	0.992734
9/30/2015	0.802421	0.84978	1.012613	0.934512	0.928965	0.925453	0.948932	0.944539	0.935131	0.885446	0.916751	1.000408
12/31/2015	0.831491	0.870472	1.04517	0.964353	0.969508	0.95642	0.986158	0.980606	0.967816	0.898012	0.946849	1.019408
3/31/2016	0.896448	0.921509	1.109739	1.006353	1.135139	1.016579	1.053719	1.078104	1.067439	0.955606	1.023633	1.053121
6/30/2016	0.892855	0.922568	1.143366	1.021523	1.175126	1.05726	1.093739	1.1264	1.097588	0.971654	1.048771	1.087391
9/30/2016	0.943398	0.984305	1.17527	1.061423	1.254027	1.116433	1.157032	1.183612	1.123965	1.000696	1.098713	1.147564
12/31/2016	0.942426	1.003422	1.204144	1.070148	1.273385	1.116995	1.323759	1.290845	1.288935	1.003826	1.148332	1.177041
3/31/2017	0.978211	1.053727	1.259515	1.107068	1.330027	1.171473	1.401804	1.348958	1.338919	1.160368	1.212716	1.223644
6/30/2017	1.030658	1.106357	1.287698	1.13206	1.370751	1.19091	1.449894	1.375363	1.36045	1.183362	1.24734	1.298562
9/30/2017	1.005088	1.089343	1.267375	1.123161	1.35482	1.192835	1.423822	1.359682	1.350342	1.164516	1.231551	1.282661
12/31/2017	1.08856	1.145577	1.316885	1.155115	1.444635	1.267629	1.451865	1.382056	1.376304	1.186599	1.281493	1.320302
3/31/2018	1.09345	1.161321	1.359876	1.167202	1.471376	1.291014	1.522755	1.414432	1.385419	1.191798	1.304762	1.415309
6/30/2018	0.941066	1.018327	1.172472	0.994493	1.224051	1.073488	1.245328	1.159028	1.111682	0.912755	1.085644	1.217568
9/30/2018	1.244983	1.221452	1.371956	1.128516	1.406412	1.214264	1.381833	1.279589	1.226157	0.992454	1.249704	1.376657
12/31/2018	1.24089	1.202823	1.366963	1.137382	1.420327	1.205257	1.386678	1.290004	1.251988	0.99974	1.253232	1.428802
3/31/2019	1.149171	1.154009	1.34425	1.119776	1.401016	1.182757	1.353327	1.264228	1.237066	0.942714	1.216655	1.445791
6/30/2019	1.21664	1.221358	1.415242	1.187579	1.488776	1.251473	1.439799	1.365759	1.355788	1.101748	1.309137	1.569178
9/30/2019	0.937018	0.939105	1.058139	0.851799	1.032817	0.876875	0.97847	0.914363	0.964574	0.790187	0.939449	1.255326

Figure 8: Net Value of Portfolios (Random Forest)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	47	48	47	48	48	47	48	47	48	48	476
12/31/2014	47	47	48	47	48	47	47	48	47	48	474
3/31/2015	47	48	48	48	48	47	48	48	48	48	478
6/30/2015	47	47	48	47	48	47	47	48	47	48	474
9/30/2015	48	48	48	48	48	48	48	48	48	49	481
12/31/2015	47	48	48	48	48	48	48	48	48	48	479
3/31/2016	48	48	48	48	48	48	48	48	48	49	481
6/30/2016	48	49	48	49	48	49	48	49	48	49	485
9/30/2016	48	49	49	49	49	48	49	49	49	49	488
12/31/2016	48	49	48	49	49	48	49	48	49	49	486
3/31/2017	48	49	49	49	49	49	49	49	49	49	489
6/30/2017	49	49	49	49	49	49	49	49	49	49	490
9/30/2017	49	49	49	49	49	49	49	49	49	49	490
12/31/2017	49	49	49	49	50	49	49	49	49	50	492
3/31/2018	49	49	49	49	50	49	49	49	49	50	492
6/30/2018	49	50	49	50	49	50	49	50	49	50	495
9/30/2018	48	49	48	49	49	48	49	48	49	49	486
12/31/2018	49	49	49	50	49	49	50	49	49	50	493
3/31/2019	49	50	49	50	50	49	50	49	50	50	496
6/30/2019	49	49	49	50	49	49	50	49	49	50	493
9/30/2019	48	49	49	49	49	49	49	49	49	49	489

Figure 9: Number of Securities for Portfolios Over Time (Random Forest) (S&P500 Pool)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	1.033253	1.028137	1.009744	1.015512	1.038741	0.999643	1.016845	1.013667	0.974811	0.982517	1.011264	1.004366
12/31/2014	0.999791	1.008482	1.017334	0.977975	1.039694	0.986028	1.005811	0.990515	0.959401	0.975745	0.997201	1.002045
3/31/2015	0.903796	0.953314	0.905954	0.875954	0.948595	0.919705	0.945944	0.924289	0.905249	0.902077	0.918688	0.932551
6/30/2015	0.907012	0.963765	0.911137	0.930968	1.009924	0.982571	1.004897	0.970396	0.937442	0.941044	0.956081	0.992734
9/30/2015	0.978455	1.01107	0.951118	0.970035	1.044696	1.016047	1.004391	0.975884	0.936784	0.918133	0.981059	1.000408
12/31/2015	0.991531	1.035421	0.984368	0.960677	1.047573	1.049434	1.041347	1.001782	0.956368	0.94854	1.000172	1.019408
3/31/2016	1.001803	1.05667	1.011393	0.976827	1.101183	1.114256	1.114445	1.035179	0.998545	0.995648	1.040868	1.053121
6/30/2016	1.022206	1.079217	1.030116	1.001129	1.174517	1.098818	1.190207	1.085229	1.024434	1.044918	1.075099	1.087391
9/30/2016	1.048535	1.112837	1.0836	1.017411	1.255855	1.177678	1.22472	1.159732	1.090146	1.066485	1.123305	1.147564
12/31/2016	1.074724	1.128483	1.115115	1.045224	1.279892	1.184276	1.269058	1.202563	1.122898	1.038516	1.14541	1.177041
3/31/2017	1.121081	1.198985	1.180557	1.070403	1.277224	1.213887	1.300321	1.247908	1.140161	1.055138	1.180318	1.223644
6/30/2017	1.192646	1.257045	1.229046	1.136457	1.325944	1.262208	1.411037	1.288116	1.217644	1.139129	1.24617	1.298562
9/30/2017	1.155239	1.2209	1.219507	1.106506	1.29717	1.250655	1.404373	1.240571	1.200908	1.16436	1.226441	1.282661
12/31/2017	1.232058	1.256079	1.232701	1.171443	1.322182	1.279282	1.394004	1.275857	1.209229	1.194909	1.258461	1.320302
3/31/2018	1.318863	1.296748	1.308375	1.205717	1.352093	1.318896	1.489845	1.370884	1.272662	1.276505	1.322745	1.415309
6/30/2018	1.156484	1.132942	1.127674	1.049782	1.206293	1.120908	1.261601	1.145032	1.03401	1.088794	1.133932	1.217568
9/30/2018	1.362323	1.323215	1.269449	1.220769	1.348567	1.263408	1.430312	1.294485	1.184593	1.260852	1.298112	1.376657
12/31/2018	1.387799	1.358061	1.311554	1.256849	1.368933	1.320918	1.48642	1.363138	1.215047	1.301599	1.339493	1.428802
3/31/2019	1.404365	1.344326	1.316289	1.238418	1.387378	1.335689	1.523634	1.381236	1.237714	1.24148	1.342923	1.445791
6/30/2019	1.510049	1.407158	1.343613	1.318789	1.462861	1.427814	1.624073	1.504749	1.333143	1.410791	1.437064	1.569178
9/30/2019	1.127815	1.123809	1.052642	1.007074	1.054908	1.000056	1.228372	1.1305	0.932722	0.782693	1.045579	1.255326

Figure 10: Net Value of Portfolios (Random Forest) (S&P 500 Pool)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	678	678	678	678	678	678	678	678	678	678	6780
12/31/2014	687	687	687	687	688	687	687	687	687	688	6872
3/31/2015	685	685	685	685	686	685	685	685	685	686	6852
6/30/2015	686	686	686	687	686	686	687	686	686	687	6863
9/30/2015	682	683	683	683	683	682	683	683	683	683	6828
12/31/2015	677	678	677	678	678	677	678	677	678	678	6776
3/31/2016	673	673	674	673	674	673	673	674	673	674	6734
6/30/2016	669	668	670	669	670	669	669	669	669	670	6692
9/30/2016	652	653	652	653	652	653	652	653	652	653	6525
12/31/2016	663	663	663	663	664	663	663	663	663	664	6632
3/31/2017	654	654	654	654	655	654	654	654	654	655	6542
6/30/2017	640	641	640	641	641	640	641	640	641	641	6406
9/30/2017	652	653	653	653	653	652	653	653	653	653	6528
12/31/2017	660	660	660	660	660	660	660	660	660	660	6600
3/31/2018	653	653	653	654	653	653	654	653	653	654	6533
6/30/2018	659	660	660	660	660	660	660	660	660	660	6599
9/30/2018	639	639	639	640	639	639	640	639	639	640	6393
12/31/2018	626	627	627	627	627	626	627	627	627	627	6268
3/31/2019	636	636	636	637	636	636	637	636	636	637	6363
6/30/2019	628	629	628	629	629	628	629	628	629	629	6286
9/30/2019	621	622	622	622	622	621	622	622	622	622	6218

Figure 11: Number of Securities for Portfolios Over Time (XGBoost)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	0.975879	1.019701	1.03078	1.02516	1.018379	1.021102	1.022297	1.017954	1.031646	1.005086	1.016798	1.004366
12/31/2014	1.110767	1.023336	1.040213	1.019952	1.02596	1.015516	1.003021	1.001743	1.012361	0.997765	1.02565	1.002045
3/31/2015	0.903503	0.89217	0.91226	0.897512	0.901078	0.919634	0.894961	0.899321	0.91847	0.910648	0.906268	0.932551
6/30/2015	0.886678	0.888012	0.908667	0.908107	0.914545	0.943224	0.92878	0.921839	0.947164	0.945087	0.920508	0.992734
9/30/2015	0.904957	0.898154	0.921005	0.932137	0.925878	0.936185	0.915909	0.913987	0.907237	0.894761	0.916751	1.000408
12/31/2015	0.959527	0.928264	0.958439	0.960785	0.958873	0.966776	0.952736	0.9346	0.93417	0.896894	0.946849	1.019408
3/31/2016	1.076453	0.997271	1.046836	1.033722	1.025106	1.02187	0.992609	1.098469	0.979756	0.945728	1.023633	1.053121
6/30/2016	1.07971	1.021426	1.078053	1.077268	1.05022	1.052209	1.030114	1.123702	1.013648	0.942781	1.048771	1.087391
9/30/2016	1.158234	1.080265	1.136952	1.124248	1.091258	1.09831	1.076908	1.168893	1.043454	0.989622	1.098713	1.147564
12/31/2016	1.33586	1.12487	1.138661	1.187313	1.108811	1.107802	1.230295	1.204441	1.070461	0.965924	1.148332	1.177041
3/31/2017	1.389192	1.173764	1.176436	1.222352	1.159767	1.1584	1.292278	1.274825	1.124463	1.123909	1.212716	1.223644
6/30/2017	1.456906	1.203005	1.217454	1.245948	1.198049	1.193213	1.324017	1.304424	1.160554	1.140519	1.24734	1.298562
9/30/2017	1.436775	1.1744	1.184454	1.241877	1.186034	1.180896	1.311308	1.295659	1.162447	1.113638	1.231551	1.282661
12/31/2017	1.461918	1.197137	1.207614	1.307699	1.24049	1.234532	1.360344	1.357172	1.243767	1.16926	1.281493	1.320302
3/31/2018	1.456359	1.204274	1.20157	1.31903	1.26532	1.279296	1.396696	1.383851	1.280928	1.219752	1.304762	1.415309
6/30/2018	1.246399	1.069428	1.060254	1.124298	1.081535	1.074451	1.138983	1.105313	1.007794	0.910474	1.085644	1.217568
9/30/2018	1.637062	1.193119	1.178601	1.257226	1.223162	1.215573	1.300663	1.250662	1.161264	1.060019	1.249704	1.376657
12/31/2018	1.624438	1.203434	1.196505	1.268951	1.218362	1.225443	1.313226	1.257738	1.154097	1.048818	1.253232	1.428802
3/31/2019	1.467052	1.116068	1.148033	1.225261	1.200215	1.216017	1.307432	1.25587	1.149307	1.033237	1.216655	1.445791
6/30/2019	1.553631	1.203703	1.233893	1.315223	1.287549	1.307148	1.429169	1.349944	1.214921	1.138148	1.309137	1.569178
9/30/2019	1.080176	0.841188	0.881309	0.94755	0.916417	0.959801	1.027571	0.966018	0.878031	0.846743	0.939449	1.255326

Figure 12: Net Value of Portfolios (XGBoost)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	47	48	47	48	48	47	48	47	48	48	476
12/31/2014	47	47	48	47	48	47	47	48	47	48	474
3/31/2015	47	48	48	48	48	47	48	48	48	48	478
6/30/2015	47	47	48	47	48	47	47	48	47	48	474
9/30/2015	48	48	48	48	48	48	48	48	48	49	481
12/31/2015	47	48	48	48	48	48	48	48	48	48	479
3/31/2016	48	48	48	48	48	48	48	48	48	49	481
6/30/2016	48	49	48	49	48	49	48	49	48	49	485
9/30/2016	48	49	49	49	49	48	49	49	49	49	488
12/31/2016	48	49	48	49	49	48	49	48	49	49	486
3/31/2017	48	49	49	49	49	49	49	49	49	49	489
6/30/2017	49	49	49	49	49	49	49	49	49	49	490
9/30/2017	49	49	49	49	49	49	49	49	49	49	490
12/31/2017	49	49	49	49	50	49	49	49	49	50	492
3/31/2018	49	49	49	49	50	49	49	49	49	50	492
6/30/2018	49	50	49	50	49	50	49	50	49	50	495
9/30/2018	48	49	48	49	49	48	49	48	49	49	486
12/31/2018	49	49	49	50	49	49	50	49	49	50	493
3/31/2019	49	50	49	50	50	49	50	49	50	50	496
6/30/2019	49	49	49	50	49	49	50	49	49	50	493
9/30/2019	48	49	49	49	49	49	49	49	49	49	489

Figure 13: Number of Securities for Portfolios Over Time (XGBoost) (S&P500 Pool)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	1.017612	1.012628	1.025555	1.001508	1.042912	1.018819	0.991942	1.019975	1.001274	0.981179	1.011264	1.004366
12/31/2014	0.981205	1.01251	1.000912	0.983516	1.042297	1.014127	0.964442	1.004931	0.994156	0.974707	0.997201	1.002045
3/31/2015	0.900574	0.925312	0.902449	0.854307	0.953031	0.951143	0.876074	0.951992	0.952576	0.920962	0.918688	0.932551
6/30/2015	0.920214	0.937252	0.942292	0.870543	1.018744	1.005072	0.903865	1.004052	0.972942	0.989153	0.956081	0.992734
9/30/2015	0.979662	0.966523	0.966523	0.888159	1.060147	1.047726	0.928136	1.007337	0.98193	0.986797	0.981059	1.000408
12/31/2015	0.987042	0.98842	0.957663	0.902072	1.064907	1.06992	0.939279	1.043367	1.01064	1.041272	1.000172	1.019408
3/31/2016	1.0533	1.005068	1.023848	0.938084	1.088986	1.119934	0.966467	1.073291	1.049033	1.092032	1.040868	1.053121
6/30/2016	1.091944	1.035062	1.083951	0.981835	1.111013	1.151474	1.007697	1.09034	1.061202	1.134147	1.075099	1.087391
9/30/2016	1.106728	1.079332	1.163398	1.016171	1.148193	1.209246	1.057785	1.179808	1.092546	1.177642	1.123305	1.147564
12/31/2016	1.097117	1.071873	1.190323	1.03366	1.183274	1.235498	1.103495	1.234198	1.114316	1.19012	1.14541	1.177041
3/31/2017	1.12822	1.123245	1.202947	1.057548	1.232335	1.302898	1.12348	1.27595	1.131816	1.2271	1.180318	1.223644
6/30/2017	1.182983	1.145948	1.266169	1.148148	1.272939	1.370155	1.204527	1.364764	1.195099	1.311417	1.24617	1.298562
9/30/2017	1.15631	1.136005	1.237648	1.102611	1.237691	1.371083	1.177556	1.349334	1.186669	1.315165	1.226441	1.282661
12/31/2017	1.231792	1.18073	1.241042	1.11346	1.24369	1.457248	1.221981	1.37646	1.220121	1.303698	1.258461	1.320302
3/31/2018	1.285046	1.220103	1.299517	1.167311	1.31276	1.505184	1.299685	1.469964	1.282085	1.391817	1.322745	1.415309
6/30/2018	1.081905	1.050179	1.143102	1.045708	1.132911	1.268663	1.127457	1.242642	1.089677	1.14984	1.133932	1.217568
9/30/2018	1.229053	1.218557	1.300287	1.213217	1.284659	1.42152	1.288424	1.391346	1.25647	1.359767	1.298112	1.376657
12/31/2018	1.245524	1.282618	1.335563	1.2487	1.319083	1.486712	1.350414	1.421595	1.303113	1.382646	1.339493	1.428802
3/31/2019	1.212712	1.260474	1.368036	1.269573	1.371734	1.492002	1.359526	1.397112	1.330652	1.346059	1.342923	1.445791
6/30/2019	1.310718	1.345379	1.487952	1.371867	1.428756	1.584684	1.441737	1.469382	1.44603	1.456109	1.437064	1.569178
9/30/2019	0.877104	1.023077	1.000292	1.060772	1.083111	1.125395	1.100086	1.036507	1.034582	1.088231	1.045579	1.255326

Figure 14: Net Value of Portfolios (XGBoost) (S&P 500 Pool)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	696	659	679	678	678	678	674	1088	272	678	6780
12/31/2014	687	687	687	686	684	688	691	687	808	567	6872
3/31/2015	685	683	688	491	879	685	685	687	683	686	6852
6/30/2015	686	685	687	687	686	686	687	686	686	687	6863
9/30/2015	683	682	719	647	683	682	684	682	559	807	6828
12/31/2015	657	695	680	678	678	677	678	678	677	678	6776
3/31/2016	673	673	680	667	674	315	1226	481	671	674	6734
6/30/2016	669	669	669	669	550	788	640	699	430	909	6692
9/30/2016	772	237	1027	684	0	1783	0	636	682	704	6525
12/31/2016	664	417	906	623	0	2376	0	320	630	696	6632
3/31/2017	654	402	557	1001	657	564	744	654	655	654	6542
6/30/2017	618	1010	381	554	688	401	846	673	770	465	6406
9/30/2017	652	653	653	652	652	654	650	656	651	655	6528
12/31/2017	659	661	660	660	753	572	655	660	660	660	6600
3/31/2018	662	999	307	0	1301	272	902	1154	274	662	6533
6/30/2018	658	661	659	661	660	660	663	657	661	659	6599
9/30/2018	639	639	639	640	639	639	640	639	639	640	6393
12/31/2018	626	627	627	627	627	626	627	627	627	627	6268
3/31/2019	636	636	636	637	636	637	636	636	903	370	6363
6/30/2019	638	362	888	626	629	628	629	640	617	629	6286
9/30/2019	621	622	622	558	0	1845	84	621	648	597	6218

Figure 15: Number of Securities for Portfolios Over Time (CatBoost)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	1.062455	1.031928	1.033838	1.022842	0.992906	0.989654	0.983726	1.014634	1.025649	1.01595	1.016798	1.004366
12/31/2014	1.08038	1.0498	1.021282	1.01892	0.993379	0.982203	1.090936	1.006779	1.015915	0.997747	1.02565	1.002045
3/31/2015	0.894854	0.890616	0.911587	0.903861	0.914406	0.870602	0.962977	0.887503	0.914084	0.897245	0.906268	0.932551
6/30/2015	0.855073	0.886443	0.928444	0.914925	0.93986	0.886883	0.986515	0.919167	0.947141	0.926535	0.920508	0.992734
9/30/2015	0.866831	0.893784	0.921464	0.917201	0.935743	0.887353	0.987235	0.901741	0.922161	0.915855	0.916751	1.000408
12/31/2015	0.881621	0.915567	0.936844	0.94705	0.961615	0.922124	1.024527	0.937909	0.965253	0.957983	0.946849	1.019408
3/31/2016	0.959953	0.978981	0.993523	0.993484	1.003067	0.975245	1.134531	1.029745	1.062375	1.060865	1.023633	1.053121
6/30/2016	0.961208	1.012031	1.02045	1.025012	1.045601	0.993294	1.16744	1.055912	1.101945	1.074018	1.048771	1.087391
9/30/2016	1.026455	1.016323	1.022389	1.063296	1.045601	1.045381	1.16744	1.144538	1.151916	1.153349	1.098713	1.147564
12/31/2016	1.058186	1.167942	1.051284	1.060621	1.045601	1.122558	1.16744	1.156103	1.188491	1.143547	1.148332	1.177041
3/31/2017	1.081439	1.214273	1.113122	1.097847	1.088261	1.170425	1.222156	1.354368	1.243354	1.214297	1.212716	1.223644
6/30/2017	1.127668	1.258745	1.120924	1.107056	1.085783	1.200306	1.280303	1.410242	1.290578	1.230584	1.24734	1.298562
9/30/2017	1.082612	1.240594	1.093744	1.086032	1.083781	1.184216	1.272991	1.403303	1.297412	1.220277	1.231551	1.282661
12/31/2017	1.172393	1.314756	1.135447	1.122548	1.105031	1.202629	1.290927	1.449897	1.379606	1.274838	1.281493	1.320302
3/31/2018	1.199809	1.330077	1.140976	1.122548	1.139155	1.232355	1.308416	1.443494	1.384997	1.34207	1.304762	1.415309
6/30/2018	1.021733	1.169446	0.988773	0.958987	0.934978	0.99866	1.065675	1.220895	1.096376	1.054931	1.085644	1.217568
9/30/2018	1.135061	1.302147	1.130314	1.083719	1.071819	1.156694	1.218309	1.400865	1.307516	1.293009	1.249704	1.376657
12/31/2018	1.139889	1.309444	1.152248	1.101807	1.086474	1.162083	1.22052	1.404222	1.272099	1.275981	1.253232	1.428802
3/31/2019	1.082303	1.261507	1.105239	1.0593	1.056411	1.139758	1.208324	1.375661	1.24371	1.239784	1.216655	1.445791
6/30/2019	1.144308	1.334159	1.166058	1.117426	1.137303	1.218687	1.277096	1.478832	1.358459	1.446402	1.309137	1.569178
9/30/2019	0.808293	1.000423	0.851412	0.819272	1.137303	0.900402	0.837869	0.994664	0.934698	0.998104	0.939449	1.255326

Figure 16: Net Value of Portfolios (CatBoost)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_total
9/30/2014	47	48	47	48	48	47	48	47	48	48	476
12/31/2014	47	47	48	47	48	47	47	48	47	48	474
3/31/2015	47	48	48	48	48	47	48	48	48	48	478
6/30/2015	47	47	48	47	48	47	47	48	47	48	474
9/30/2015	48	48	48	48	48	48	48	48	48	49	481
12/31/2015	47	48	48	48	48	48	48	48	48	48	479
3/31/2016	48	48	48	48	48	48	48	48	48	49	481
6/30/2016	48	49	48	49	48	49	48	49	48	49	485
9/30/2016	48	54	44	49	58	39	49	49	49	49	488
12/31/2016	48	49	48	42	56	48	49	48	49	49	486
3/31/2017	40	56	49	48	82	0	54	46	60	54	489
6/30/2017	43	36	98	21	32	56	101	5	76	22	490
9/30/2017	42	73	34	6	159	0	50	27	92	7	490
12/31/2017	49	49	49	49	50	49	49	49	49	50	492
3/31/2018	49	49	49	49	50	49	49	49	49	50	492
6/30/2018	49	50	49	50	49	50	49	50	49	50	495
9/30/2018	48	49	48	49	49	48	49	48	49	49	486
12/31/2018	49	49	49	50	49	49	50	49	49	50	493
3/31/2019	49	50	49	50	50	49	50	49	50	50	496
6/30/2019	49	49	49	50	49	49	50	49	49	50	493
9/30/2019	48	49	49	49	49	49	49	49	49	49	489

Figure 17: Number of Securities for Portfolios Over Time (CatBoost) (S&P500 Pool)

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio8	portfolio9	portfolio10	portfolio_ave	sp500
9/30/2014	1.047396	1.032372	1.024765	1.061378	0.985337	1.002735	0.977641	1.025461	1.003888	0.952816	1.011264	1.004366
12/31/2014	1.030094	1.050002	1.001805	1.056562	0.966548	1.00904	0.936077	1.018458	0.987923	0.920348	0.997201	1.002045
3/31/2015	1.015087	0.912675	0.949055	0.936141	0.871542	0.910217	0.861978	0.9579	0.932875	0.843181	0.918688	0.932551
6/30/2015	0.99258	0.911558	1.011975	0.988789	0.906456	0.967976	0.900457	1.005196	0.996951	0.877713	0.956081	0.992734
9/30/2015	1.0686	0.955155	1.042695	1.050835	0.908591	0.973145	0.906162	1.030954	0.997405	0.88129	0.981059	1.000408
12/31/2015	1.070604	0.947453	1.039637	1.057019	0.918102	1.020614	0.955146	1.062091	1.001937	0.92504	1.000172	1.019408
3/31/2016	1.154091	0.996392	1.113662	1.10703	0.971073	1.046582	0.966975	1.090423	1.011207	0.950535	1.040868	1.053121
6/30/2016	1.1951	1.013403	1.167983	1.121614	0.997682	1.084436	0.955384	1.14701	1.034904	1.032807	1.075099	1.087391
9/30/2016	1.220858	1.043676	1.19895	1.174415	1.044724	1.140293	1.003353	1.225745	1.084246	1.093022	1.123305	1.147564
12/31/2016	1.277965	1.082525	1.269196	1.197484	1.050536	1.174242	0.971769	1.234824	1.145604	1.060243	1.14541	1.177041
3/31/2017	1.277993	1.064587	1.313487	1.24411	1.08071	1.174242	0.998125	1.297063	1.213321	1.110634	1.180318	1.223644
6/30/2017	1.316216	1.148423	1.376382	1.330165	1.138547	1.243173	1.059893	1.40326	1.290549	1.139646	1.24617	1.298562
9/30/2017	1.223148	1.096479	1.349411	1.278938	1.138327	1.243173	1.052507	1.391758	1.291902	1.125868	1.226441	1.282661
12/31/2017	1.299882	1.139311	1.389491	1.313606	1.187399	1.259786	1.030809	1.429863	1.342073	1.126515	1.258461	1.320302
3/31/2018	1.340154	1.162272	1.415733	1.452369	1.229659	1.336561	1.130757	1.521388	1.4362	1.136319	1.322745	1.415309
6/30/2018	1.180702	1.045609	1.286104	1.260704	1.04156	1.130036	0.927191	1.248208	1.200179	0.962442	1.133932	1.217568
9/30/2018	1.310979	1.183898	1.450708	1.426604	1.186328	1.29269	1.073978	1.479428	1.377735	1.127059	1.298112	1.376657
12/31/2018	1.35261	1.233183	1.491889	1.457905	1.194259	1.344984	1.096681	1.552053	1.404076	1.192944	1.339493	1.428802
3/31/2019	1.355891	1.217742	1.478077	1.471696	1.213764	1.36032	1.107886	1.572076	1.404922	1.174089	1.342923	1.445791
6/30/2019	1.487524	1.293337	1.532516	1.557695	1.277439	1.437512	1.219878	1.650098	1.489045	1.321158	1.437064	1.569178
9/30/2019	1.138335	0.987949	1.129884	1.215255	0.954188	1.053573	0.852968	1.211026	1.054368	0.804477	1.045579	1.255326

Figure 18: Net Value of Portfolios (CatBoost) (S&P 500 Pool)