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AI Stock-Screening Methodology for Portfolio Construction

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Abstract

Selecting profitable stocks is crucial in constructing an all-equity portfolio. Investors need to rely on screening mechanisms to aid investment decision making. New stock selection methods are highly desired, and existing methods are constantly improved. In this research, we investigate the potential of relying on artificial intelligence to guide the stock selection process. The developed model employed genetic algorithms to optimize the selection of screening rules from among a set of widely accepted fundamental indicators. The model robustness and performance are tested using stock market real data over a 14-year period from 2006 till 2019. Based on portfolio quality factors of risk and return, the obtained results outperformed three commonly used stock screeners and the relative market indices as well. The findings of this work reveal that the proposed genetic algorithm provides a powerful dynamic tool to assist in screening and selecting valuable stocks.

JEL classification: G11, G17, C63

Keywords: Stock-Screening, Artificial Intelligence in Finance, Genetic Algorithms

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1. Introduction

The first known official modern stock market was the Amsterdam Stock Exchange, which was established in 1602 (Petram, 2011) and was the first to issue paper shares that were bought, sold, and traded across investors (Gelderblom, Jong, & Jonker, 2013). Since then, more exchanges were founded, and listed companies globally reached more than 43 thousand (World-Bank, 2019). Given the huge number of listed companies, when investors approach the stock market for investment, they face a great challenge of identifying profitable investment opportunities, as with such count of listings, it becomes nearly impossible for a human to process all the available information and identify profitable stocks. Accordingly, to save time and effort, investors usually rely on filtering mechanisms to narrow down their focus to a subset of companies to invest in. Therefore, stock screening rules are known for their importance in helping investors when picking stocks for investment. However, the benefit of these screening filters extends beyond saving time and effort; it also guarantees that the selection process will not be influenced by the investor's behavioral or emotional bias. Because screening filters narrow down the focus to a subset of investment opportunities, it is crucial to rely on reliable screening mechanisms that can select profitable investments since an investment portfolio's performance is linked to the selected investments. Thus, due to the importance of screening filters, many research has been directed towards finding screening rules capable of identifying profitable investments. Such importance is amplified when constructing an all-equity portfolio, as is the case in our intended research. Existing well-known and commonly used screening filters such as those developed by Benjamin Graham (Graham, The Intelligent Investor, 1949) and Joseph Piotroski (Piotroski, 2000). The reliance on computer systems to find hidden patterns in datasets and induce profitable screening rules has been introduced as a concept in 1960 (Clarkson & Meltzer, 1960) and since then has shown great potential. Continuous advancements in artificial-intelligence driven by the rapid enhancements in the computing capabilities have led the industry giant BlackRock – which manages more than $5.1 trillion in assets under management – to announce that they started relying on systems powered by artificial intelligence to perform the task of stock selection instead of having this task done manually (Tokic, 2018). This announcement followed the statement made by Laurence Fink (BlackRock CEO) that linked the underperformance of 11% of their active equity funds in 2016 to the limited human discretion in active portfolio management and stock selection. Such announcements from leading industry companies emphasize the great potential behind utilizing artificial intelligence to enhance investment management processes. This thesis is believed to be in line with the industry trend as our main objective is to explore the benefit of using one of the artificial intelligence models, which is the genetic algorithm, to optimize stock screening rules to achieve better financial performance compared to some commonly used stock screeners when trading on the U.S market. This research work addresses the gap in the literature regarding the lack of using fundamental ratios in the application of genetic algorithms addressing the stock selection process. The developed model is expected to provide a stock screening tool capable of aiding investment decisions with dynamic screening rules.

This thesis is structured as follows, the second section will explore the published literature in the same research focus area, an in-depth review of the used dataset and the proposed model will be presented in the third section, the fourth section will be dedicated to the model performance results, and finally, the conclusion will be presented in section five. Additionally, an appendix is made available to include the full details of the performance assessment reports for the model and the reference screeners.

2. Literature Review

This section brings up an overview of relevant literature that is in the scope of this work and connects to our research questions. The presented literature review is divided into the following sections that discuss separately pertinent topics from selected previous studies.

2.1 Importance of security selection

Whenever approaching the stock market for investment, one needs to address two main tasks; select the securities desired for investing and decide how much to allocate for each of the selected securities. Although it has been argued earlier that the importance of asset allocation is superior to the security selection (Brinson, Singer, & Beebower, 1991), others argued the complete opposite (Kritzman & Page, 2003). Such extreme claims have been criticized in a study that focused on evaluating the relative importance of each of the two tasks (Assoé, L'Her, & Plante, 2006). In their study, the authors addressed several gaps observed in previous studies. After extensive analysis of the importance of selection versus allocation, the study concluded that it could not be explicitly declared that one particular activity is structurally more-or-less important than the other. Accordingly, both activities of asset allocation and security selection have been addressed in our study.

2.2 Stock Screeners

Given the number of assets available to investors in the global markets, the asset screening and selection process is crucial to identify good quality stocks that are the potential to outperform the market by having an excess return in the future. The process of selecting stocks can be difficult, tedious, time-consuming, and subject to emotional or behavioral bias. Obviously, there is neither a unique best asset screener nor a screener that is valid for eternity. Therefore, the development of stock screening criteria is highly desired and constantly evolving over time. In the following sub-sections, we will review some of the well-known stock screeners and explore examples of different studies that assess the performance of these stock screeners under different markets. This review is done to support the selection of reference stock screeners that will be used to benchmark the performance of our model, as well as identifying the candidate fundamental ratios that will be used to feed our model.

2.2.1 Benjamin Graham NCAV screener

In 1934 the famous economist Benjamin Graham published in his book “Security Analysis” one of the famous stock screening strategies which rely on the Net Current Asset Value “NCAV”[1] (Graham & Dodd, Significance of the Current-Asset Value, 1934). Benjamin had tested the proposed rule on the period between 1930 and 1932 and believed that investors could find undervalued stocks that are trading below their intrinsic value by searching for stocks that have a market-capital less than 2/3 of their NCAV. The NCAV strategy has been investigated by several researchers over time to test if it still holds or not. In 1986 the NCAV was tested over a 13-year period from 1970 till 1982 (Oppenheimer, Ben Graham’s Net Current Asset Values: A Performance Update, 1986); the test focused on a total of 645 stock that were selected from NYSE, AMEX, and OTC exchanges, it was reported that the portfolios created using the NCAV and held for a year had a higher return when compared to NYSE and AMEX indices. A more recent study that investigates over the period from April 2003 till March 2011 if the NCAV is still effective on the U.S market in generating excess return (Dudzinski & Kunkel, 2014), the study concluded that relying on the NCAV generated 24.7% annualized geometric returns that were not explained by either the CAPM or the Fama-French models. In 2015 another paper was published that tested the NCAV strategy over the period from 1999 till 2012 (An, Cheh, & Kim, 2015); after completing

[1] NCAV = Current Assets - Total Liabilities - Preferred Shares

their tests, they concluded that the NCAV strategy still holds and generated excess return when compared to S&P 500 index as a benchmark. Another test for the NCAV strategy was done on the stock market of Saudi Arabia as an example of emerging (Zakaria & Hashim, 2017). The study tested the strategy for ten years and concluded that relying on the NCAV strategy generate significant excess returns compared to the indices. The study highlighted a drawback related to the count of stocks in compliance with the NCAV rules, as a significant decrease in the count of qualified stocks was observed from 23 stocks in 2000 to only four stocks in 2011.

2.2.2 Benjamin Graham Defensive Investor

Another famous screening strategy proposed by Benjamin Graham in 1949 in his book "The Intelligent Investor" is the Defensive Investor strategy (Graham, The Intelligent Investor, 1949). Graham described the defensive investor as someone who does not have enough time to dedicate to the portfolio management process, and in chapter 14, Graham introduced a checklist for a defensive investor to select stocks according to. The checklist imposes constraints on any selected company to have an annual sale of at least 2 billion dollars, a current ratio to be at least 2, working capital to be more than the long-term debt, positive earnings over the past 10 years, dividends paid over the past 20 years, a price to 3-year average earnings less than 15, 10-year earnings growth of at least 33%, price to book ratio that is less than 1.5, and finally to have a Graham multiplier[2] less than 22.5. The importance of the last rule was to add an exception for companies with a low price to earnings ratio; the last rule would allow them to qualify even if their price to book was greater than 1.5 if their Graham multiplier is less than 22.5. In 1981, a paper was published with test results for Graham's defensive investor strategy to check if it would succeed in generating an excess return; the test was applied on the US Stock Market over the period

[2] Graham Multiplier = price to earnings ratio * price to book ratio

from 1956 till 1975, the results showed that by relying on the rules proposed by Graham the portfolios generated positive risk-adjusted return compared to market portfolios. Under the conditions of emerging markets, the defensive investor strategy was tested in a study on the Malaysian stock market over the period from 2000 till 2009 (Chang, 2012). In that study, the author highlighted an exception to the original screening rules since the constrain on the sales was not feasible in the Malaysian market. Despite the modification introduced on the original Graham's checklist, the study reported significant excess return. The defensive investor strategy was tested again on the Turkish stock market (Terz, 2016) to check if it still holds for the period from 2005 till 2014, and it has been found that the strategy generated excess return when compared to the BIST-100 Index as a benchmark.

2.2.3 Piotroski F-Score

A more recent well-known and commonly used screener was proposed in 2000 by Joseph Piotroski (Piotroski, 2000). The presented model was named Piotroski F-Score, and it consists of 9 rules; each rule counts as a point if the condition is satisfied. Accordingly, each company would get a score from 0 to 9. The company would get one point if any of the rules were met. The F-Score rules check the company for having: a positive Return on Assets (ROA), a positive year-on-year change in ROA, positive cash flow from operations, a negative year-on-year change in the long-term debt, a positive year-on-year change in its current ratio, a year-on-year decrease or no change in common shares outstanding, and if the net income is less than its cash flow from operations. Piotroski F-Score was found to be the top-performing screener in comparison to 12 other common screening strategies in a paper published in 2014 (Gray, Vogel, & Xu, 2014). The study covers the period from 1963 till 2013 on three exchanges: NYSE, AMEX, and NASDAQ. The authors stated that a portfolio based on Piotroski F-Score screener generated the highest return and had the highest risk-adjusted-return. In 2016 Piotroski F-Score strategy was tested again to investigate if it still holds and is capable of identifying profitable companies (Geyfman, Wimmer, & Rada, 2016), the experiment focused on the constituents of S&P 500 for the period between 2007 and 2014, and it was reported that relying on Piotroski F-Score yielded higher returns when compared to S&P 500 index as a benchmark. A recent comprehensive study on Piotroski F-score over international markets investigated its potential to generate an excess return when compared to the indices (Walkshäusl, 2020). The study covered 20 developed markets excluding the US, in addition to 15 emerging markets for the period from 2000 till 2018. The study confirmed that relying on F-score was successful in identifying profitable companies. Additionally, the paper summarized the methodological aspects and performance-related findings obtained from 10 previous studies published over the period from 2000 till 2019, and it was concluded that the results were consistent with the previous studies confirming the importance of the F-score.

2.3 Stock Screening using Artificial Intelligence

As time goes by, some of the screening filters designed a long time ago may start to fail in capturing the correct investment opportunities due to the changes that happen in the underlying market condition. Accordingly, a screening filter would need to be re-calibrated to perform as intended. Computer systems and artificial intelligence have offered a lot of capabilities that can be used to calibrate screening filters to have them adapt to current market conditions. There is a wide variety of available models under the artificial intelligence domain, and the literature is rich with papers testing different models with different datasets to find reliable screening filters that would guide investors when selecting stocks. In the following sub-sections, some commonly used algorithms applied in the field of stock screening are explored through selected examples of relevant studies. This review helps to examine these algorithms to identify the proper technique that most suits our research objectives.

2.3.1 Decision Tree

In 1991 a paper was published where decision tree algorithms were used to induce stock screening rules (Tam, Kiang, & Chi, 1991). The experiment was done on the period from March 1985 till December 1988; it was found that the portfolios designed based on the screening rules generated from the algorithm experienced better returns when compared to the NYSE Composite Index and S&P 500 index. The performance was also assessed based on the risk-adjusted return and found to be superior to that of the indices, which confirms that the higher returns were not achieved by taking a position with higher risk. An interesting paper used a hybrid model capitalizing on the power of rough set theory and decision tree algorithms using 14 fundamental ratios to guide the process of stock selection (Cheng, 2013). The experiment was applied to 993 companies listed on the Taiwan stock exchange for the period 2009-2011. Conclusions of the experiment indicated that the proposed model could generate stock screening rules that managed to provide higher returns than the general market return.

2.3.2 Support Vector Machines (SVM)

In 2001 a paper was published where the support vector machines (SVM) were applied (Fan & Palaniswami, 2001). The experiment was done on the Australian stock market for the period from 1992 till 2000; it was found that SVM succeeded in generating an excess return when compared to an equally weighted market portfolio. Another study considering the use of SVM for portfolio selection relying on a set of 22 technical indicators was tested on the Brazilian stock market using the constituents of the Bovespa Index (Paiva, Cardoso, Hanaoka, & Duarte, 2019).

It was concluded that the model provided significant excess return when compared to the index and the performance of another model using the random forest technique.

2.3.3 Particle Swarm Optimization (PSO)

In 2011 an interesting paper was published to tackle the topic of selecting trading rules by using particle swarm optimization (Briza & Naval, 2011). The hypothesis the paper is built upon is that if traders stick to a single trading rule, they might end up missing other opportunities that other trading rules might have provided; accordingly, a weight reward strategy (WRS) was developed based on two well-known technical trading strategies: Moving average (MA) and the trading range break-out (TRB). The particle swarm optimizer works mainly to maximize the WRS, which relies on 140 sub-rules related to the considered trading strategies. The research was implemented on the constituents of the NASDAQ 100 index over the period from 2003 till 2010. It was found that the trading model based on the particle swarm optimization had a higher average return when compared to the MA and TRB strategies. A recent study aimed at extending the benefits of PSO by adding a Recurrent Reinforcement learning (RRL) component was published in 2019 (Almahdi & Yang, 2019). The RRL component is used to maximize the Calmar ratio of the portfolio to enhance the portfolio drawdown. The authors tested their model using the S&P100 constituents over the period from 2011 till 2015 and concluded that their proposed model succeeded in outperforming the considered benchmark.

2.3.4 Genetic Algorithms

In 1999 a paper was published in the journal of financial economics used genetic algorithms to find trading rules depending on technical indicators (Allen & Karjalainen, 1999). The research covered the period from 1928 till 1995, and the algorithm was trained and tested on S&P 500 index daily prices. The presented model operated on day trading and would decide the position for the next day based on the historical price movement and the performance of some technical indicators. The model succeeded in creating the trading rules; however, the results were not impressive since the model failed to beat the buy and hold strategy when considering the transaction costs. In a research presented at the International Conference on Intelligent Data Engineering and Automated Learning (Chan, Wong, Tse, Cheung, & Tang, 2002), the authors successfully used a genetic algorithm model to solve a stock screening and ranking problem. A more recent study aiming to develop a model to assist the investor in picking stocks (Zhou, Yu, Huang, Wang, & Lai, 2006) was applied to 100 random companies listed on Shanghai Stock Exchange over the period from January 2002 till December 2004. The model presented relied on only four fundamental ratios: ROCE, P/E, EPS, and the Liquidity Ratio. The presented model works on ranking the companies rather than filtering some out where the objective function of the genetic algorithm was set to minimize the error between the ranking generated by the model and the actual ranking, which was based on the annual price change for each of the 100 companies. The results from this experiment showed that the proposed model generated excess return when compared to a benchmark of an equally weighted portfolio composed of the random set of stocks initially selected. The study stated that a genetic algorithm is the most appropriate technique to address stock selection and ranking problems. The study also criticized relying on other artificial intelligence techniques such as neural networks and the fuzzy approach for being subject to over-fitting and lacking the ability to learn, respectively. In a literature survey paper that reviewed 51 published literature related to evolutionary computing and the problem of stock screening (Hu, et al., 2015), it has been demonstrated that the dominance is for genetic algorithms with a total of 31 papers, and in the second place came the genetic programming with a total of 10 papers, and the remaining 10 papers used 4 different models. In addition to what was highlighted in this survey paper (Hu, et al., 2015), it was identified that there is a gap in the literature regarding the lack of using fundamental ratios in the application of genetic algorithms addressing the stock selection process since out of the 31 paper that used genetic algorithms, 24 of them used technical indicators, 4 used a mixture of fundamental ratios and technical indicators, and only 2 used fundamental ratios.

Genetic Algorithms are a component of Evolutionary Computing in the field of Artificial Intelligence. Evolutionary Computing (EC) is an exciting development in Computer Science. EC offers a variety of algorithms that can be used in problem-solving, optimization, design, simulation, and classification for a wide range of applications in different disciplines (De Jong, Fogel, & Schwefel, 1997). The core idea that stands behind the different algorithms that belong to the EC family is inspired by Darwin’s theory of Evolution, a population of individuals is put through a certain recurring process in which the fittest of them would survive (Eiben & Schoenauer, 2002). EC has been introduced around the mid-1950’s by several researchers across U.S and Europe (Back & Schwefel, 1999); however, it was not labeled as “Evolutionary Computing” until early 1990s. EC is a family of a huge variety of algorithms (Eiben & Schoenauer, 2002); such as are: Genetic Algorithm (GA), Evolution strategies (ES), Evolutionary programming (EP), Genetic programming (GP), Differential Evolution (DE), Ant Colony Optimization, and Particle Swarm Optimization. In a survey paper discussing the idea behind different EC algorithms and providing the pseudocode of the algorithms (Slowik & Kwasnicka, 2020), the authors performed a comparative analysis on the count of publications and patents per each algorithm over the period 2000-2018. The analysis revealed that GA publications represent 89% of the total count of publications related to EC in the WoS database. Accordingly, the survey emphasized the popularity of GA among the family of EC algorithms.

3. Dataset and Model Methodology

3.1 Dataset

The dataset used in this study is composed of two components. The first component is the historical daily stock prices comprising: ISIN, ticker, pricing date, and adjusted[3] daily stock close price. The second component is the historical annual company-fundamental-ratios, and it is structured in terms of: ISIN, ticker, period end-date, and a tabulation containing the value for each fundamental ratio; both dataset components are linked via the ISIN which uniquely identifies each traded security. The fundamental ratios utilized in this research are those used by the well known reference stock screeners: Benjamin Graham Defensive Investor, Benjamin Graham NCAV, and Piotroski F-Score. Description of the fundamental ratios included in the dataset are summarized in the following table.

Ratio Name	Description
Earnings Yield %	(EPS / Price) *100
Return on Capital Employed %	EBIT / (Total Assets – Total Current Liabilities)
Price to Net Current Asset Value	Price / (Current Assets – Total Liabilities)
Long Term Debt to Net Asset Value	Long Term Debt / (Total Assets – Total Liabilities)
Current Ratio	Current Assets / Current Liabilities
Price to Earnings	Price / EPS
Price to Book Ratio	Price / ((Shareholder's Equity – Preferred Equity) / Shares #)
Earnings Per Share $ (EPS)	As reported EPS
Dividend Per Share $ (DPS)	As reported DPS
10Y Earnings Per Share Growth %	EPS growth over 10 Years
Price to 3 Year Average Earnings	Price / (Average or 3-year EPS)
Piotroski F-Score	As proposed by Joseph Piotroski (Piotroski, 2000)
Sales in million $	As reported, Sales in million US dollars
10 Year Earnings Per Share Streak	Count of consecutive years with reported profit over 10 years
10 Year Dividend Streak	Count of consecutive years with paid dividend over 10 years
Graham Multiplier	(P/E) * (P/B)

Table 1: Summary of fundamental Ratios included in dataset

[3] Stock prices are adjusted to account for splits and dividends.

The dataset is accessed and retrieved through the official Reuters API (Refinitiv Eikon) and covers 15 years starting from January 2005 till December 2019. With approximately 6000 companies, the dataset is rich with a huge variety of companies as it includes all listed companies on the two biggest stock exchanges according to market value (Statista, 2020): New York Stock Exchange and Nasdaq. The date range covered in the dataset captures several key events that affected the selected exchanges, such as the financial crisis, which impacted the markets significantly in 2008 (Claessens, Kose, & Terrones, 2010), another key event that has taken place during the study time horizon and reflected on the dataset is the trade-war between U.S and China which adversely impacted U.S listed companies by lowering their market capital by an estimate of $1.7 Trillion (Amiti, Kong, & Weinstein, 2020).

3.2 Proposed Model

In this study, an artificial intelligence model is developed to generate a set of screening rules that can filter the universe to identify well-performing stocks that are the potential to achieve excess return in the future. Given the wide variety of existing artificial intelligence techniques, selection of the appropriate technique is essentially a problem-specific undertaking (Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira, 2016). Evidence from relevant literature (Zhou, Yu, Huang, Wang, & Lai, 2006) suggests that a genetic algorithm is the most appropriate technique to address stock screening problems. Accordingly, in this study, it was decided to use a genetic algorithm model relying on fundamental ratios to implement the aimed stock screening process. Once the set of screening rules is generated by the model, a portfolio of the qualified stocks is constructed and monitored to assess the aptitude of the applied set of rules in selecting well-performing stocks. In this process, the portfolio asset allocation is optimized to maximize the expected Sharpe ratio according to the modern portfolio theory. Performance of the constructed portfolio is judged against the performance of relative market indices and the performance of portfolios created according to three commonly used stock screeners. The judgment on model performance is based on the holding period return in addition to some common financial ratios. Obviously, the trading cost can influence profitability, and the effect is amplified by higher trading frequencies. Therefore, such influence becomes rather insignificant when the trading frequency is low. In addition, reliance on fundamental indicators implies lower trading frequency when compared to technical ones (Hu, et al., 2015). Moreover, since constructed portfolios in this study are bought and held without rebalancing, it has been decided to ignore the effect of trading cost.

3.2.1 Model Design

Genetic Algorithms (GA) follow a standard framework that is divided into a multi-step sequential process that needs to be followed to reach the goal of finding the best solution (Melanie, 1999); in our case a solution is a set of recommended rules to select stocks according to. Figure 1 (Majkowski, et al., 2017) shows the standard process of the GA and its main steps. The first step in the GA is to instantiate a random population of solutions. Solutions are sometimes referred to as individuals or chromosomes. Each solution has genes that define the characteristics and the details of the solution. In our case, a solution is the set of rules to be used for selecting stocks, and the genes are the details of each rule in that set. Once the initial population is generated, all solutions are then evaluated to assess their performance. The qualified solutions are passed to a set of functions called GA operators. The first GA operator is a selection function to select a subset of the solutions that meet a minimum requirement, and the second GA operator is the crossover function, which is

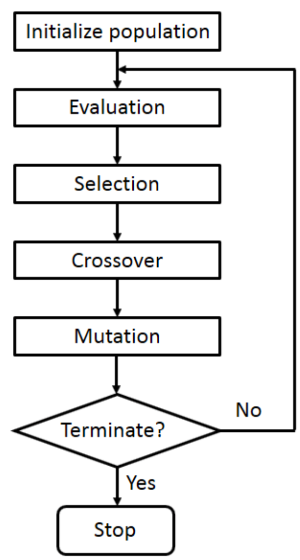

Figure 1: GA Framework

executed to generate a new set of solutions based on mixing parts of the old solutions that passed the selection phase, the third and final GA operator is the mutation operator which simply changes the value of random parts of the solution to help the GA explore the solution-space without being stuck in a local maxima/minima. After each iteration of evaluation followed by the GA operators, the GA checks to see if the termination criterion is met or not; if met, the algorithm is terminated, and if not, the process is repeated until the termination criteria are met. Each full cycle in the GA is called a generation. The beauty of the GA framework is that it can easily adapt to different kinds of problems by customizing the evaluation function, selection criteria, crossover mechanism, mutation function, and termination criteria.

In this study, we are using the GA to find a set of screening rules that can select well-performing stocks. To achieve this goal, the GA will try to find the thresholds for the fundamental ratios discussed previously in table 1. In this study, we preferred to express the genes in real numbers as there was no benefit to be gained from other encoding schemas available in the literature (Kumar A. , 2013), since the desired final output needs to be represented in real numbers. The structure of chromosomes is represented in the following figure guided by (Chan, Wong, Tse, Cheung, & Tang, 2002)

		Feature 1			Feature 2				Feature n		
	#	Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction
Individuals	1	4057.058	17537.61	2	3.763218	5.951233	1	• • •	-15.6164	11.23627	3
	2	7980.132	13954.87	1	0.735476	4.57446	0		8.412527	9.013121	1
	3	10743.48	13180.41	0	1.373399	5.547754	0		4.807619	10.35538	1
	⋮	⋮			⋮				⋮		
	k	7316.525	8444.892	3	4.895891	5.536388	2	• • •	-6.28544	13.83038	2

Compare Direction Mapping	
0	Ignore Feature
1	<= Lower Bound
2	>= Upper Bound
3	<= Upper Bound
4	>= Lower Bound
5	Inner Range
6	Outer Range

Figure 2: GA Initial population design

Each feature is represented in the chromosomes using three genes: a lower bound, upper bound, and a compare direction, which is a selector bit that enables the model to decide to ignore a feature by setting the compare direction to 0; if the feature is not ignored the model decides whether to select the lower range or the upper range or the inner range between both values. The values assigned for the genes are generated randomly based on the range of values between the minimum and maximum for each of the features.

Once the model generates the initial population of solutions, each solution is used to create a one-year buy-and-hold portfolio. Evaluation of each solution is based on the count of qualified and invested stocks, return, risk, and risk-adjusted-return (Sharpe Ratio). The model is designed to limit the count of held stocks in a portfolio to a maximum of 30 stocks, being the recommended optimal value to diversify the unsystematic risk (Chong & Phillips, 2013). The asset allocation for the portfolio created is optimized in accordance with the modern portfolio theory (Markowitz, Portfolio Selection, 1952) to maximize the expected Sharpe ratio. The output of the evaluation step is concatenated to the chromosome, as shown in the following figure.

		Feature 1			Feature 2				Feature n			Assessment Parameters				
	#	Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction	Return	Risk	Qualifed Count	Invested Count	Sharpe
Individuals	1	4057.058	17537.61	2	3.763218	5.951233	1	. . .	-15.6164	11.23627	3	0.0296	0.087	20	14	0.2249
	2	7980.132	13954.87	1	0.735476	4.57446	0		8.412527	9.013121	1	0.0302	0.059	33	26	0.3417
	3	10743.48	13180.41	0	1.373399	5.547754	0		4.807619	10.35538	1	0.0131	0.065	18	18	0.0482
	⋮		⋮			⋮				⋮				⋮		
	k	7316.525	8444.892	3	4.895891	5.536388	2	. . .	-6.28544	13.83038	2	-0.001	0.056	32	19	-0.199

Figure 3: GA Chromosome structure post Evaluation phase

For the selection, individuals are sorted descending based on the Sharpe ratio, and the bottom 10% are excluded. Additionally, solutions that qualify less than ten companies are also excluded. The remaining solution a tournament selection process. In this process the main goal is to identify the parents that will reproduce and create the next generation of solutions. To identify each of the parents, we randomly select 2 solutions from the available solutions and the solution with higher Sharpe ratio is the first parent, we repeat the same process to identify the second parent.

This process of the selection of the mating pool is repeated until we a full pool of couples ready to reproduce. The following figure shows the solution set during this phase.

	#	Feature 1			Feature 2				Feature n			Assessment Parameters				
		Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction	Return	Risk	Qualifed Count	Invested Count	Sharpe
Individuals	1	4057.058	17537.61	2	3.763218	5.951233	1	. . .	-15.6164	11.23627	3	0.0296	0.087	20	14	0.2249
	2	7980.132	13954.87	1	0.735476	4.57446	0		8.412527	9.013121	1	0.0302	0.059	33	26	0.3417
	3	10743.48	13180.41	0	1.373399	5.547754	0		4.807619	10.35538	1	0.0131	0.065	18	18	0.0482
	⋮	⋮			⋮				⋮					⋮		
	k	7316.525	8444.892	3	4.895891	5.536388	2	. . .	-6.28544	13.83038	2	-0.001	0.056	32	19	-0.199

Figure 4: GA Solutions during selection phase

After the selection phase is completed, for easier visual representation, individuals have been color-coded in the following figure to easily track the crossover and mutation phases. Blue is the first parent and orange is second parent.

	#	Feature 1			Feature 2				Feature n			Assessment Parameters				
		Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction	Return	Risk	Qualifed Count	Invested Count	Sharpe
Individuals	50	13344.68	23732.95	0	2.861057	3.787991	0	. . .	7.509358	12.58432	1	0.152	0.133	40	7	1.0702
	89	1823.134	5036.957	0	3.702032	5.49186	3		10.30754	12.74981	0	0.141	0.127	37	11	1.0313
	41	1691.443	12700.31	0	4.051467	4.280096	3		-14.6816	6.32971	2	0.1367	0.124	40	13	1.0234
	2000	10167.99	13620.59	1	0.627956	4.115245	3		-5.90423	9.040855	2	0.1364	0.124	40	11	1.0226
		⋮			⋮				⋮					⋮		

Figure 5: GA Crossover and Mutation Phase

Solutions can be crossed-over based on several methods such as single-point crossover in which data after a certain gene is swapped between parents; and multipoint crossover in which several swapping points are set. The crossover method selected for this research is the multipoint crossover with a crossover point being set after each feature (3 Genes), and this method was selected as it was observed during testing that multipoint provided faster convergence. In the presented model, the mutation rate was set to 10% and is implemented by randomly selecting 10% of the solutions and randomly changing the value of 2% of the genes by new random values. The crossover and mutation steps produce a new set of solutions called the offspring. Since the offspring still did not go through the evaluation phase, accordingly, assessment parameter genes will still be empty. The following figure shows the structure of the solutions after crossover and mutation.

		Feature 1			Feature 2				Feature n			Assessment Parameters				
	#	Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction	Return	Risk	Qualifed Count	Invested Count	Sharpe
Individuals	1	13344.68	23732.95	0	3.702032	5.49186	3		3.8	12.58432	1					
	2	1823.134	2697	0	2.861057	3.787991	0	. . .	10.30754	12.74981	0					
	3	1691.443	12700.31	0	0.627956	2.5	3		-14.6816	20.01	2					
	4	10167.99	13620.59	1	4.051467	4.280096	3		-5.90423	9.040855	2					
	5	3201	15887.8	0	2.953367	5.917344	5		-14.2146	9.493933	3					
	6	9806.396	18183.92	0	1.484486	4.515667	3		10.38473	11.66228	0					
			⋮			⋮				⋮						

Figure 6: GA Solutions after Crossover and Mutation

After the completion of the crossover and mutation, we start repeating the above steps again, starting with the evaluation of the new individuals, followed by the selection, crossover, and mutation until termination criteria are met. The following figure shows the structure of the solution set after first-generation; this solution set will be the input for the next cycle.

		Feature 1			Feature 2				Feature n			Assessment Parameters				
	#	Lower Bound	Upper Bound	Compare Direction	Lower Bound	Upper Bound	Compare Direction		Lower Bound	Upper Bound	Compare Direction	Return	Risk	Qualifed Count	Invested Count	Sharpe
Individuals	1	13344.68	23732.95	0	3.702032	5.49186	3		3.8	12.58432	1	0.1608	0.137	40	11	1.0989
	2	1823.134	2697	0	2.861057	3.787991	0	. . .	10.30754	12.74981	0	0.1613	0.137	40	12	1.1014
	3	1691.443	12700.31	0	0.627956	2.5	3		-14.6816	20.01	2	0.1078	0.102	40	9	0.9575
	4	10167.99	13620.59	1	4.051467	4.280096	3		-5.90423	9.040855	2	0.1023	0.097	40	10	0.9486
	5	3201	15887.8	0	2.953367	5.917344	5		-14.2146	9.493933	3	0.091	0.097	40	12	0.8385
	6	9806.396	18183.92	0	1.484486	4.515667	3		10.38473	11.66228	0	0.1367	0.124	40	14	1.0234
			⋮			⋮				⋮				⋮		

Figure 7: GA output after first generation

A termination criterion is needed to have the GA terminate and return the best solution available. The design of the termination criterion depends on the addressed problem. In our model, the termination criterion was selected based on experimenting and was set to occur when the count of the remaining individuals is less than or equal 10% of the initial population size.

3.2.2 Model Assessment Criteria

To assess the model thoroughly, it was decided to perform a robustness test and a simulation to a real-trading experience. The robustness test is implemented by running the GA in a parallel-mode environment; such setup will allow us to repeat the training and testing of the model 250 times for each year in the dataset. Each instance of the GA will create its own population and will assign it to a unique container that will be referred to as an "Island" and will execute the full GA process on it until it provides an output. Given the fact that the proposed model is of a stochastic nature, the final output from each island depends on the randomly instantiated population as well as the random mutation the individuals are exposed to. Accordingly, the robustness test is implemented in this way, using real data to examine the performance boundaries of the model and to identify the mean of the model performance. The following figure represents the robustness test environment.

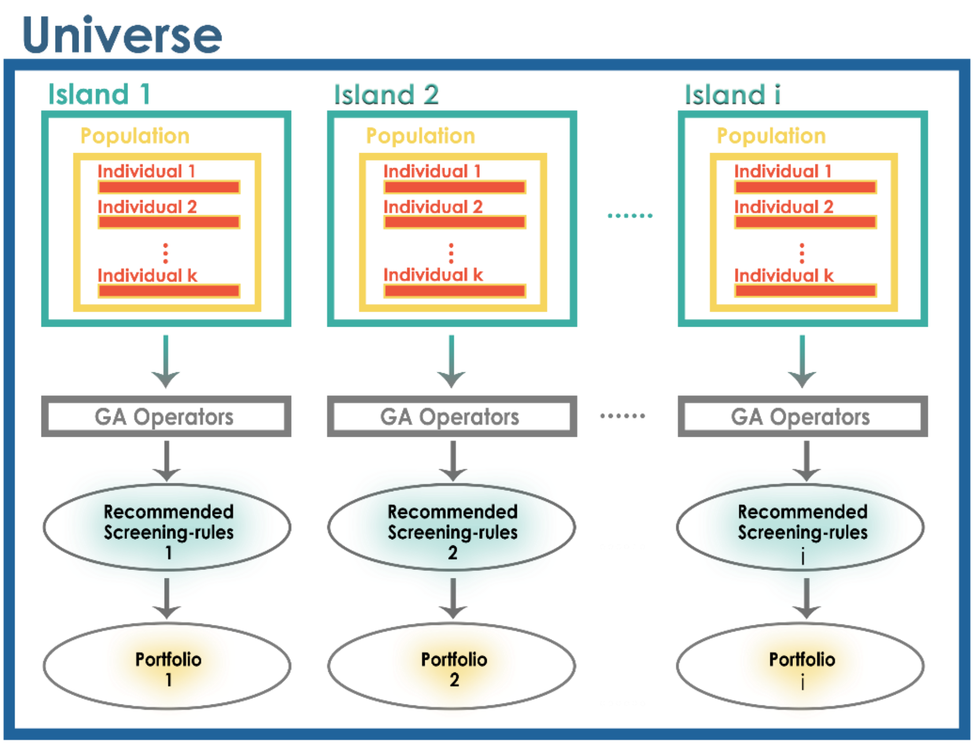

Figure 8: GA Robustness test environment

The real-trading experience simulation will replicate what a real user will go through when using the proposed model. The model will be triggered starting January 2006 and will operate till the end of 2019. The model will be trained annually, and a 1-year buy and hold portfolio will be constructed accordingly to the output of the annual training of the model. The asset allocation in the constructed portfolios are optimized according to the modern portfolio theory (Markowitz, Portfolio Selection, 1952) to maximize the expected Sharpe ratio. Two extra constraints have been added, the first constrain limits the exposure to any stock to a maximum of 10%, and the second constrain limits the maximum count of invested stocks to a maximum of 30 stocks. Model daily returns will be recorded over the 14 years of the simulation and will be contrasted with the returns of the benchmark index and the returns achieved from using three common stock screeners that were explored through the literature. The comparison comprises annual returns, cumulative returns, risk-adjusted returns, and several other common financial metrics that will be presented in the form of a factsheet.

The following figure demonstrates the first year in the simulation runs. The model will be triggered at the beginning of 2006; accordingly, the training will be done on the previous year's fundamental data, which is labeled as in-sample, the asset allocation optimization will be done on ten years of historical price data, which is labeled as historical data. As a result of the training, the model will generate a recommended set of screening rules that will be used to construct a portfolio at the beginning of 2006. The performance of the portfolio created at the beginning of 2006 will be monitored over a full year, which is the testing phase labeled as out-of-sample.

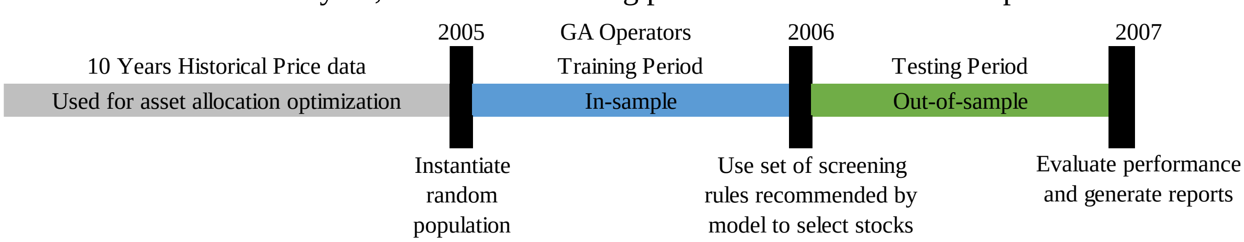

Figure 9: Model execution timeline assuming current year is 2006

4. Results

In this study, a genetic algorithm model, relying on fundamental ratios, was developed to perform stock screening and selection of the most valuable stocks. This section comprises the analysis, presentation, and interpretation of the findings resulting from this study. The results indicated that the model outperformed the index and three well-known stock screeners; the outperformance aspects included portfolio return, risk-adjusted-return, and several other financial assessment metrics. As discussed in the previous section, the model has undergone two performance tests: the robustness test and the real-trading simulation. Both tests were implemented using real data covering a period of 14 years. In our dataset, the first and last training years were 2005 and 2018, respectively, and the first and last test years were 2006 and 2019, respectively. Results of the model performance testing are presented and discussed in the following sections.

4.1 Robustness test results:

The robustness test was executed by running the model in the parallel-mode environment discussed earlier. Each year in the dataset, the model was trained and tested 250 times on both exchanges selected. The robustness test resulted in a total of 7000 successful training runs[4] that were semantic-error-free and syntax-error-free, which confirms the model is stable and valid from the code implementation perspective. The 7000 validation runs were executed on an Nvidia DGX A100 [5] machine, which took around 28 hours. Assessing the model reliability was a challenging task since the nature of the problem does not have a single best answer since as the same group of stocks can be filtered out of the universe using different screening rules, and since the nature of the model is stochastic (initial population is generated randomly and mutation occurs randomly) it’s not a must to converge every time towards the same solution; accordingly, it was decided to

[4] 2 Exchanges * 14 Years of training data * 250 Training runs = 7000 runs
[5] Nvidia DGX A100: https://www.nvidia.com/en-us/data-center/dgx-station-a100/

inspect the model reliability by relying on the plots of the out-of-sample results of the robustness test. To make the plots indicative, it was decided to plot the mean, 25th percentile, and 75th percentile of the out-of-sample results and compare it against the mentioned benchmarks. To prepare the out-of-sample testing results, the recommended screening rules from each training year were used to create a buy-and-hold portfolio that was held for the following year, the weights in the created portfolio were optimized to maximize the expected Sharpe ratio. The returns of the portfolio were recorded on a daily basis, and the same process was repeated for each year in the dataset. The results for all years are then aggregated per exchange and used for the performance analysis.

4.1.1 NYSE:

This section will present the results of the robustness test of the model when trading on NYSE. The following figure shows the model mean annual returns versus the NYSE composite index. The model has outperformed in almost all years except in 2017.

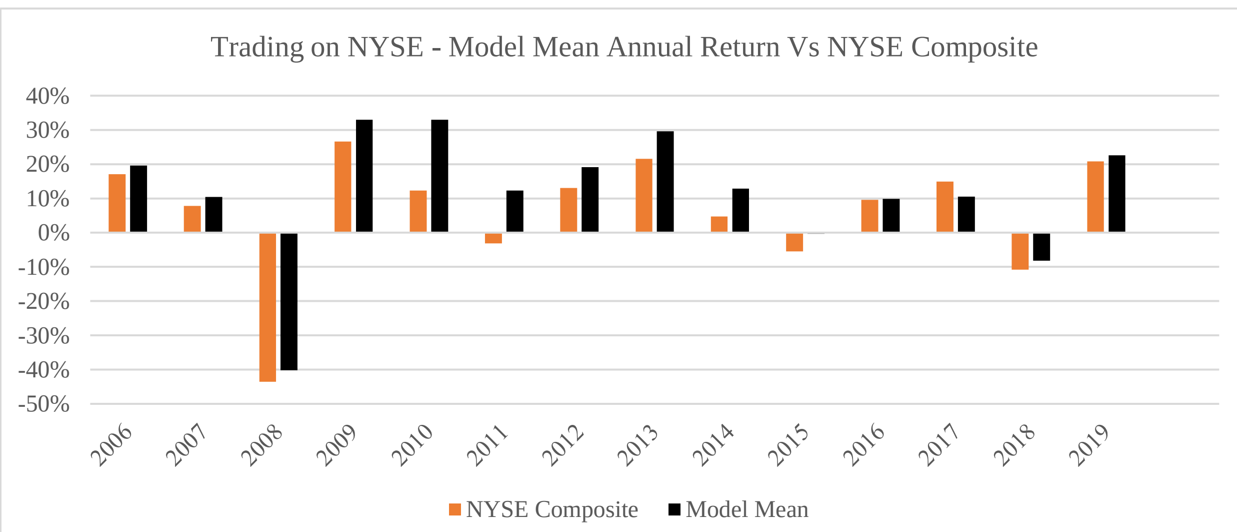

Figure 10: Robustness Test - NYSE - Model Vs Index (Annual Returns)

The following figure presents the returns in a cumulative format to observe the total return over the 14 years. The model had a mean return that outperformed the NYSE Composite index and generated an extra 72% over the 14 years.

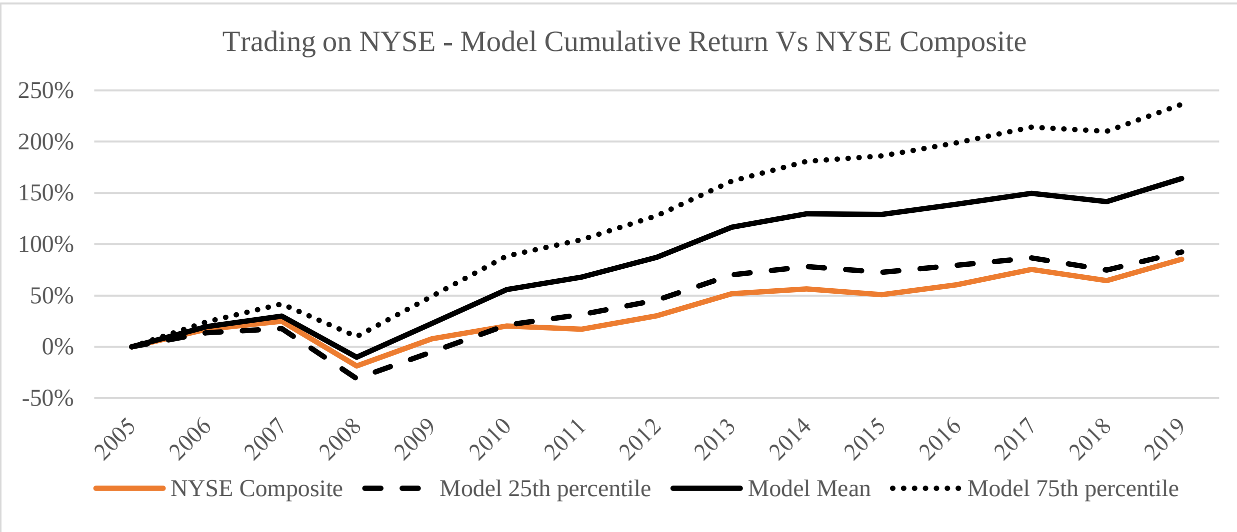

Figure 11: Robustness Test - NYSE - Model Vs Index (Cumulative Returns)

The following figure compares the model mean a risk-adjusted return to the NYSE Composite index. The model outperformed the index for 9 years based on the risk-adjusted return.

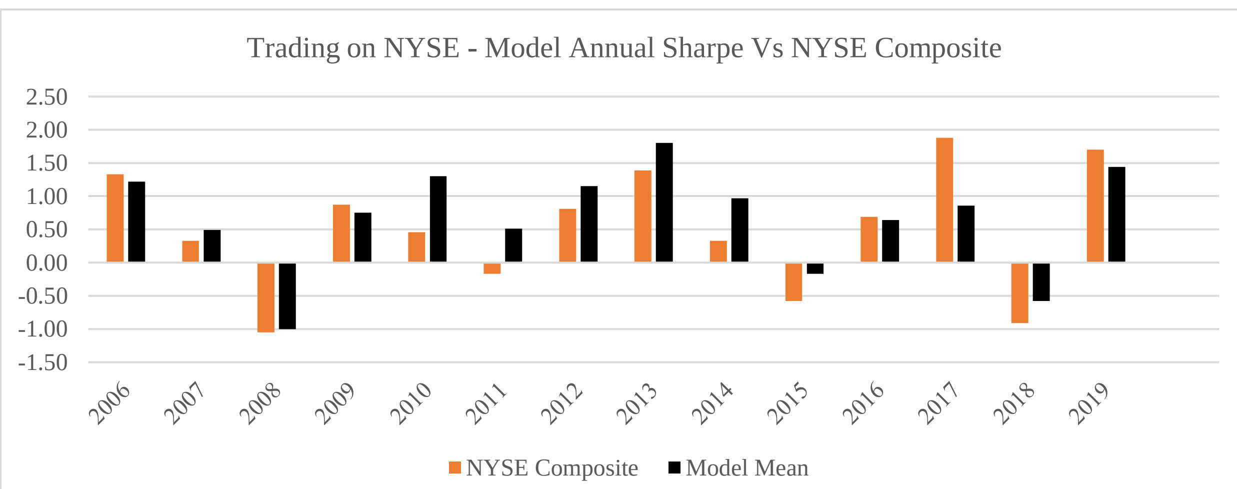

Figure 12: Robustness Test - NYSE - Model Vs. Index (Annual Sharpe)

The following figure shows the cumulative returns of the reference screening rules versus the mean, 25th percentile, and 75th percentile of the model returns. The model mean-return outperformed all the reference stock screeners with a 14-year cumulative mean return of 164%;

meanwhile, the best performing reference stock screener was Benjamin Graham NCAV, which had a cumulative return of 117%. The performance of the Benjamin Graham Defensive investor stock screener was better than the other two screeners; however, due to the loss that occurred in 2018, it was outperformed by the other screeners. The 25th percentile of cumulative returns from the model ended the 14 years at 92% return while shadowing the reference screeners.

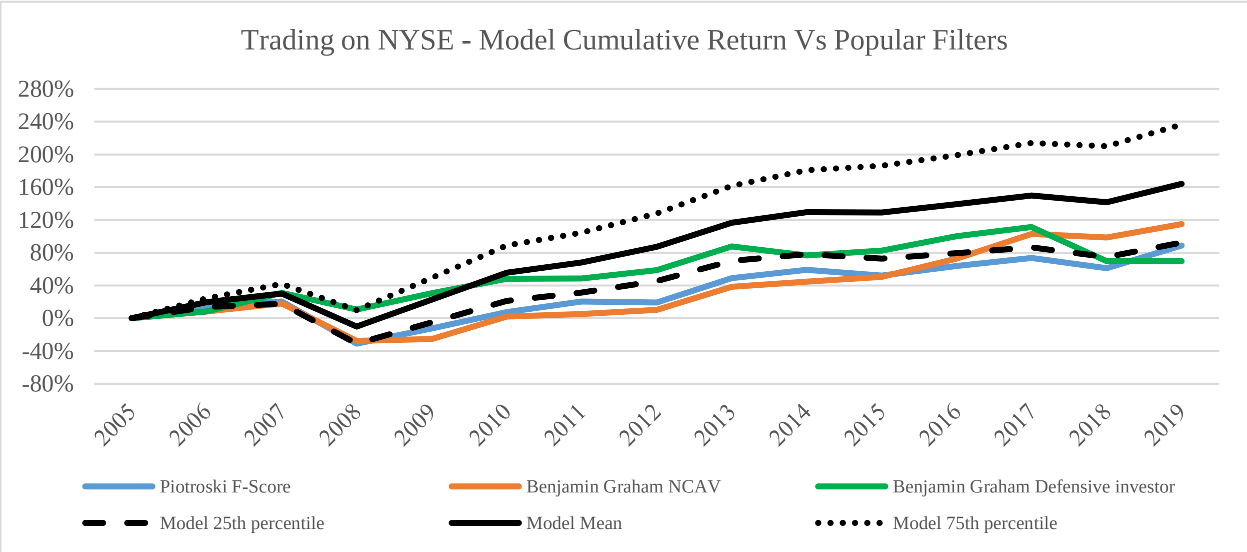

Figure 13: Robustness Test - NYSE - Model Vs Reference rules (Cumulative Returns)

4.1.2 NASDAQ:

This section will present the results of the robustness test of the model when trading on NASDAQ. The following figure shows the model mean annual returns versus the NASDAQ composite index. The model has outperformed the index for eight years.

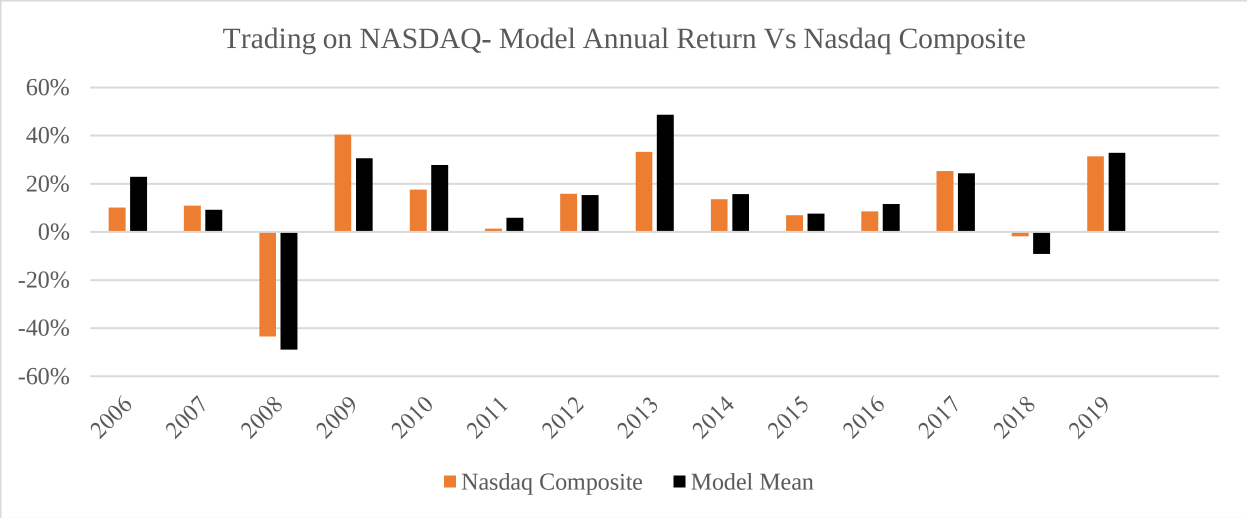

Figure 14: Robustness Test - NASDAQ - Model Vs Index (Annual Returns)

The following figure presents the returns in a cumulative format to observe the total return over the 14 years. The model had a mean return that outperformed the NASDAQ Composite index and generated an extra 29% over the 14 years.

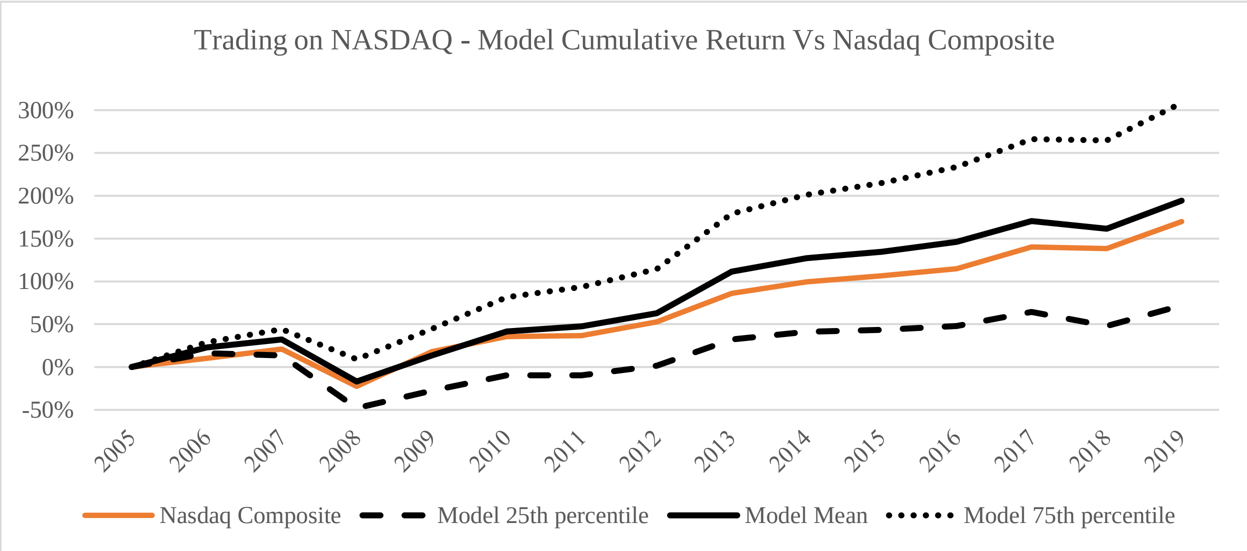

Figure 15: Robustness Test - NASDAQ - Model Vs Index (Cumulative Returns)

The following figure compares the model mean a risk-adjusted return to the NASDAQ Composite index. The model outperformed the index for five years based on the risk-adjusted return.

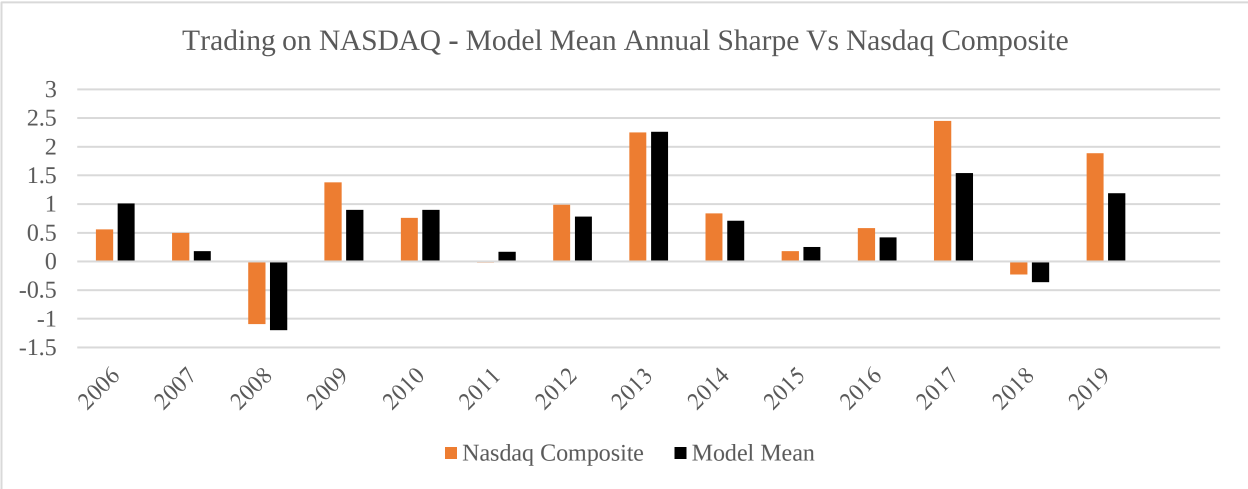

Figure 16: Robustness Test - NASDAQ - Model Vs Index (Annual Sharpe Ratio)

Moving to the test results for NASDAQ, we will find that the model outperformed the reference stock screeners while the 25th percentile of the returns was shadowing the worst-performing stock screener, which is Piotroski F-Score. Based on the model mean, which was 194%, the model generated an extra 24% of return over the best performing screener

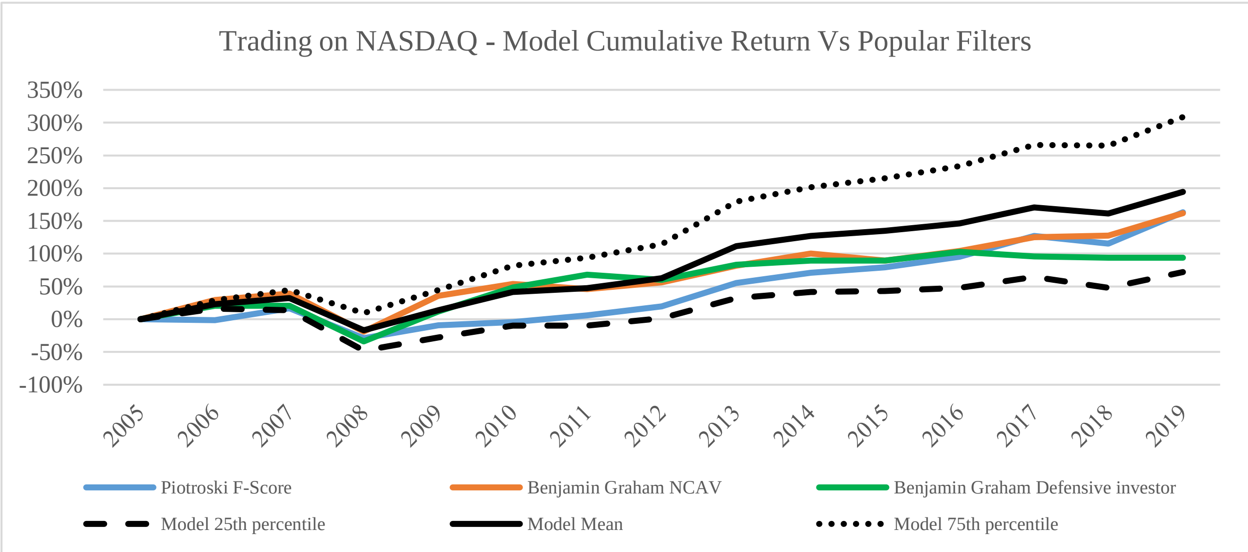

Figure 17: Robustness Test - NASDAQ - Model Vs Reference Screeners (Cumulative Returns)

4.2 Real-trading Simulation results:

The second performance test is a simulation of what a user will go through when using the proposed model. This test is done by running the model in a single-run mode for 14 years. The model is trained each year using the previous year's data. Accordingly, a set of screening rules is recommended each year, and a portfolio is constructed using these rules. The daily performance of the constructed portfolios is recorded for further analysis. Since the model is coded in Python, QuantStats[6] library is used to generate a performance report for the model, which includes a variety of assessment metrics and graphs covering the entire investment horizon. The results of this section are grouped by traded exchange and presented in the following order, firstly, model-recommended screening rules for each year are summarized, then the portfolio constituents and sector exposure for each year are reviewed, and finally, plots visualizing the portfolio performance against a benchmark index are discussed. For NYSE, we will be using the NYSE Composite Index as a benchmark, and for NASDAQ, we will be using the NASDAQ composite index as a benchmark. Extra details related to the model performance assessment are included in an appendix.

[6] QuantStats is an opensource python library used for portfolio analytics by quants https://github.com/ranaroussi/quantstats

4.2.1 NYSE:

The following table summarizes the recommended set of screening rules generated by the model for each year. The fundamental ratio “Price to 3-Year average earnings” appeared in most of the model-generated screening rules indicating its importance as an input feature to the model.

Trading on NYSE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Earnings Yield%	>12.96		> 12.04	<12.66			< 28.15	< 21.4	< 30.6					
ROCE%		< 2.31				< 16.1		< 17.11	> 4.85					> 9.21
P/NCAV										< 0.21				
LTD/NAV	< 4.69	> 0.83			> -2.80	> -0.27				> -1.08	> -1.04		> 1.77	
Current Ratio		< 2.83			< 2.46						> 1.42	< 3.27	< 1.95	
P/E			< 26.86				> 10.95		> 5.30				< 35.8	> 8.27
P/B		< 4.11												
EPS	< 0.532								< 4.3		> 0.79	< 4.54		
DPS	< 0.81		> 0.27		< 1.34			< 0.62		> 0.15	< 0.79		> 1.75	
10Y EPS Growth%		< 48.43	< 517	< 471			> 18.08				< 338	< 124	> 48.8	> -66.5
P/3Y Avg Earnings	< 29.9	< 18.91	< 23.06		< 7.67	< 15.6	< 13.04	< 16.9	< 13.1			< 17.8		>10.35
Piotroski	> 3		> 3	< 6		< 5	> 5	< 6			> 4	> 3		
Sales (million USD)				<10617	> 1085	< 2222		< 7426	<12805	> 4215	< 9366	<13031		< 1832
10 Years EPS Streak		> 7	> 7	> 8			> 9		> 7	> 8			> 6	
10 Years Div Streak	> 3		> 1	> 0					>2	> 7			> 4	
Graham Multiplier			< 100										> 49.2	> 77
Sort Direction	asc	asc	asc	asc	asc	desc	asc	asc	desc	asc	asc	asc	asc	desc
Sort variable is highlighted in														

Table 2: Trading Simulation - NYSE - Model-recommended set of screening rules

The following table presents the details of the held stocks, and the lower section displays the sector exposure for each year. The average count of held stocks per year was 14 stock, and the most invested in the sector was the Industrials sector meanwhile, the least was the Real Estate sector.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Qualified Companies Ticker	GEL	ATO	MO	SXT	KAR	CIEN	ACN	WCC	SAH	VFC	CULP	RAMP	SWK	HEP
	AP	CULP	B	VFC	VFC	HP	DVA	EQM	LAD	BA	SKX	CLF	FDX	USPH
	BRO	FLS	HPQ	SHW	HFC	BRO	NEE	ATGE	THO	LAD1	LH	CRD.B	SHW	TYL
	GHM	TUP	AWR	HRL	TTC	AOS	IBM	CBRE	UGI	LIN1	UNF	UGI	SJM	WWE
	FLO	SCL	APD	UGI	ARW	AWR	AP	SKX	TWI	GPC0	TTC	KEM	HON	USNA
	SCS	CXW	D	SCL	AOS	CSV	RS	CRD.B	BR	ADM3	ALG	RRC	LHX	FICO
	WAB	FMC	PPL	KSU	ENS	EE	B	AXL	MLR	CF	FDP	ACCO	DGX	MED
	HEI	EE	ODC	RES	STZ	CBZ	RBC	REX	CW	GLP4	SCL	NOV	LVS	HEI
	FLS	DDS	JNJ	SNA	DG	KAMN	BLK	FDP	WLK	SYK2	AYI	EAT	HSY	DL
	VHI	SPXC	RTX	PPL	CMI	MSGN	MD	CDE	IDA	DUK9	DAN	CBB	UNP	MSCI
	KAMN	AGCO	NFG	FUL	AN	PLOW	EAT	A	NJR	UNP0	TREC	BAX	PH	FUN
	RES	SON	JW.A		UNP	KWR	EPC	CE	CTB	MA	AGCO	CLH	NOC	WST
		ALB	UNP			GNRC		MLR	FL	GPI	SPB			TREX
			ALB					HBI		LMT				ROL
								NOW						IDT
								EPC						WNS
								GPI						
								BWXT						
Qualified Count	12	13	14	11	12	13	12	18	13	14	13	12	12	16

		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Sector exposure	Financials	10%					4%	10%	3%				10%		10%
	Health Care			2%				20%	1%		8%	10%	4%	10%	4%
	Real Estate	10%	10%												
	Consumer Discretionary	10%	8%		5%	21%	10%		28%	27%	28%	20%	10%	1%	11%
	Information Technology			10%		10%	1%	20%	10%	10%	10%		17%		25%
	Utilities	10%	20%	30%	20%		15%	10%		27%	1%		10%		
	Industrials	32%	23%	23%	20%	49%	50%	20%	24%	26%	27%	35%	20%	59%	21%
	Energy	10%			10%	10%	10%		12%		8%		20%		2%
	Materials	18%	39%	14%	35%		1%	11%	10%	10%	15%	20%	5%	10%	
	Consumer Staples			20%	10%	10%		9%	10%		3%	15%		20%	15%
	Communication Services						10%						4%		12%

Table 3: Trading Simulation - NYSE - Model-generated portfolio constituents & sector exposure

A variety of financial metrics commonly used to assess the performance of portfolios are listed in the following table. The definition of financial metrics computed is available in the appendix. The metrics are computed over the entire 14 years investment horizon and compared against the NYSE Composite index as a benchmark. The model generated ~2.5x return compared to the benchmark index, which translates to an excess return of 126%. The outperformance was also observed on the risk-adjusted-return as the model had a Sharpe ratio of 0.65; meanwhile, the benchmark Sharpe ratio was 0.31.

	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	211.51%	85.40%
CAGR%	8.45%	4.51%
Sharpe	0.66	0.31
Sortino	0.94	0.43
Max Drawdown	-60.32%	-59.01%
Longest DD Days	943	2247
Volatility (ann.)	22.99%	19.61%
R^2	0.75	
Calmar	0.22	0.07
Skew	-0.04	-0.2
Kurtosis	5.66	11.69
Expected Daily %	0.05%	0.02%
Expected Monthly %	1.04%	0.35%
Expected Yearly %	13.28%	4.26%
Kelly Criterion	5.77%	0.20%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.32%	-2.01%
Expected Shortfall (cVaR)	-2.32%	-2.01%
Payoff Ratio	0.91	0.86
Profit Factor	1.13	1.06
Common Sense Ratio	1.11	0.94
CPC Index	0.57	0.49
Tail Ratio	0.98	0.88
Outlier Win Ratio	4	5.09
Outlier Loss Ratio	3.85	4.89

	Model	Index
MTD	2.71%	2.70%
3M	11.29%	7.11%
6M	11.03%	6.72%
YTD	38.39%	20.77%
1Y	39.48%	21.51%
3Y (ann.)	9.89%	7.72%
5Y (ann.)	5.75%	5.09%
10Y (ann.)	9.88%	5.85%
All-time (ann.)	8.45%	4.51%
Best Day	11.32%	12.22%
Worst Day	-9.22%	-9.73%
Best Month	22.44%	11.39%
Worst Month	-18.17%	-19.54%
Best Year	44.68%	24.80%
Worst Year	-31.03%	-40.89%
Avg. Drawdown	-3.52%	-2.28%
Avg. Drawdown Days	34	51
Recovery Factor	7.84	1.35
Ulcer Index	1.01	1.02
Avg. Up Month	5.01%	3.27%
Avg. Down Month	-5.07%	-4.33%
Win Days %	55.03%	53.96%
Win Month %	62.50%	61.31%
Win Quarter %	64.29%	69.64%
Win Year %	78.57%	71.43%
Beta	1.01	
Alpha	0.09	

Table 4: Trading Simulation - NYSE - Model Vs Index (Performance Metrics)

The following two figures represent the model annual and cumulative returns, respectively. Although the model was outperformed by the index in 2018, however, this has not significantly impacted the cumulative returns of the model.

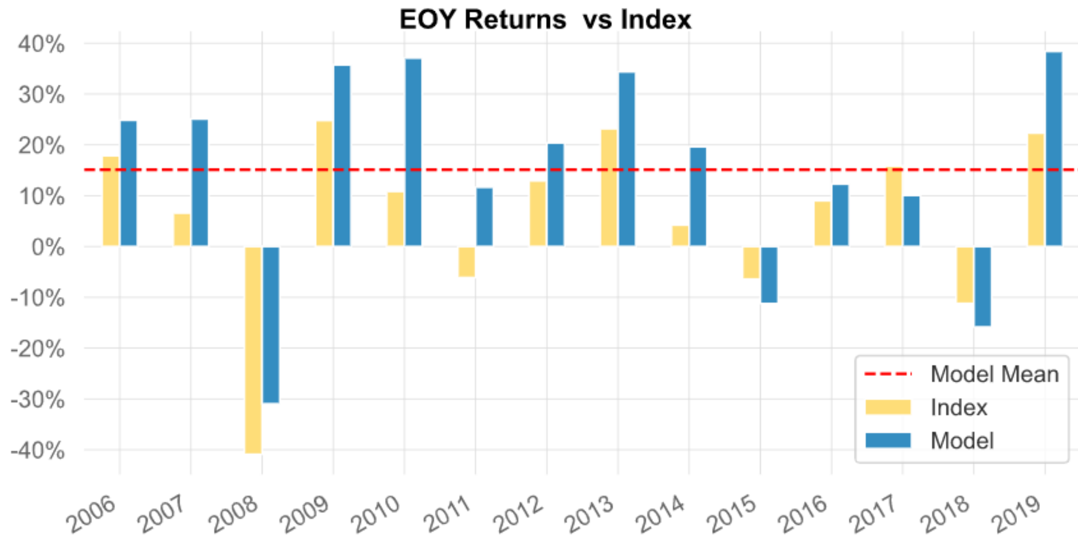

Figure 18: Trading Simulation - NYSE - Model Vs Index (Annual Return)

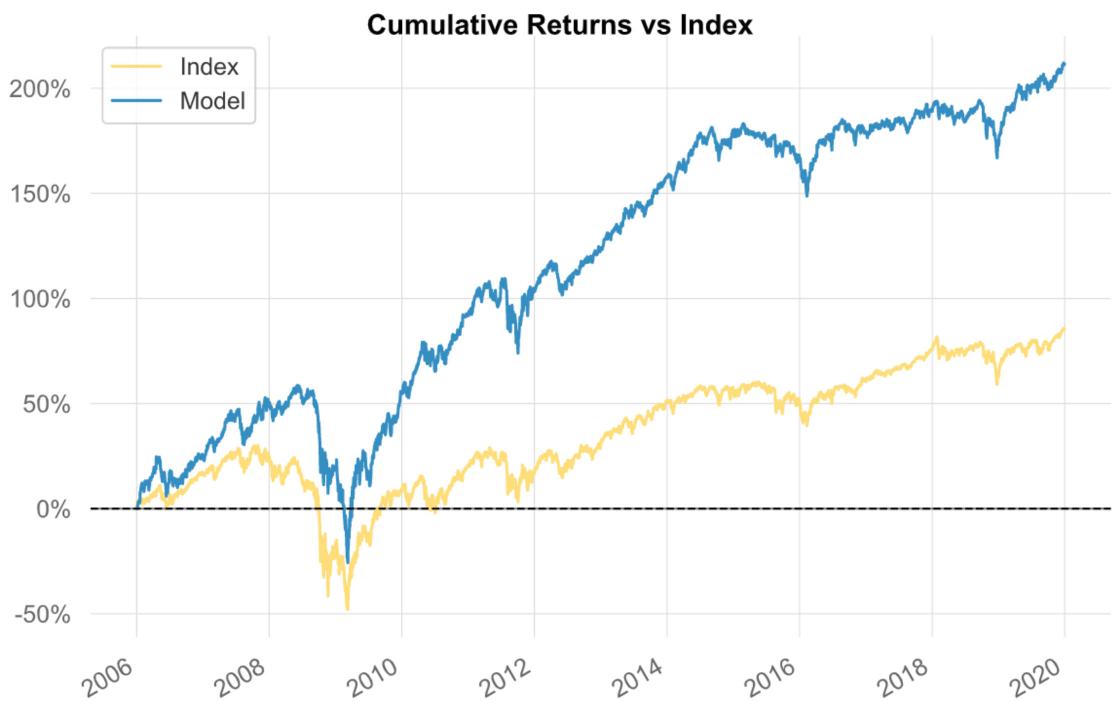

Figure 19: Trading Simulation - NYSE - Model Vs Index (Cumulative Returns)

The following two figures present details of the top 5 drawdown periods and the drawdown% of the portfolio, respectively. The worst drawdown% for the portfolio was during the global financial crisis; the model experienced a -60% drawdown and fully recovered in 676 days.

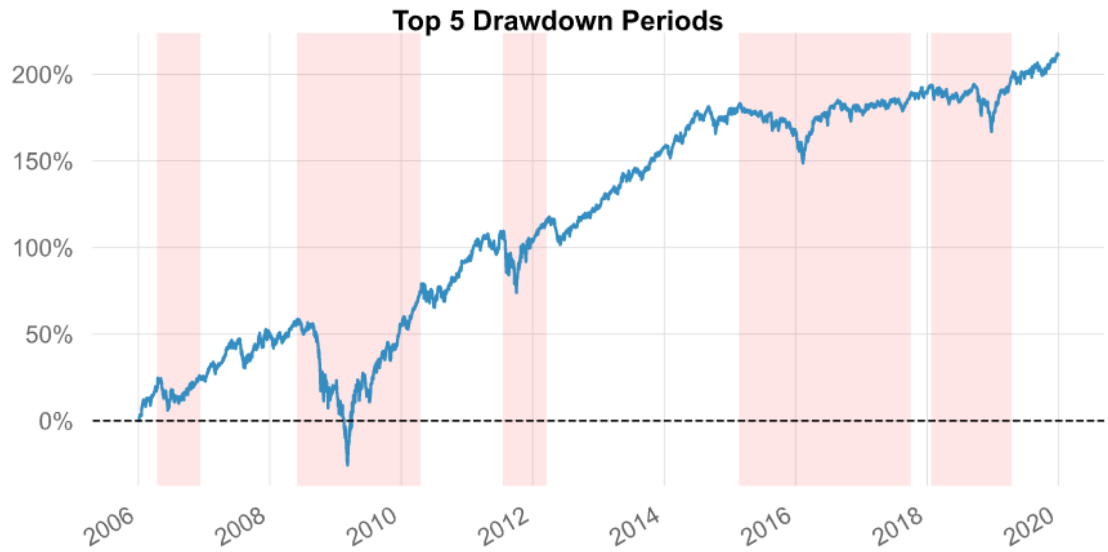

Figure 20: Trading Simulation - NYSE - Model top 5 drawdown periods

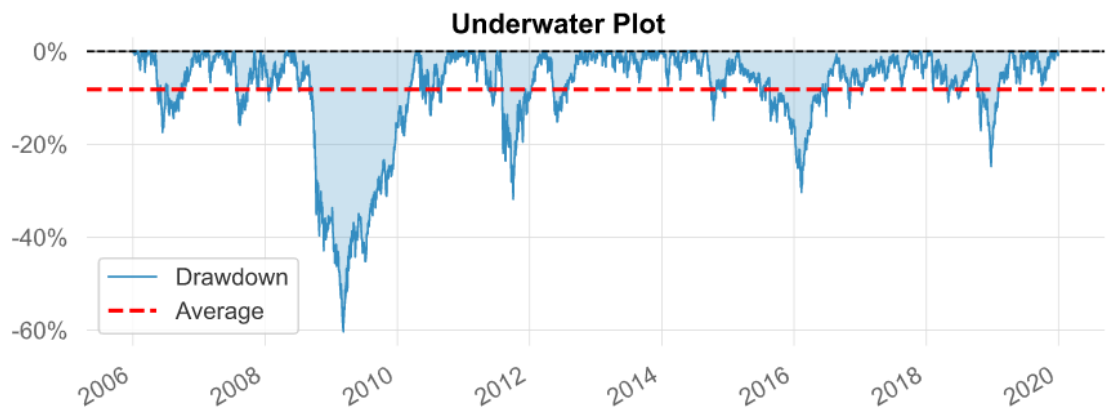

Figure 21: Trading Simulation - NYSE - Model drawdown%

The following table summarizes the details of the previously mentioned drawdown periods.

#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	6/6/2008	3/9/2009	4/13/2010	676	-60.32	-57.14
2	7/25/2011	10/3/2011	3/13/2012	232	-31.79	-28.36
3	2/26/2015	2/11/2016	9/26/2017	943	-30.34	-25.57
4	1/29/2018	12/24/2018	4/10/2019	436	-24.75	-20.82
5	4/20/2006	6/13/2006	12/6/2006	230	-17.41	-16.35

Table 5: Trading Simulation - NYSE - Model top 5 drawdown periods (details)

4.2.2 NASDAQ:

The following table summarizes the recommended set of screening rules generated by the model for each year. The fundamental ratio “Price to 3-Year average earnings” showed consistency and appeared again in the runs done on NASDAQ as the most used rule by the model. The consistency of the use of that fundamental ratio confirms its importance as an input feature to the model.

Trading on NASDAQ	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Earnings Yield%	< 25.1			< 25.8	> 7.56		> -5.85	< 18.7		< 15.38				
ROCE%	> 5.93				> -5.80	> 9.05					> -6.70		> -7.79	
P/NCAV		< 0.27		> -0.13		< 0.4				> -0.16		< 0.3		< 0.61
LTD/NAV				<1.12				< 0.67		< 2.64			< 1.69	< 1.78
Current Ratio							> 2.32		< 4.57					
P/E	< 22.5			> 3.55			> 12.61	< 12.4				< 33.3	> 27.23	< 43
P/B	< 3.95	< 5.24											> 1.81	
EPS				> 0.26	> 0.94	< 1.22		< 1.08	< 0.64	> -0.12				
DPS			< 0.64		< 0.55			< 0.46	< 0.84	< 0.57	< 0.42		< 1.08	
10Y EPS Growth%				< 516	< 402		> 100				> -54.1	< 401		< 347
P/3Y Avg Earnings	< 23.05		< 10.05	> 9.37		< 22.7	< 21.6	> -5.31	< 24.99	< 27.17	< 14.6			> 27.2
Piotroski		< 6	< 5			> 4			> 4					
Sales (million USD)				< 2351		< 3623	< 4467	< 3998				< 5482	< 3785	< 4269
10 Years EPS Streak				> 7			> 5	< 9				> 5	> 5	
10 Years Div Streak	< 3					< 3		< 4	< 9		< 7		< 7	
Graham Multiplier	< 43.1	< 223								< 161	> 53.1			
Sort Direction	asc	desc	asc	asc	desc	desc	asc	desc	desc	asc	desc	asc	asc	asc
Sort variable is highlighted in														

Table 6: Trading Simulation - NYSE - Model-recommended set of screening rules

The following table presents the held stocks' details and shows in the lower section the sector exposure for each year. The average count of held stocks per year was 14 stock; it was observed that the most invested in the sector was Information Technology; meanwhile, the least invested in the sector was the Materials sector.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Qualified Companies Ticker	USAP	LCUT	ITIC	VIVO	SPTN	IIVI	FCFS	ZIXI	EXTR	CNXN	FLWS	JCOM	IPGP	XLNX
	MRTN	MANH	GABC	WIRE	IAC	SP	HIBB	ADUS	MDCA	MERC	PDCE	ODFL	CSGP	VG
	GIII	CMTL	MNTA	EXPO	JCOM	LPSN	SHOO	NVAX	FTEK	HIBB	TTEK	LNT	CAMP	IPAR
	TTMI	OTTR	MYL	HCSG	TECD	IDXX	ATRI	CUTR	GIFI	SHOO	PRSC	PRSC	HSTM	SWIR
	CVCO	SSP	PODD	FORR	NATH	MPWR	STMP	HOLI	CLNE	EXPO	FRPH	MGIC	SILC	EXPO
	NTGR	GPOR	HBNC	NEOG	GTLS	SVA	SSYS	MPAA	PLAB	ATVI	CPRT	EGOV	MGIC	TXRH
	EXPO	WDC	HLIT	POWI	DISH	SWKS	SYNA	MGIC	RMBS	CRUS	SPWR	THRM	ILMN	ATRO
	SCVL	VLGEA	HOMB	TWIN	PLCE	TSCO	HLIO	INSM	HCKT	FSTR	ASRT	SIMO	WETF	PRSC
	NSIT	CSX	LKFN	JJSF	AMED	LKQ	LPSN	ACAD	PODD	DORM	IMMR	SRCL	NSSC	BRKR
	FIZZ	MMLP	NDSN	ECOL	IDCC	MNST	MGIC	CLVS	HLIT	MGIC	UTHR	BECN	ISRG	MPWR
	KFRC	PLXS	NATH	NWPX		THRM	SYKE	TREE	CTRN	OSIS	CAR	HAIN	MRCY	CECE
	TESS	NEOG	ZIOP	MTRX		ALGN	CALM	CTRN	GLDD	NVMI	NVDA	CONN	SPSC	EXEL
	NATH	NTCT		POWL		NATH	ALGN	INO		NVDA	HA		OLED	SIMO
	JOUT	ERIE					AKAM	AMAG					CHUY	WETF
		ORLY					JJSF							NSSC
														SNPS
Qualified Count	14	15	12	13	10	13	15	14	12	13	13	12	14	16

Sector exposure		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Financials		10%	34%				10%	10%					3%	7%
	Health Care	10%	5%	36%	20%	10%	23%	17%	57%	10%		30%	9%	21%	21%
	Real Estate											10%			
	Consumer Discretionary	40%	11%	10%		20%	34%	16%	12%	10%	22%	3%	10%	9%	10%
	Information Technology	13%	21%	10%	1%	30%	23%	34%	21%	32%	46%	27%	40%	56%	31%
	Utilities		3%										10%		
	Industrials	10%	10%	10%	67%	10%	10%	10%		20%	20%	24%	21%	11%	19%
	Energy	10%	20%		3%					18%		6%			
	Materials										2%				
	Consumer Staples	17%	10%		10%	10%	10%	12%					10%		4%
	Communication Services		10%			20%				10%	10%				7%

Table 7: Trading Simulation-NASDAQ-Model-generated portfolio constituents & sector exposure

The following table provides a collection of financial metrics commonly used to assess portfolios' performance; as mentioned earlier, the definition of financial metrics computed is available in the appendix. The model generated ~1.9x return compared to the benchmark index, which translates to an excess return of 153%. The outperformance was also observed on the risk-adjusted-return as the model had a Sharpe ratio of 0.85; meanwhile, the benchmark Sharpe ratio was 0.58.

	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	322.97%	169.91%
CAGR%	10.85%	7.35%
Sharpe	0.85	0.59
Sortino	1.25	0.83
Max Drawdown	-59.07%	-55.63%
Longest DD Days	1736	1273
Volatility (ann.)	27.13%	20.55%
R^2	0.63	
Calmar	0.36	0.19
Skew	0.54	-0.12
Kurtosis	14.05	7.48
Expected Daily %	0.08%	0.04%
Expected Monthly %	1.63%	0.84%
Expected Yearly %	21.42%	10.54%
Kelly Criterion	5.19%	3.82%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.72%	-2.08%
Expected Shortfall (cVaR)	-2.72%	-2.08%
Payoff Ratio	0.91	0.87
Profit Factor	1.17	1.12
Common Sense Ratio	1.1	1
CPC Index	0.58	0.54
Tail Ratio	0.94	0.9
Outlier Win Ratio	3.53	4.86
Outlier Loss Ratio	3.42	4.48

	Model	Index
MTD	3.90%	3.52%
3M	9.42%	12.39%
6M	6.54%	11.95%
YTD	31.35%	31.42%
1Y	32.47%	32.19%
3Y (ann.)	18.42%	15.77%
5Y (ann.)	14.97%	11.14%
10Y (ann.)	14.21%	9.64%
All-time (ann.)	10.85%	7.35%
Best Day	23.37%	11.81%
Worst Day	-12.48%	-9.14%
Best Month	23.62%	12.35%
Worst Month	-21.53%	-17.73%
Best Year	135.48%	43.89%
Worst Year	-39.61%	-40.54%
Avg. Drawdown	-3.52%	-2.37%
Avg. Drawdown Days	34	27
Recovery Factor	23.92	5.52
Ulcer Index	1.01	1.02
Avg. Up Month	5.77%	4.16%
Avg. Down Month	-6.00%	-4.97%
Win Days %	54.88%	55.28%
Win Month %	65.48%	62.50%
Win Quarter %	71.43%	71.43%
Win Year %	92.86%	78.57%
Beta	1.05	
Alpha	0.1	

Table 8: Trading Simulation - NASDAQ - Model Vs Index (Performance Metrics)

The following two figures represent the model annual and cumulative returns, respectively. The model lost in front of the index for four years out of the entire investment horizon. The most significant loss against the index was in 2009 following the global financial crisis. The index then compensated the losses with an annual return of 40%; meanwhile, the model only gained 7%. The model underperformance against the index in 2009 could be attributed to the fact that NASDAQ composite index follows a daily rebalancing mechanism (Nasdaq, 2020); meanwhile, our model follows a 1-year buy-and-hold strategy without inter-period rebalancing. However, despite the four years of underperformance, the model still had higher overall returns.

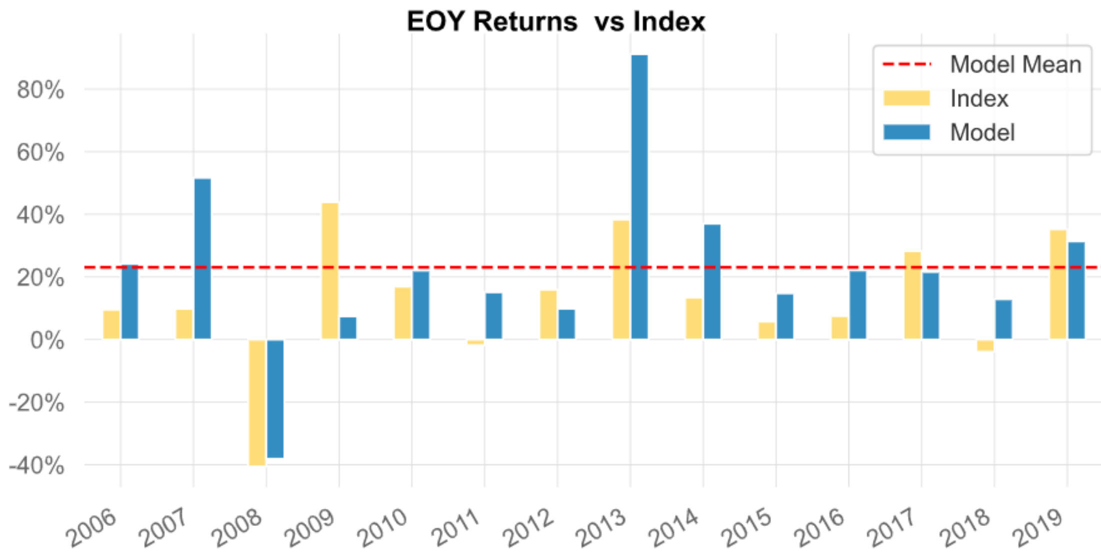

Figure 22: Trading Simulation - NASDAQ - Model Vs Index (Annual Return)

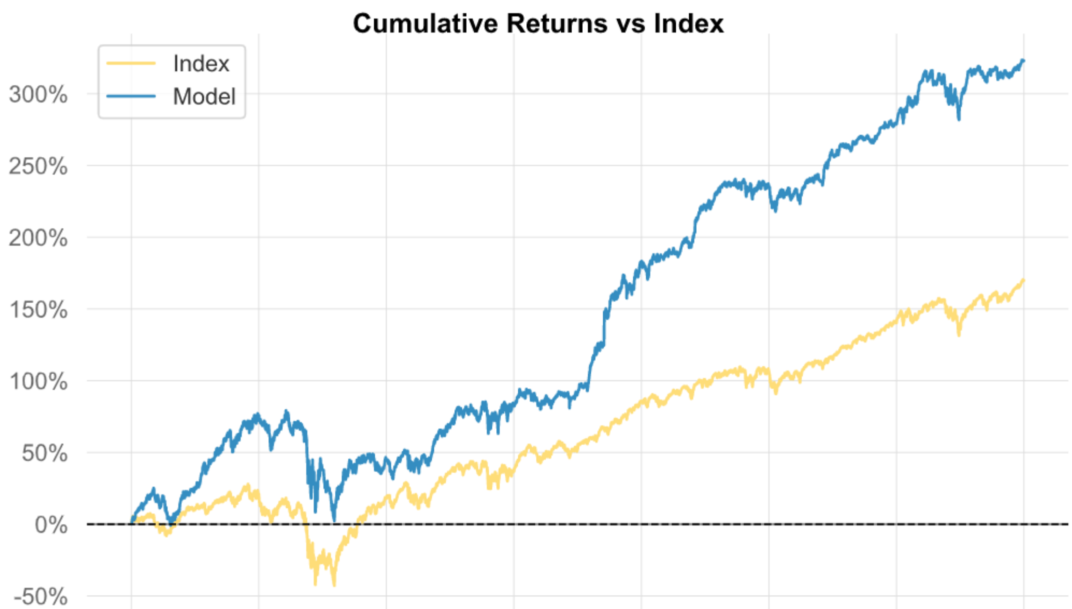

Figure 23: Trading Simulation - NASDAQ - Model Vs Index (Cumulative Return)

The following figures present the top 5 drawdown periods and the drawdown% of the portfolio, respectively. The worst drawdown% for the portfolio occurred during the global financial crisis; the model experienced a -59% drawdown and fully recovered in 1736 days; however, the model still outperformed the index despite the long recovery duration to the profitability metrics. Drawdown period details are shown in the following table.

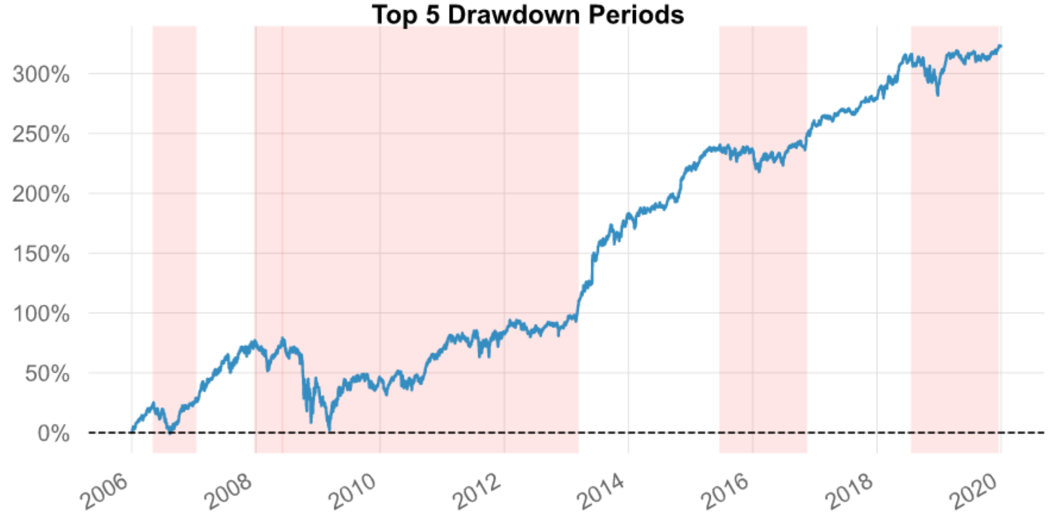

Figure 25: Trading Simulation - NASDAQ - Model top 5 drawdown periods

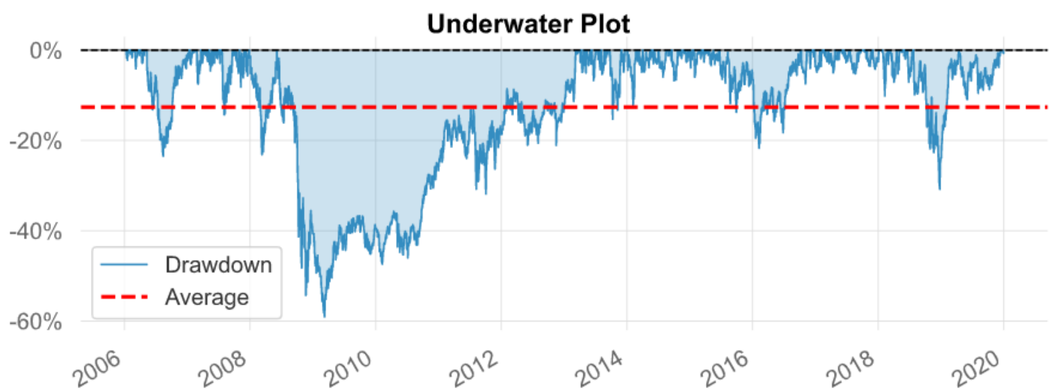

Figure 24: Trading Simulation - NASDAQ - Model drawdown%

#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	6/6/2008	3/9/2009	3/8/2013	1736	-59.07	-54.94
2	7/26/2018	12/24/2018	12/12/2019	504	-30.85	-26.00
3	5/10/2006	8/14/2006	1/11/2007	246	-23.49	-22.54
4	12/27/2007	3/10/2008	6/5/2008	161	-23.13	-20.92
5	6/24/2015	2/8/2016	11/11/2016	506	-21.73	-20.12

Table 9: Trading Simulation - NASDAQ - Model top 5 drawdown periods (details)

5. Conclusion

In this study, we address the issue of stock selection by developing a model that capitalizes on the power of genetic algorithms to recommend a set of screening rules to be used each year. The model development relies on a set of 16 fundamental ratios associated with three common stock screeners, namely, Benjamin Graham Defensive Investor, Benjamin Graham NCAV, and Piotroski F-Score. The study is performed on NYSE and NASDAQ using data accessed from Reuters covering the period from 2005 till 2019. A huge number of simulation runs have been done to back-test the model and benchmark its performance against indices and the three common stock screeners mentioned earlier. The achieved results demonstrate that the model outperforms the mentioned benchmarks and that the model provides a powerful tool to assist investors in selecting valuable stocks. The following table summarizes the results collected from the back-testing.

		Model	**Composite Index**	**Graham Defensive Investor**	**Graham NCAV**	**Piotroski F-Score**
NSYE	***14Y HPR%***	211.51%	85.40%	95.84%	114.94%	88.86%
	CAGR%	8.45%	4.51%	4.92%	5.62%	4.65%
	Sharpe	0.66	0.31	0.22	0.4	0.29
NASDAQ	***14Y HPR%***	322.97%	169.91%	94.05%	161.79%	157.24%
	CAGR%	10.85%	7.35%	4.85%	7.12%	6.98%
	Sharpe	0.85	0.59	0.23	0.5	0.47

Table 10: Results Summary

Based on the presented results, the model outperformance was observed over different profitability metrics such as the holding-period return% (HPR%) and risk-adjusted return represented by the Sharpe ratio. The model's portfolios followed a 1-year buy-and-hold strategy where constituents were selected at the beginning of each year. Accordingly, relative comparisons of the model-returns to the indices need to be looked at cautiously as the rebalancing frequency differs; the NYSE Composite index is rebalanced quarterly and the NASDAQ Composite Index is rebalanced daily. Although the importance of some of the used input fundamental ratios such as “Price to 3-year average earnings” was confirmed by being frequently present in the recommended screening rules generated by the model, on the other hand, some other ratios were not frequently present. Accordingly, to fully evaluate the model's capability in recommending screening rules that can select profitable stocks, it is important to do further research to identify the optimal set of fundamental ratios to be used by the model.

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Appendices

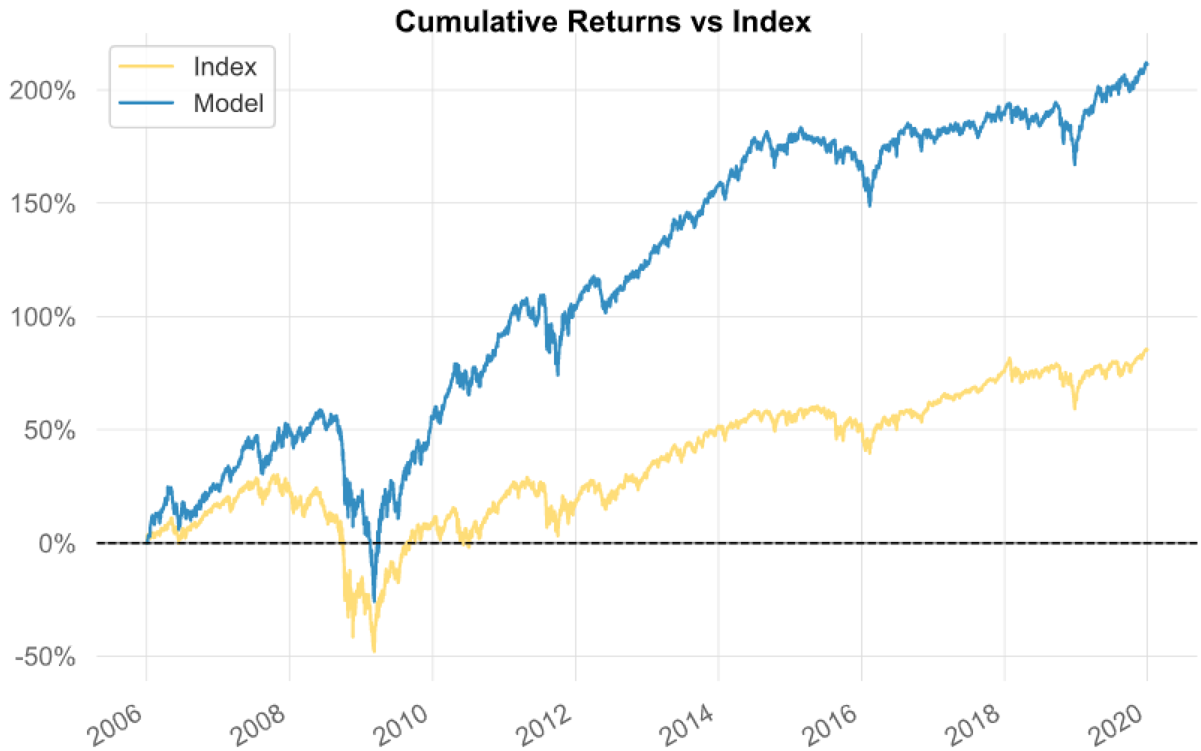
Appendix 1 – Detailed Model Performance
A: Trading on NYSE

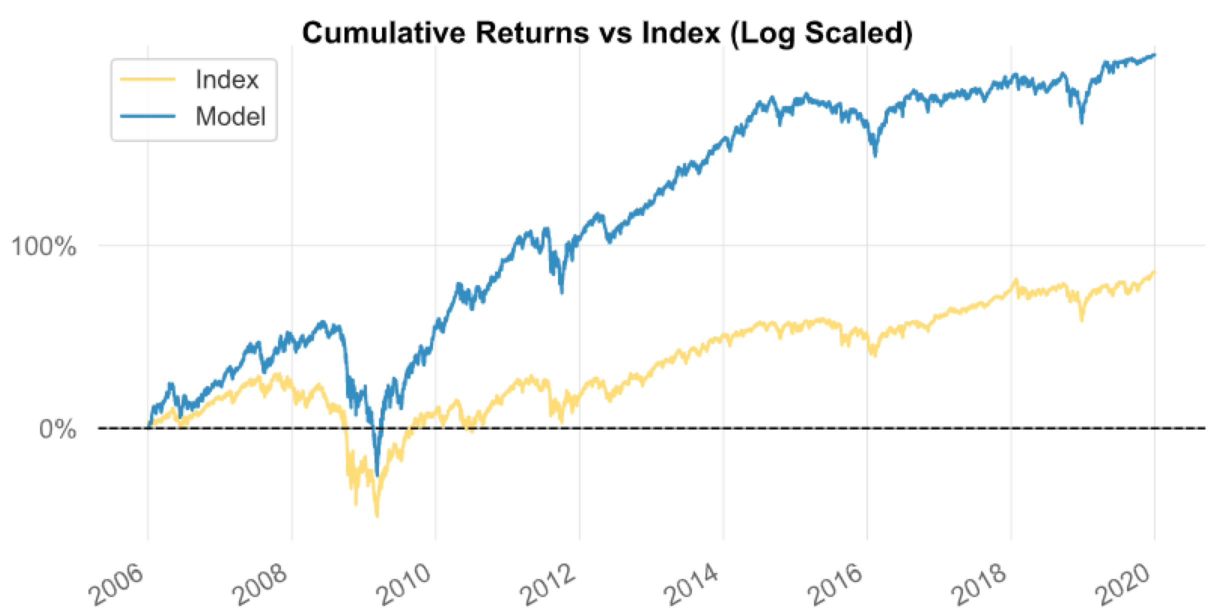
A.1 Summary of Model Performance from Jan 2006 till Dec 2019:

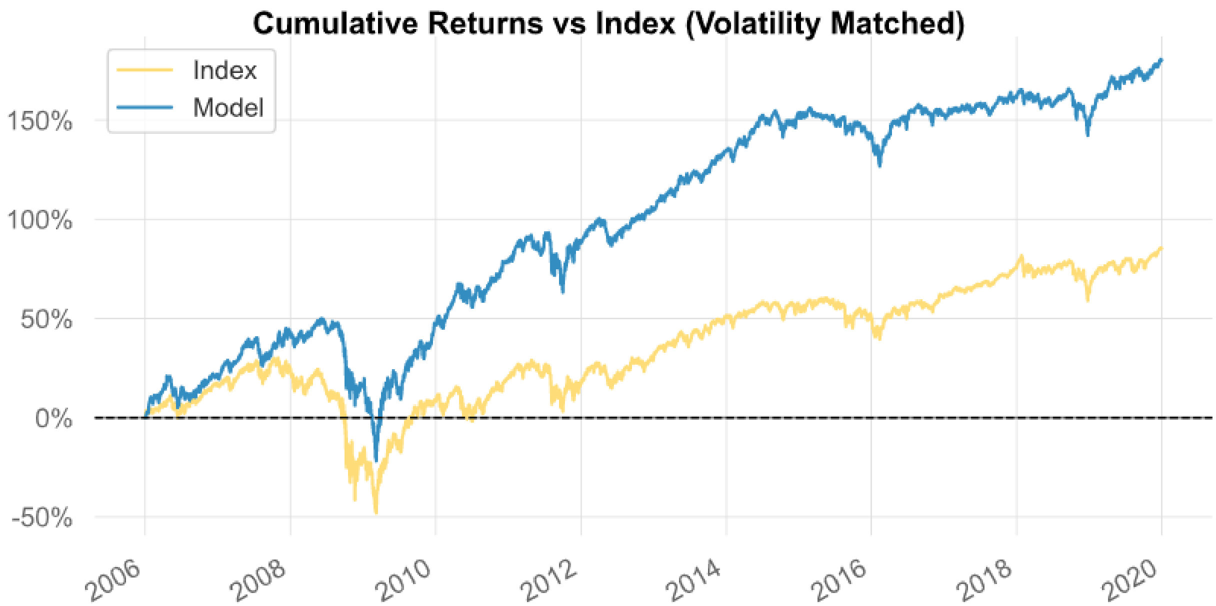
** Performance is benchmarked against NYSE Composite Index*

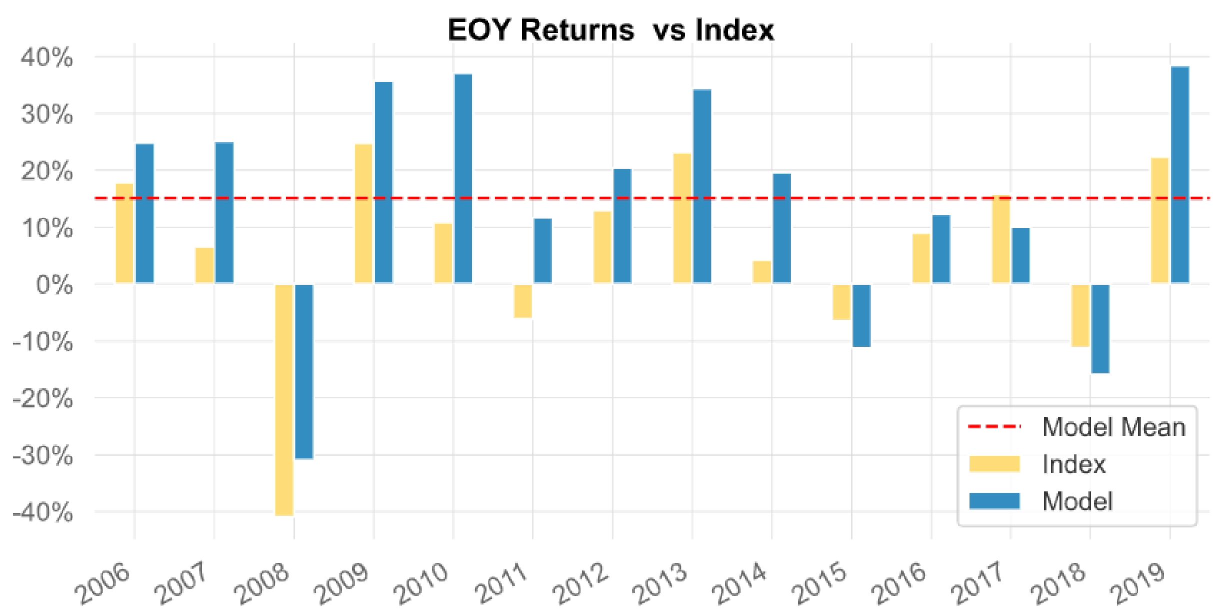
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	211.51%	85.40%
CAGR%	8.45%	4.51%
Sharpe	0.66	0.31
Sortino	0.94	0.43
Max Drawdown	-60.32%	-59.01%
Longest DD Days	943	2247
Volatility (ann.)	22.99%	19.61%
R^2	0.75	
Calmar	0.22	0.07
Skew	-0.04	-0.2
Kurtosis	5.66	11.69
Expected Daily %	0.05%	0.02%
Expected Monthly %	1.04%	0.35%
Expected Yearly %	13.28%	4.26%
Kelly Criterion	5.77%	0.20%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.32%	-2.01%
Expected Shortfall (cVaR)	-2.32%	-2.01%
Payoff Ratio	0.91	0.86
Profit Factor	1.13	1.06
Common Sense Ratio	1.11	0.94
CPC Index	0.57	0.49
Tail Ratio	0.98	0.88
Outlier Win Ratio	4	5.09
Outlier Loss Ratio	3.85	4.89

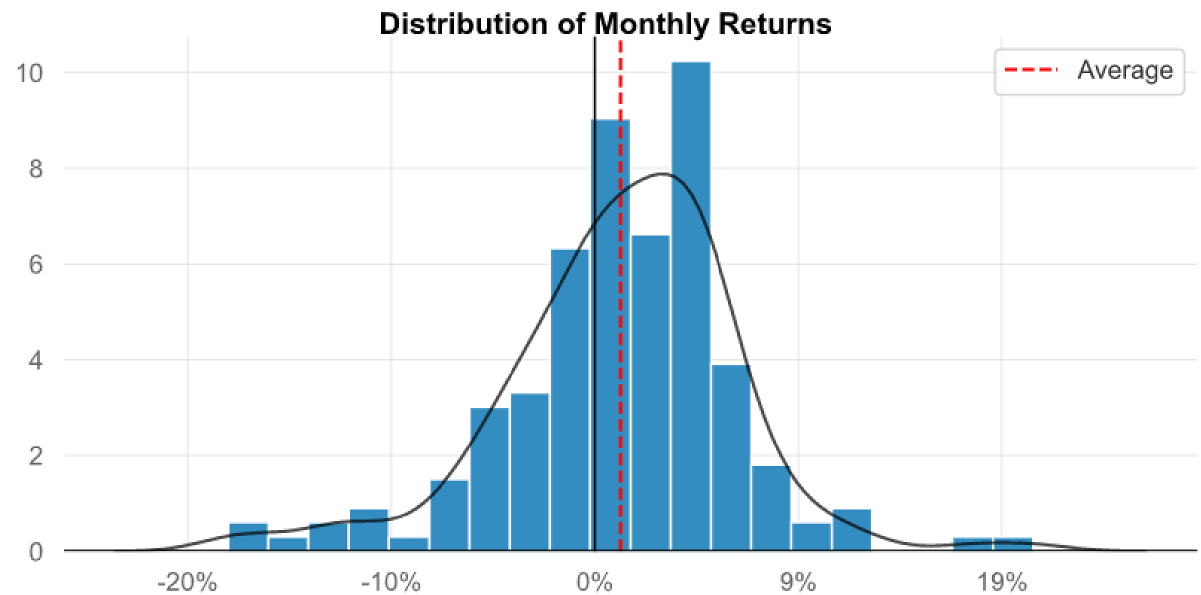
	Model	Index
MTD	2.71%	2.70%
3M	11.29%	7.11%
6M	11.03%	6.72%
YTD	38.39%	20.77%
1Y	39.48%	21.51%
3Y (ann.)	9.89%	7.72%
5Y (ann.)	5.75%	5.09%
10Y (ann.)	9.88%	5.85%
All-time (ann.)	8.45%	4.51%
Best Day	11.32%	12.22%
Worst Day	-9.22%	-9.73%
Best Month	22.44%	11.39%
Worst Month	-18.17%	-19.54%
Best Year	44.68%	24.80%
Worst Year	-31.03%	-40.89%
Avg. Drawdown	-3.52%	-2.28%
Avg. Drawdown Days	34	51
Recovery Factor	7.84	1.35
Ulcer Index	1.01	1.02
Avg. Up Month	5.01%	3.27%
Avg. Down Month	-5.07%	-4.33%
Win Days %	55.03%	53.96%
Win Month %	62.50%	61.31%
Win Quarter %	64.29%	69.64%
Win Year %	78.57%	71.43%
Beta	1.01	
Alpha	0.09	


Cumulative Returns vs Index
Index
Model
200%
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020


Cumulative Returns vs Index (Log Scaled)
Index
Model
100%
0%
2006
2008
2010
2012
2014
2016
2018
2020

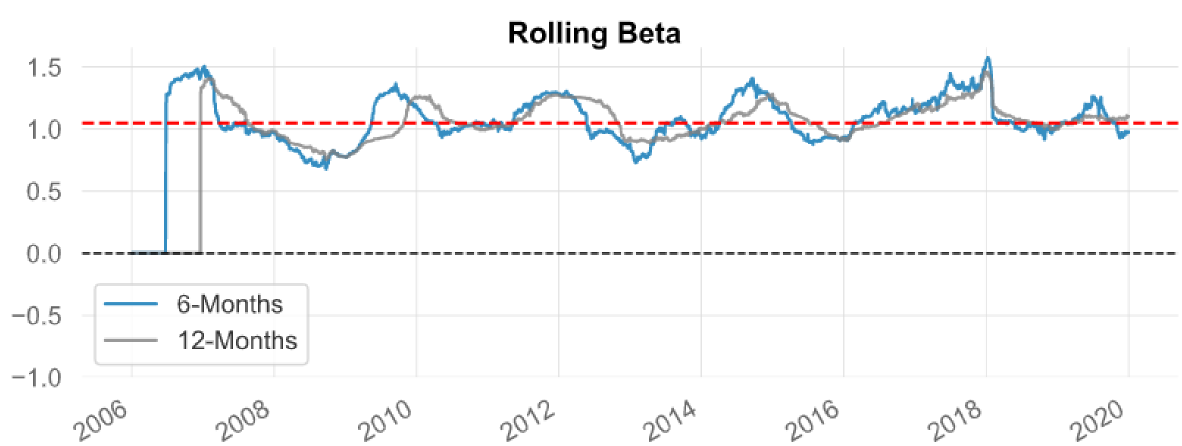

Cumulative Returns vs Index (Volatility Matched)
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020


EOY Returns vs Index
40%
30%
20%
10%
0%
-10%
-20%
-30%
-40%
Model Mean
Index
Model
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

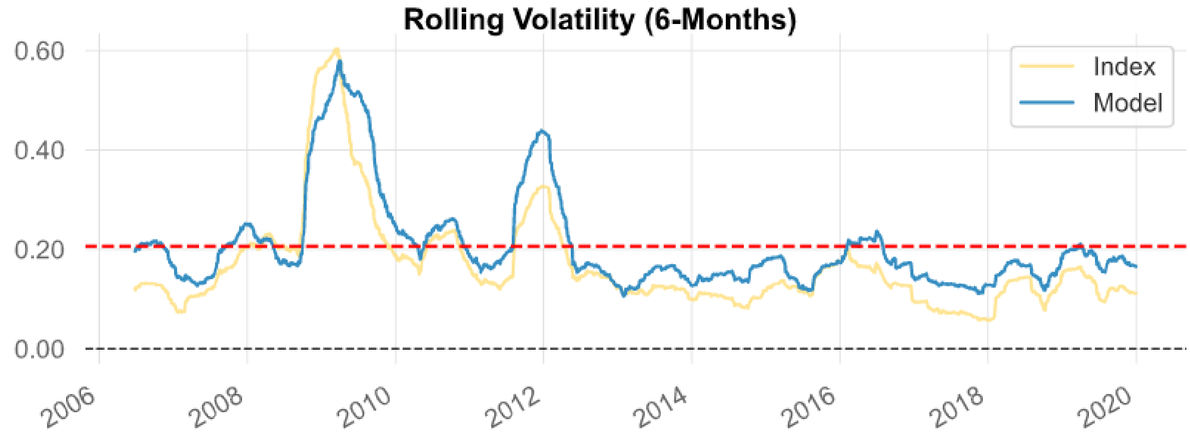


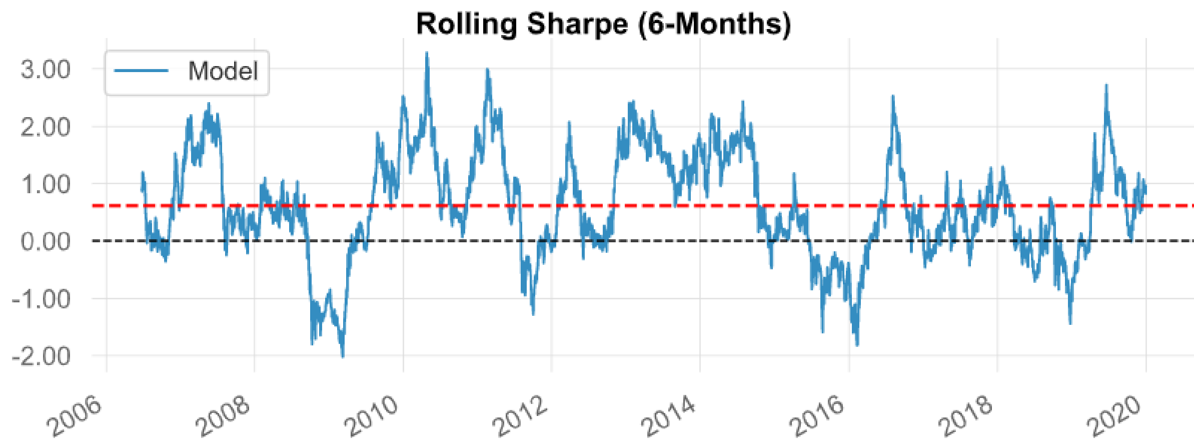
Distribution of Monthly Returns
Average
10
8
6
4
2
0
-20%
-10%
0%
9%
19%

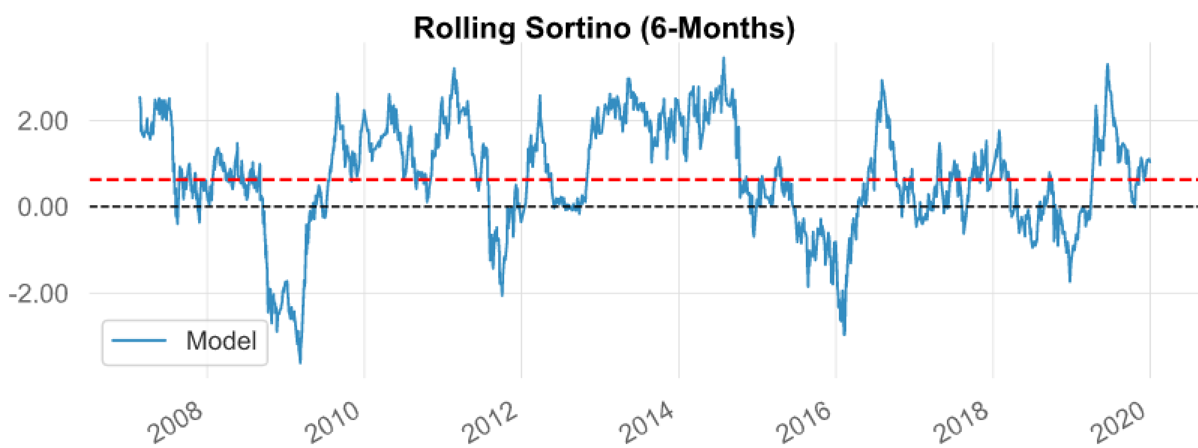
Daily Returns
10%
5%
0%
-5%
-10%
2006
2008
2010
2012
2014
2016
2018
2020

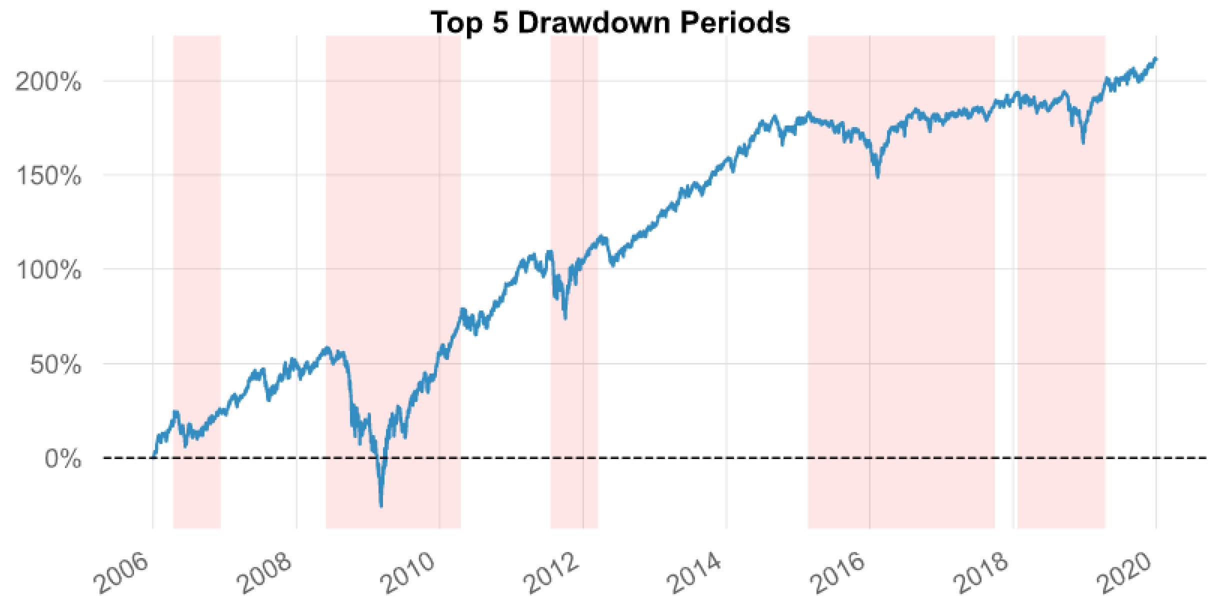


Rolling Beta
1.5
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

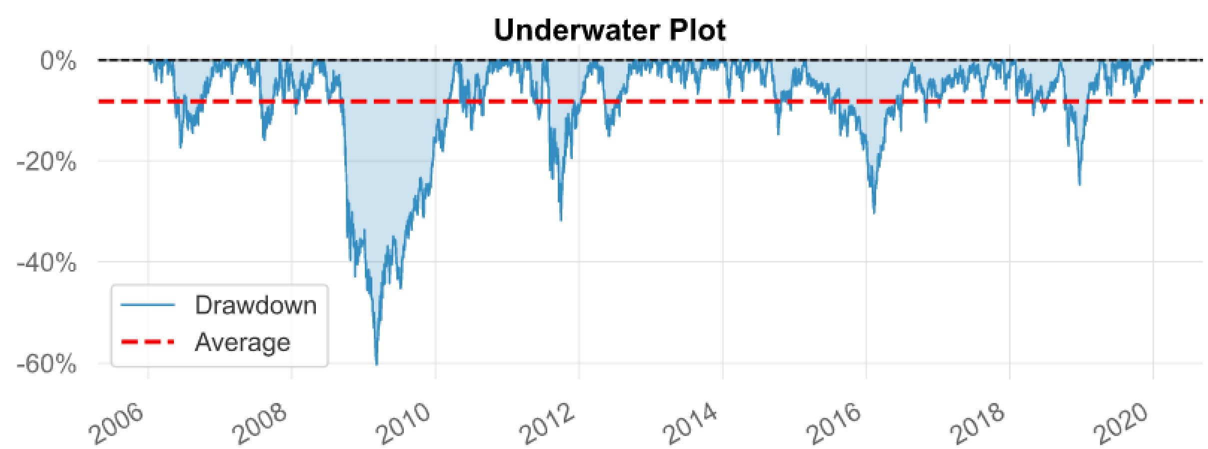

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
Model
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020

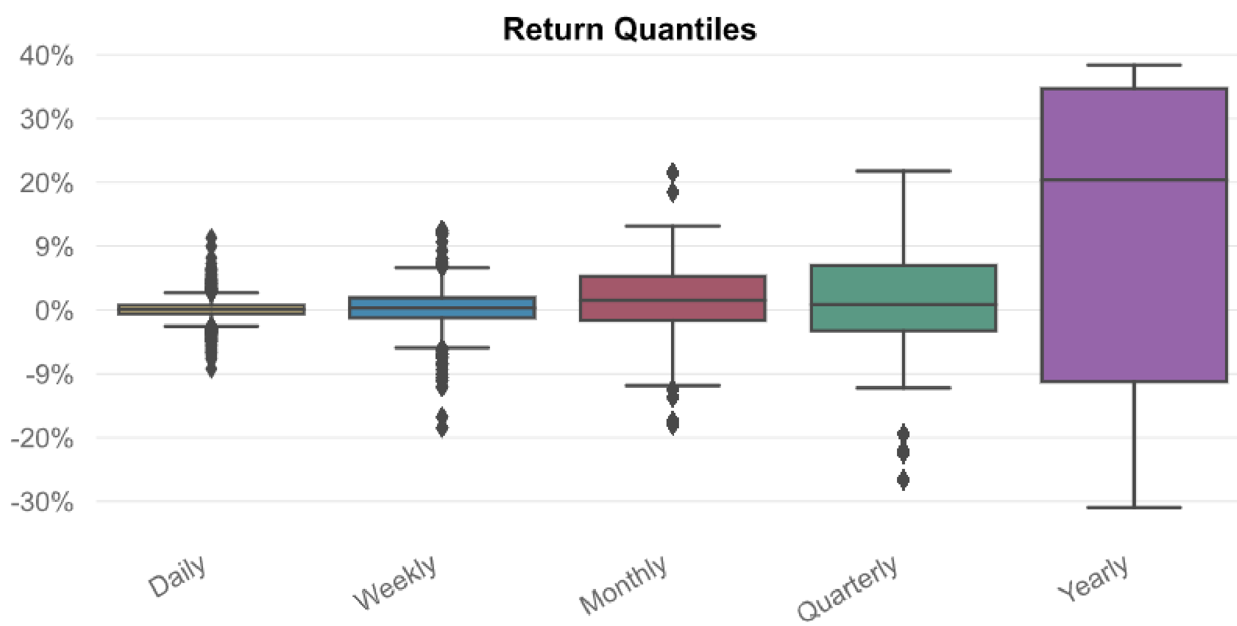


#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	6/6/2008	3/9/2009	4/13/2010	676	-60.32	-57.14
2	7/25/2011	10/3/2011	3/13/2012	232	-31.79	-28.36
3	2/26/2015	2/11/2016	9/26/2017	943	-30.34	-25.57
4	1/29/2018	12/24/2018	4/10/2019	436	-24.75	-20.82
5	4/20/2006	6/13/2006	12/6/2006	230	-17.41	-16.35



Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	11.64	-0.19	5.37	6.33	-8.34	2.39	-3.29	-0.46	4.02	3.89	2.68	0.81
2007	5.33	-0.11	1.98	5.41	7.85	-2.12	-3.70	-1.64	2.21	7.59	1.32	0.96
2008	-4.86	2.40	0.47	6.35	3.86	-4.93	1.66	-0.22	-13.66	-17.40	-4.51	-0.13
2009	-15.75	-12.00	5.30	21.52	5.17	-6.13	10.25	6.14	5.39	-3.51	6.17	13.18
2010	-1.23	6.22	8.59	8.84	-4.59	-6.45	9.15	-6.24	10.09	2.28	5.35	5.07
2011	5.13	7.86	1.42	0.92	-3.30	1.55	-1.07	-7.55	-18.02	18.48	6.28	-0.04
2012	4.15	5.41	3.39	-0.15	-11.84	4.03	3.17	0.25	4.99	1.40	4.42	1.17
2013	5.49	0.78	5.15	0.51	4.75	-0.42	3.24	-3.42	5.76	5.53	3.43	3.57
2014	-3.29	7.59	1.38	3.56	5.10	5.29	-3.97	6.55	-7.87	2.79	-1.51	4.00
2015	-0.50	4.58	-3.17	-2.20	0.02	-1.04	1.13	-5.09	-1.69	3.36	-2.02	-4.60
2016	-5.72	-0.75	7.28	6.54	2.52	0.52	4.69	1.81	-0.60	-7.15	4.32	-1.15
2017	1.45	1.71	2.52	-1.33	-2.05	4.24	-1.39	-1.34	4.80	0.67	4.21	-3.42
2018	4.33	-3.30	-1.11	-4.26	1.28	-1.71	5.90	0.11	2.38	-12.45	3.54	-10.55
2019	12.34	4.56	1.69	8.53	-4.65	4.88	1.47	2.74	-3.22	2.27	5.05	2.71



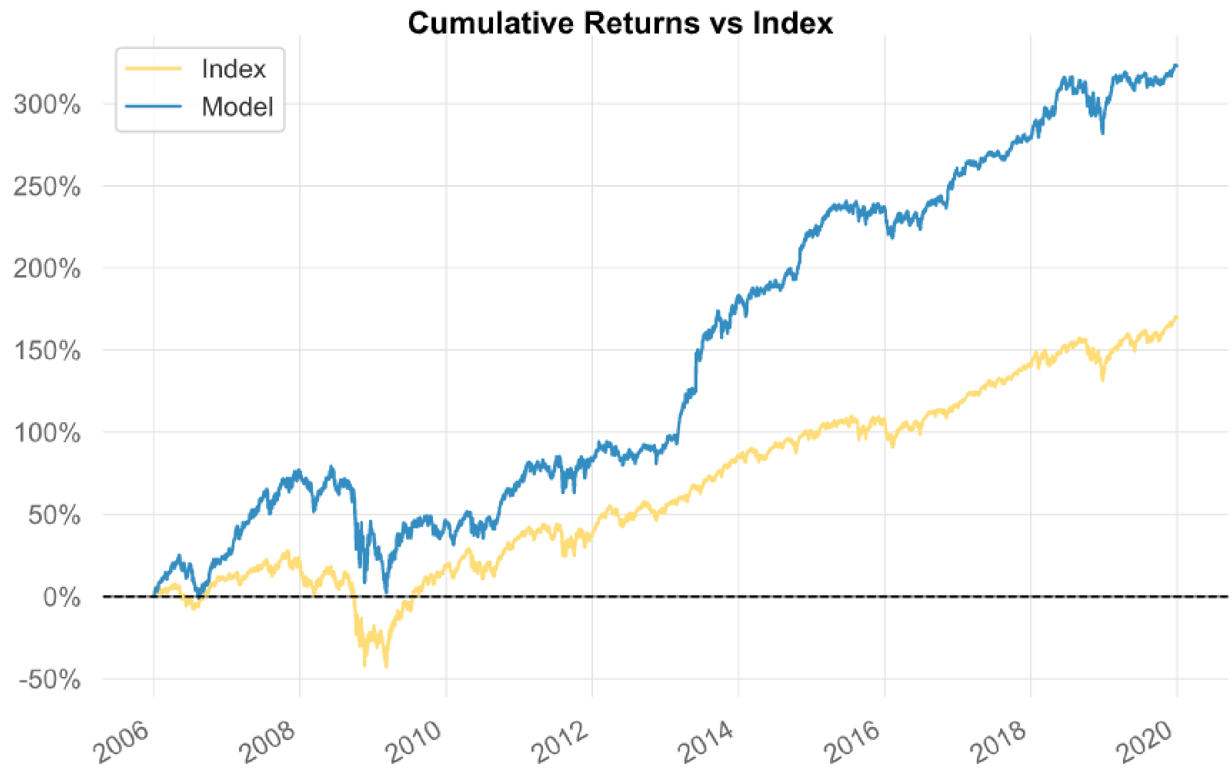
B: Trading on NASDAQ

B.1 Summary of Model Performance from Jan 2006 till Dec 2019:

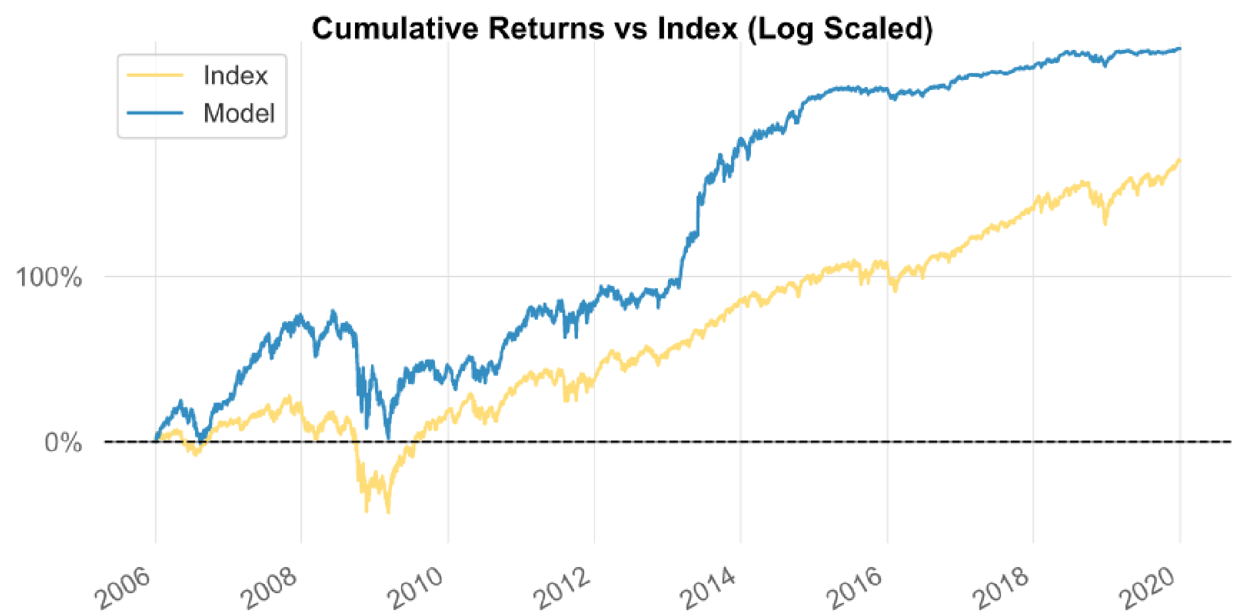
** Performance is benchmarked against Nasdaq Composite Index*

	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	322.97%	169.91%
CAGR%	10.85%	7.35%
Sharpe	0.85	0.59
Sortino	1.25	0.83
Max Drawdown	-59.07%	-55.63%
Longest DD Days	1736	1273
Volatility (ann.)	27.13%	20.55%
R^2	0.63	
Calmar	0.36	0.19
Skew	0.54	-0.12
Kurtosis	14.05	7.48
Expected Daily %	0.08%	0.04%
Expected Monthly %	1.63%	0.84%
Expected Yearly %	21.42%	10.54%
Kelly Criterion	5.19%	3.82%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.72%	-2.08%
Expected Shortfall (cVaR)	-2.72%	-2.08%
Payoff Ratio	0.91	0.87
Profit Factor	1.17	1.12
Common Sense Ratio	1.1	1
CPC Index	0.58	0.54
Tail Ratio	0.94	0.9
Outlier Win Ratio	3.53	4.86
Outlier Loss Ratio	3.42	4.48

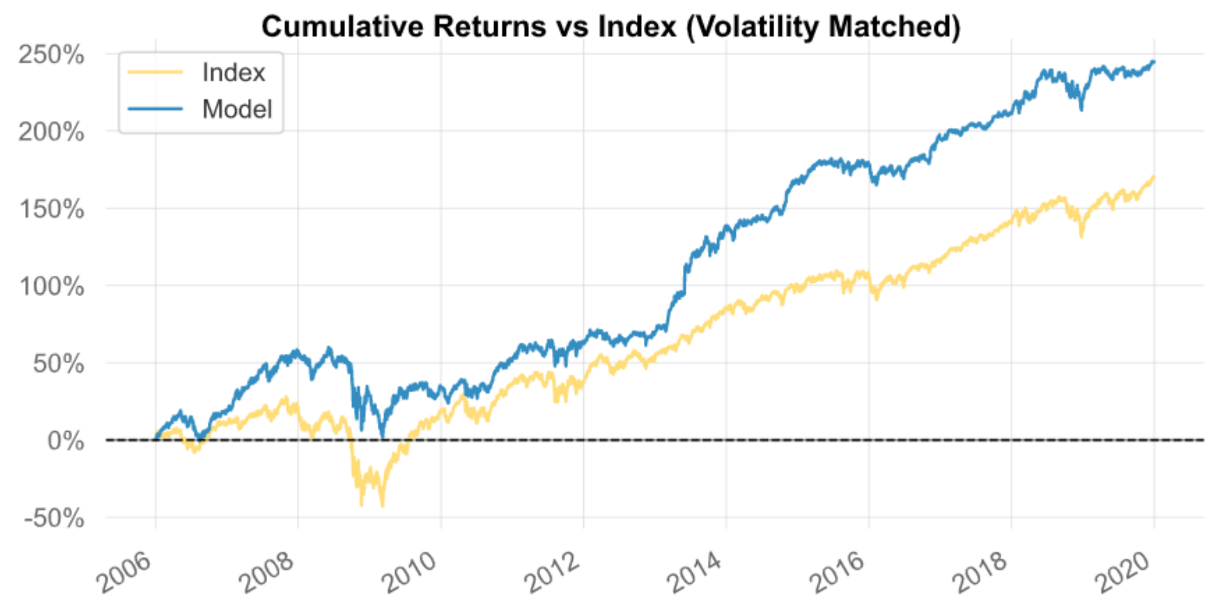
	Model	Index
MTD	3.90%	3.52%
3M	9.42%	12.39%
6M	6.54%	11.95%
YTD	31.35%	31.42%
1Y	32.47%	32.19%
3Y (ann.)	18.42%	15.77%
5Y (ann.)	14.97%	11.14%
10Y (ann.)	14.21%	9.64%
All-time (ann.)	10.85%	7.35%
Best Day	23.37%	11.81%
Worst Day	-12.48%	-9.14%
Best Month	23.62%	12.35%
Worst Month	-21.53%	-17.73%
Best Year	135.48%	43.89%
Worst Year	-39.61%	-40.54%
Avg. Drawdown	-3.52%	-2.37%
Avg. Drawdown Days	34	27
Recovery Factor	23.92	5.52
Ulcer Index	1.01	1.02
Avg. Up Month	5.77%	4.16%
Avg. Down Month	-6.00%	-4.97%
Win Days %	54.88%	55.28%
Win Month %	65.48%	62.50%
Win Quarter %	71.43%	71.43%
Win Year %	92.86%	78.57%
Beta	1.05	
Alpha	0.1	



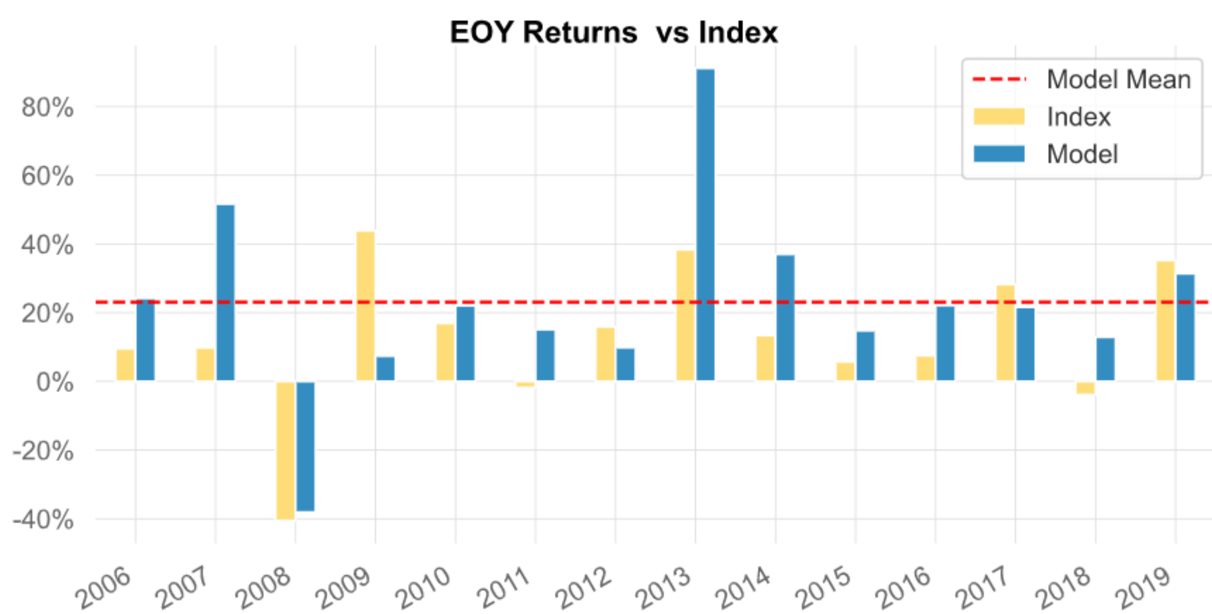
Cumulative Returns vs Index
Index
Model
300%
250%
200%
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020



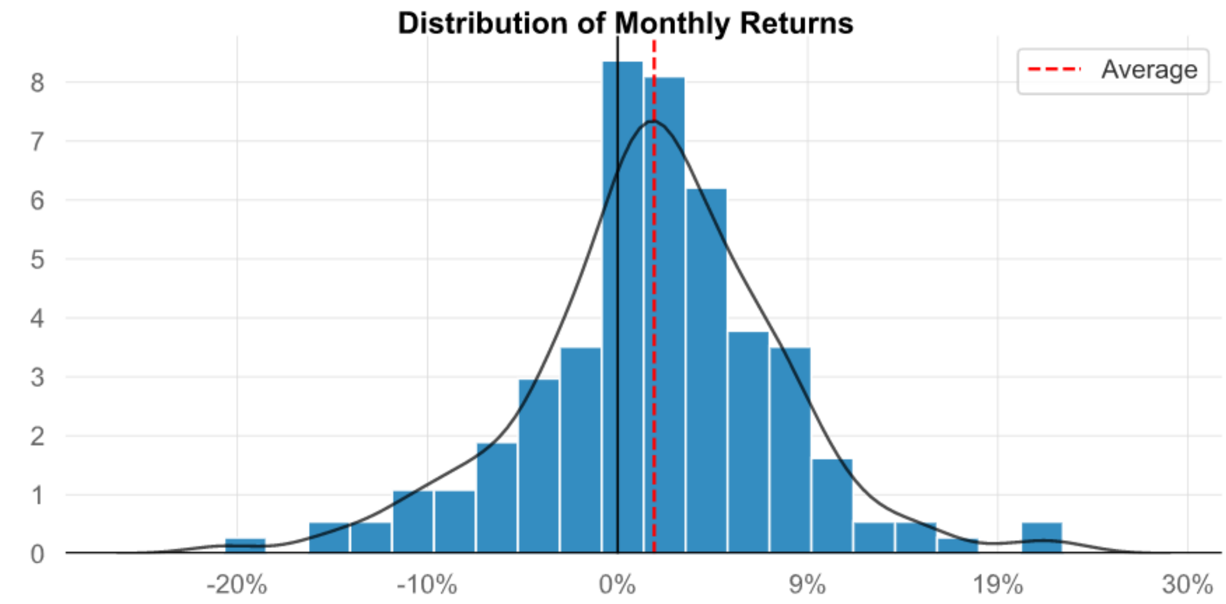
Cumulative Returns vs Index (Log Scaled)
Index
Model
100%
0%
2006
2008
2010
2012
2014
2016
2018
2020

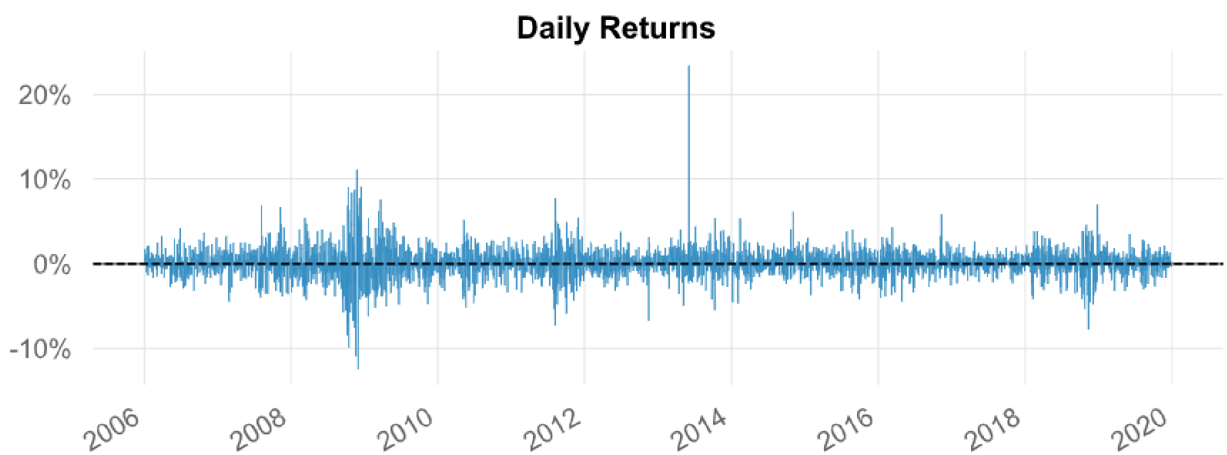


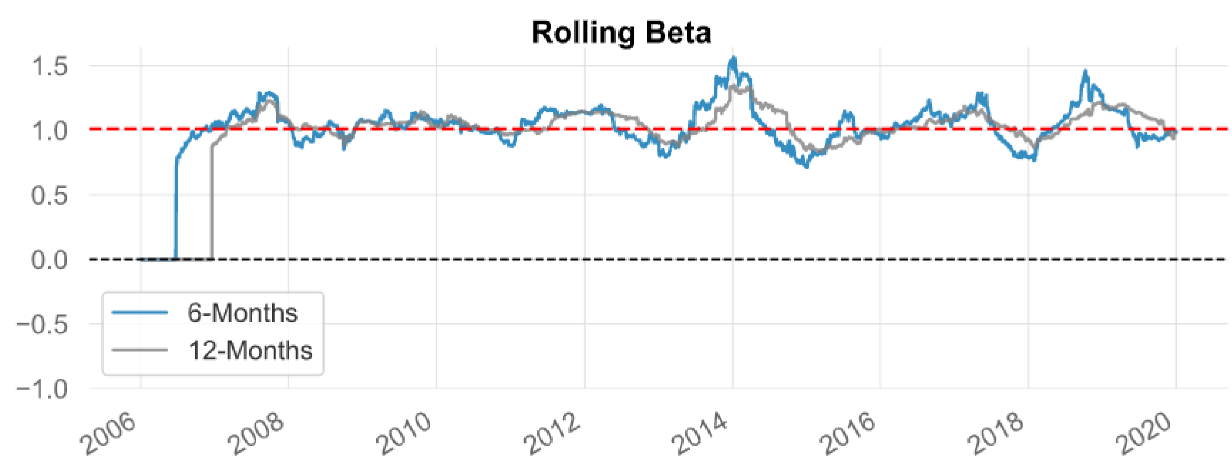
Cumulative Returns vs Index (Volatility Matched)
Index
Model
250%
200%
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

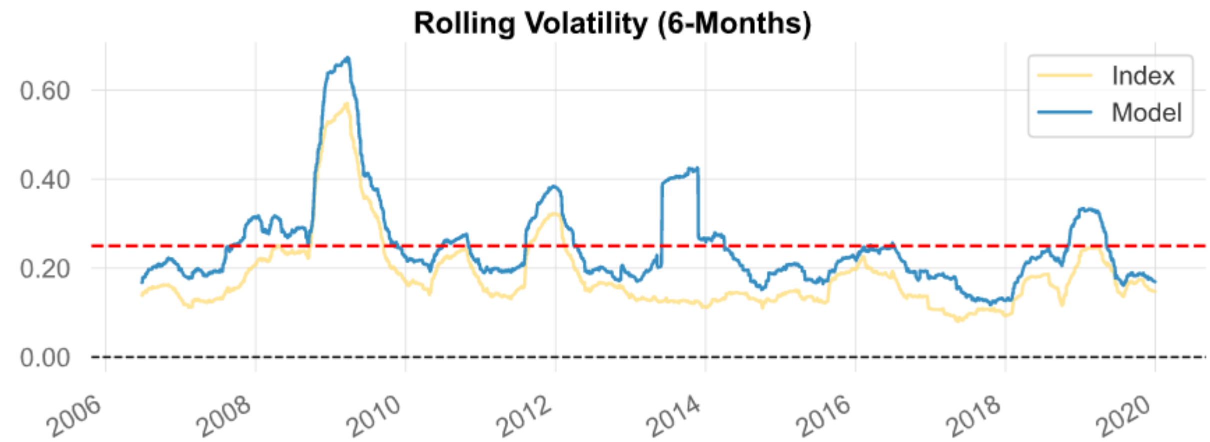


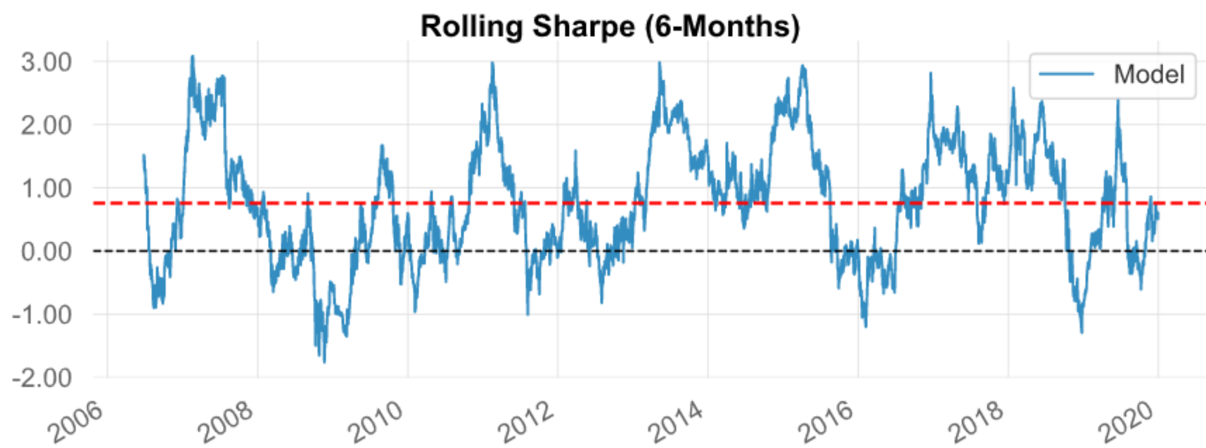
EOY Returns vs Index
Model Mean
Index
Model
80%
60%
40%
20%
0%
-20%
-40%
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

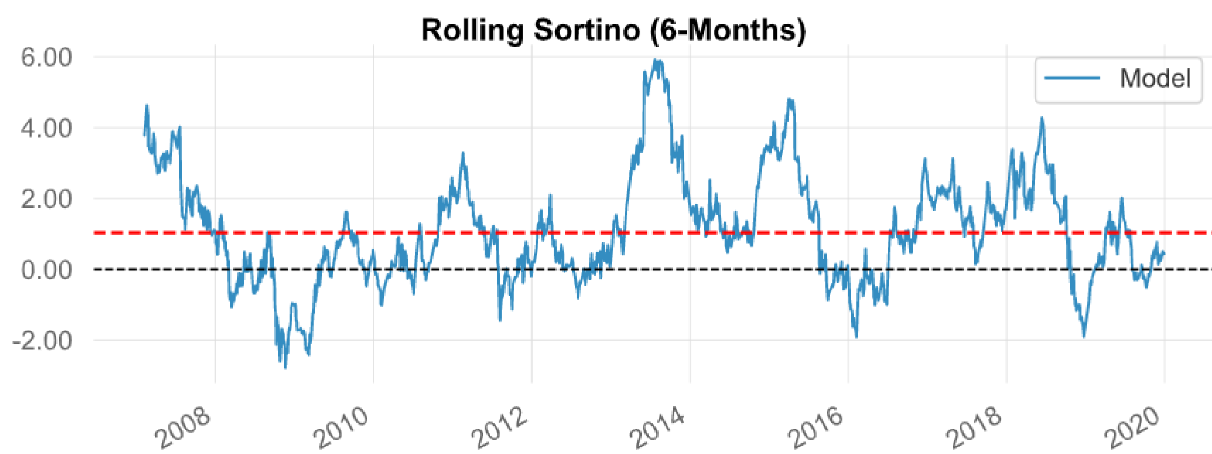

Distribution of Monthly Returns
Average
8
7
6
5
4
3
2
1
0
-20%
-10%
0%
9%
19%
30%


Daily Returns
20%
10%
0%
-10%
2006
2008
2010
2012
2014
2016
2018
2020

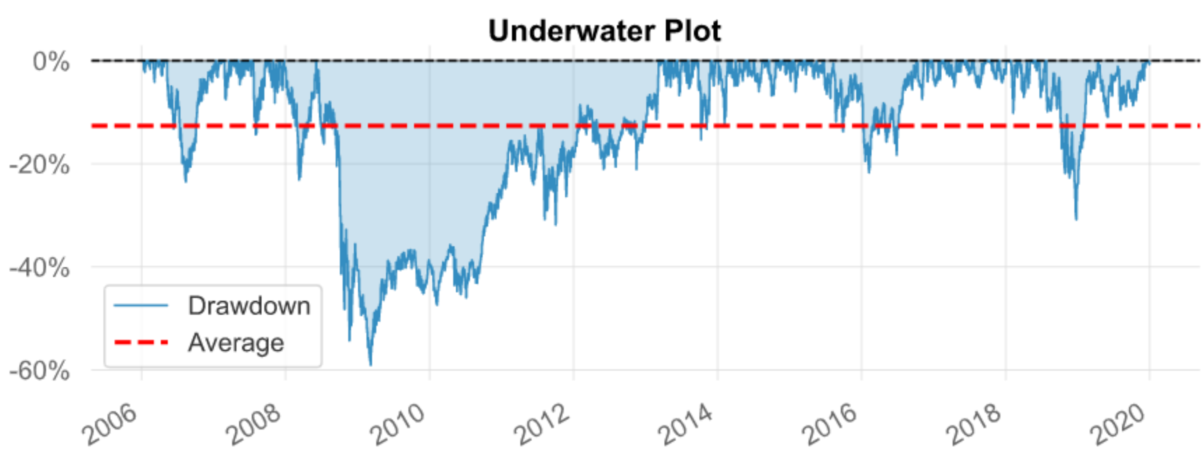

Rolling Beta
1.5
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

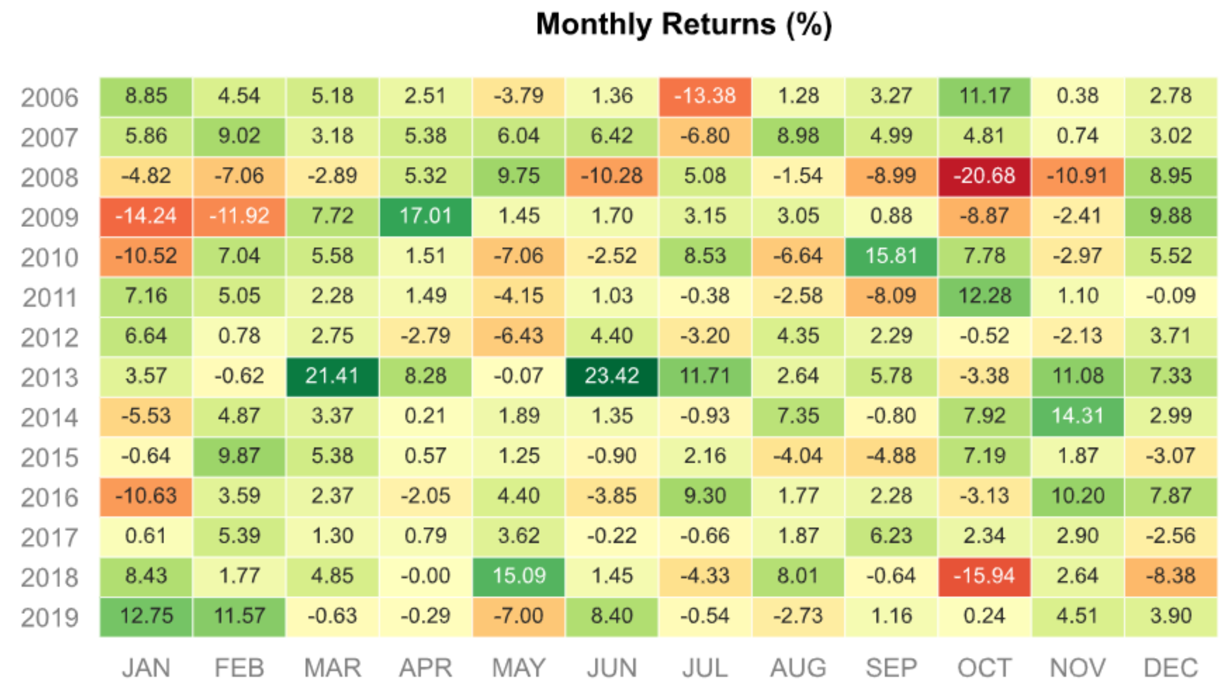

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020

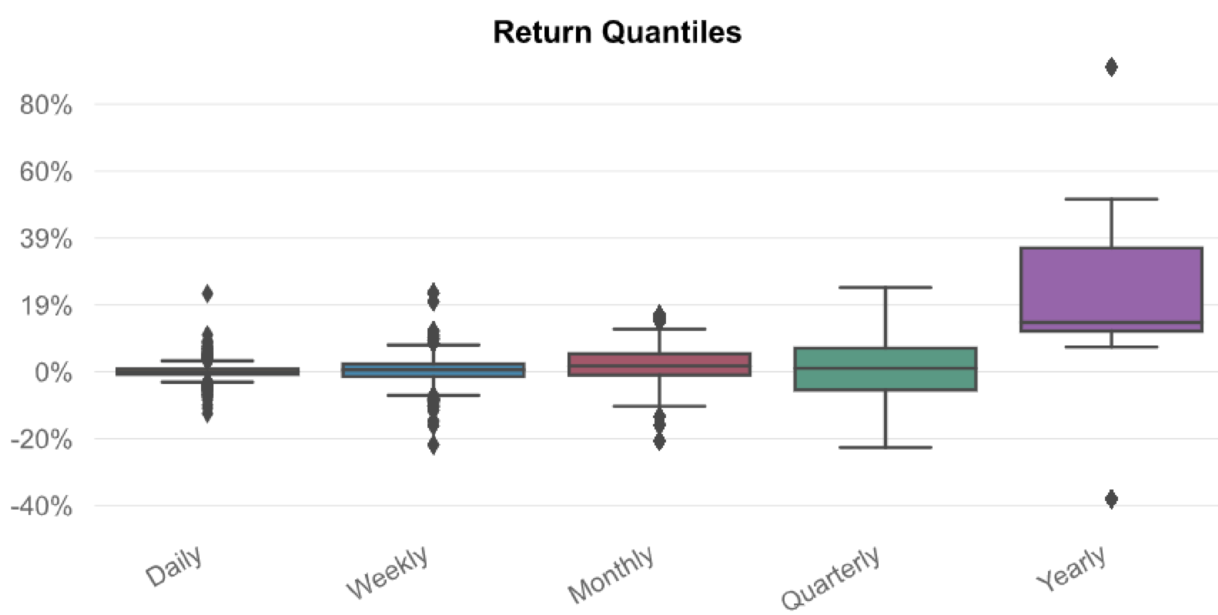

Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
Model
6.00
4.00
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020

#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	6/6/2008	3/9/2009	3/8/2013	1736	-59.07	-54.94
2	7/26/2018	12/24/2018	12/12/2019	504	-30.85	-26.00
3	5/10/2006	8/14/2006	1/11/2007	246	-23.49	-22.54
4	12/27/2007	3/10/2008	6/5/2008	161	-23.13	-20.92
5	6/24/2015	2/8/2016	11/11/2016	506	-21.73	-20.12




Monthly Returns (%)
2006 8.85 4.54 5.18 2.51 -3.79 1.36 -13.38 1.28 3.27 11.17 0.38 2.78
2007 5.86 9.02 3.18 5.38 6.04 6.42 -6.80 8.98 4.99 4.81 0.74 3.02
2008 -4.82 -7.06 -2.89 5.32 9.75 -10.28 5.08 -1.54 -8.99 -20.68 -10.91 8.95
2009 -14.24 -11.92 7.72 17.01 1.45 1.70 3.15 3.05 0.88 -8.87 -2.41 9.88
2010 -10.52 7.04 5.58 1.51 -7.06 -2.52 8.53 -6.64 15.81 7.78 -2.97 5.52
2011 7.16 5.05 2.28 1.49 -4.15 1.03 -0.38 -2.58 -8.09 12.28 1.10 -0.09
2012 6.64 0.78 2.75 -2.79 -6.43 4.40 -3.20 4.35 2.29 -0.52 -2.13 3.71
2013 3.57 -0.62 21.41 8.28 -0.07 23.42 11.71 2.64 5.78 -3.38 11.08 7.33
2014 -5.53 4.87 3.37 0.21 1.89 1.35 -0.93 7.35 -0.80 7.92 14.31 2.99
2015 -0.64 9.87 5.38 0.57 1.25 -0.90 2.16 -4.04 -4.88 7.19 1.87 -3.07
2016 -10.63 3.59 2.37 -2.05 4.40 -3.85 9.30 1.77 2.28 -3.13 10.20 7.87
2017 0.61 5.39 1.30 0.79 3.62 -0.22 -0.66 1.87 6.23 2.34 2.90 -2.56
2018 8.43 1.77 4.85 -0.00 15.09 1.45 -4.33 8.01 -0.64 -15.94 2.64 -8.38
2019 12.75 11.57 -0.63 -0.29 -7.00 8.40 -0.54 -2.73 1.16 0.24 4.51 3.90
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC


Return Quantiles
80%
60%
39%
19%
0%
-20%
-40%
Daily
Weekly
Monthly
Quarterly
Yearly

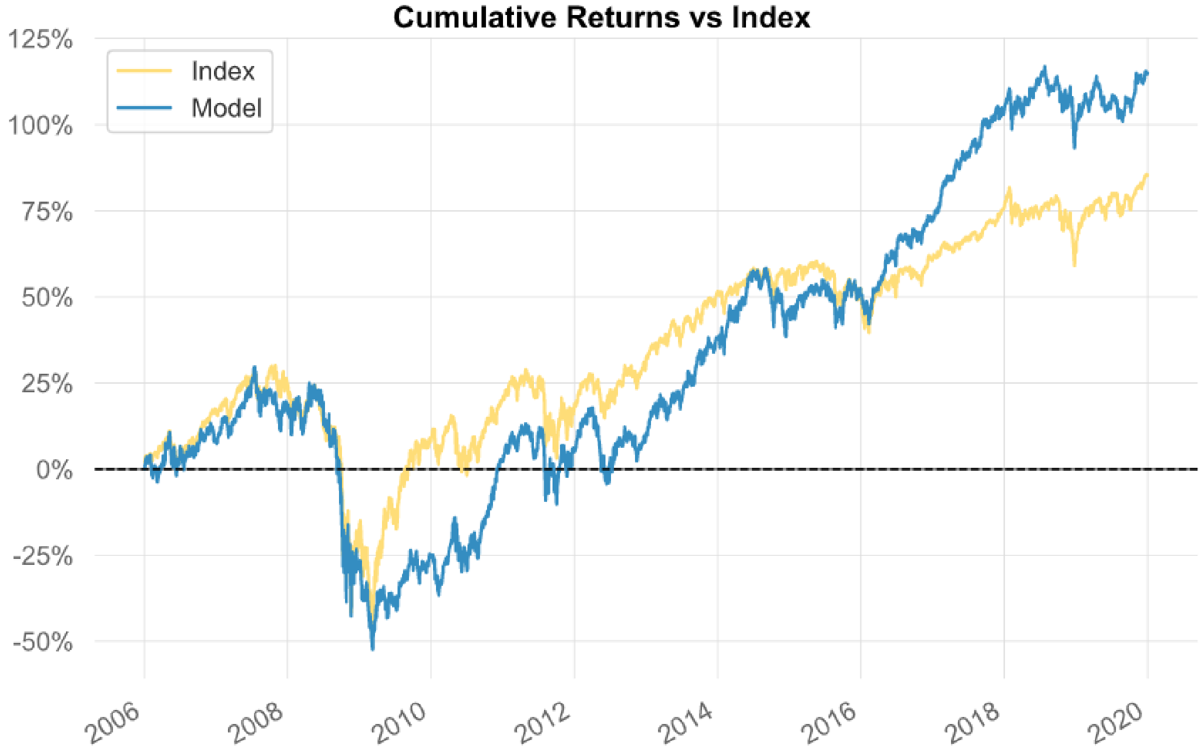
Appendix 2 – Benjamin Graham NCAV Screener Performance
A: Trading on NYSE

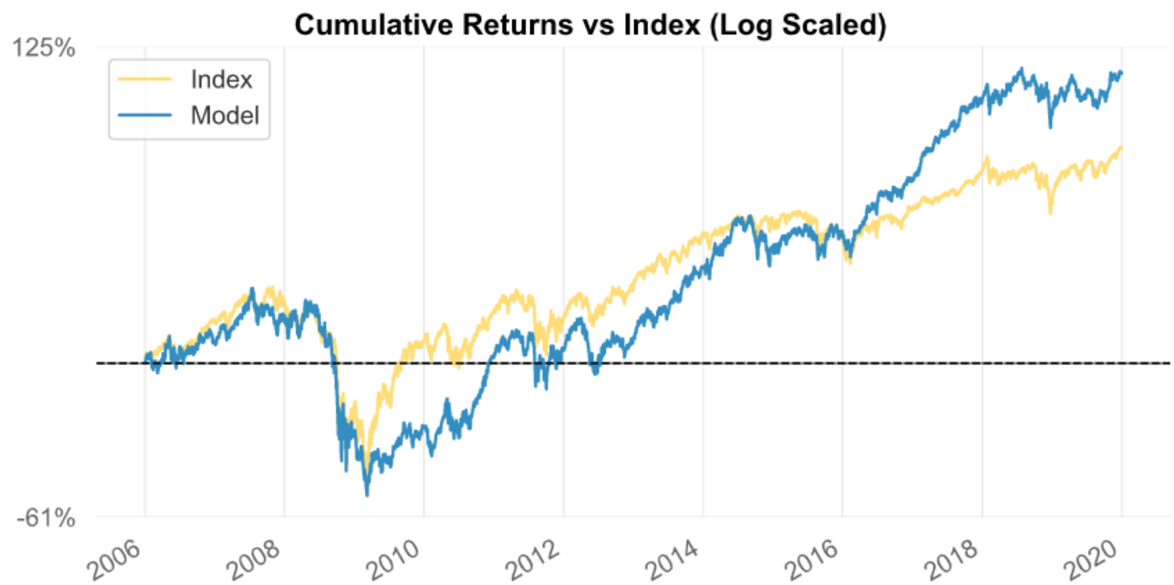
A.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

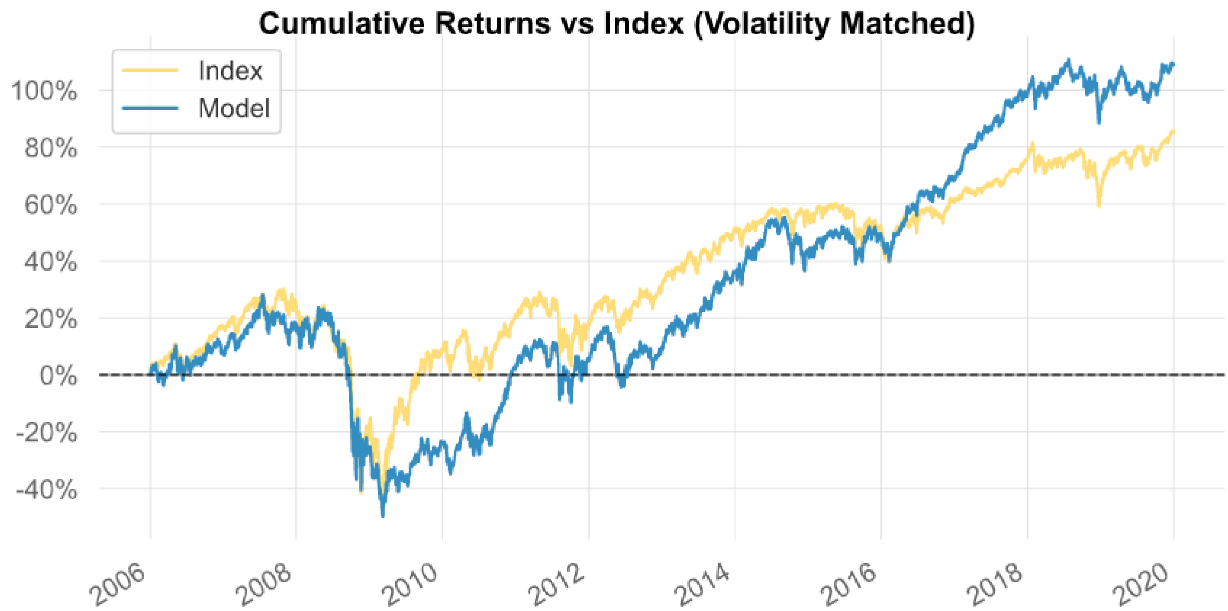
** Performance is benchmarked against NYSE Composite Index*

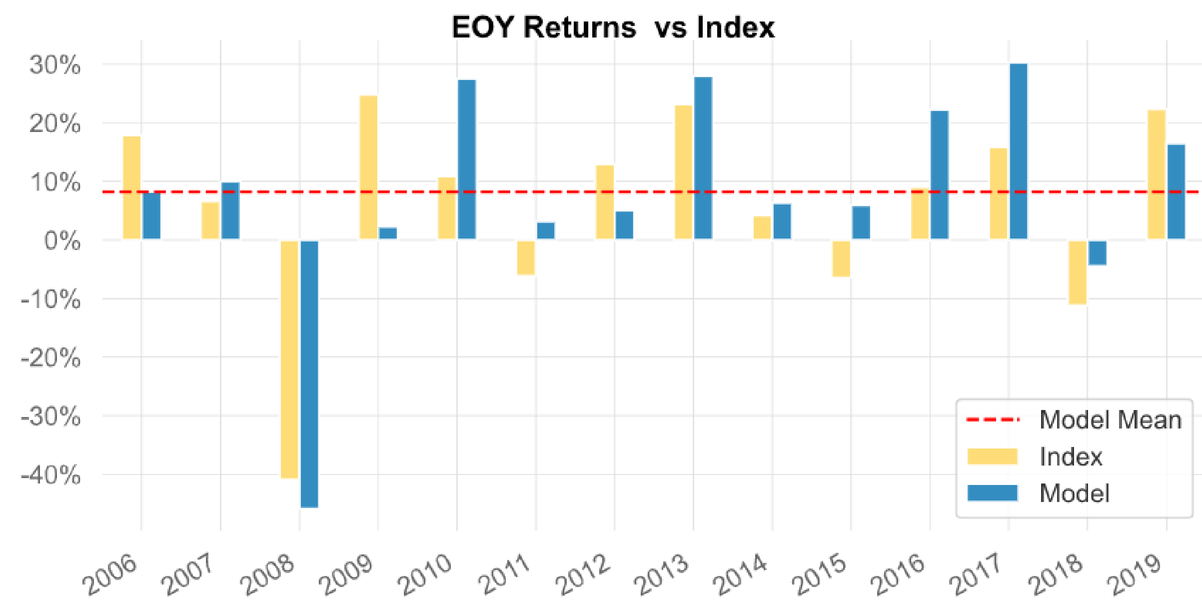
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	114.94%	85.40%
CAGR%	5.62%	4.51%
Sharpe	0.4	0.31
Sortino	0.55	0.43
Max Drawdown	-60.76%	-59.01%
Longest DD Days	2505	2247
Volatility (ann.)	20.67%	19.61%
R^2	0.71	
Calmar	0.1	0.07
Skew	-0.29	-0.2
Kurtosis	7.38	11.69
Expected Daily %	0.02%	0.02%
Expected Monthly %	0.51%	0.35%
Expected Yearly %	6.26%	4.26%
Kelly Criterion	1.38%	1.58%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.11%	-2.01%
Expected Shortfall (cVaR)	-2.11%	-2.01%
Payoff Ratio	0.92	0.88
Profit Factor	1.07	1.06
Common Sense Ratio	1.03	0.94
CPC Index	0.52	0.5
Tail Ratio	0.96	0.88
Outlier Win Ratio	3.86	4.57
Outlier Loss Ratio	3.97	4.47

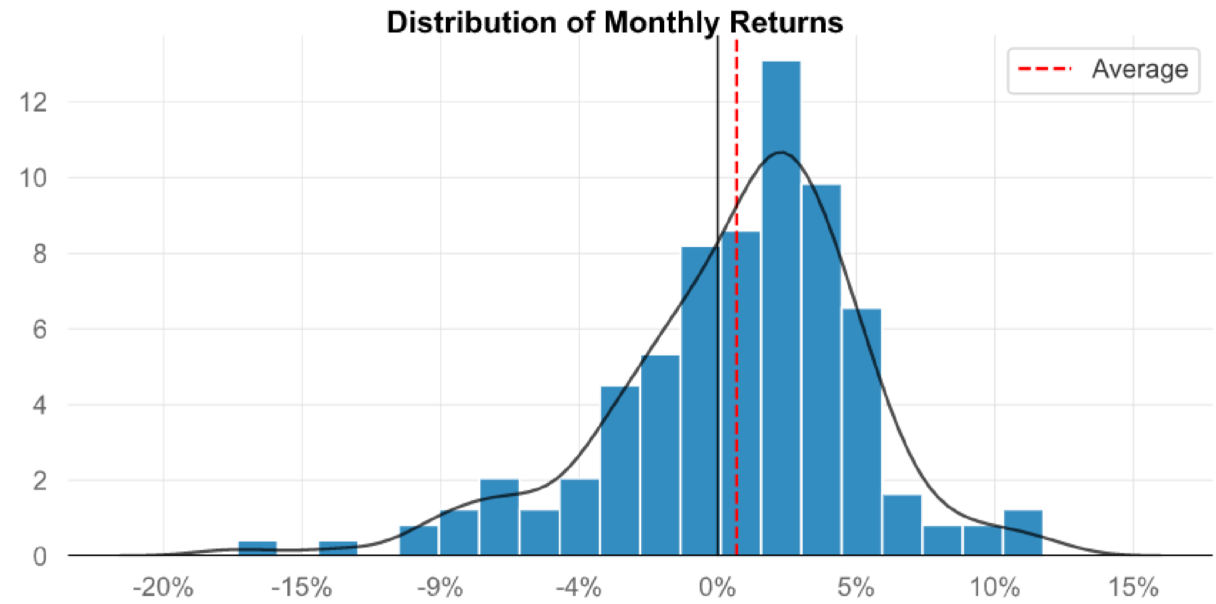
	Model	Index
MTD	1.40%	2.70%
3M	8.43%	7.11%
6M	8.82%	6.72%
YTD	16.45%	20.77%
1Y	16.94%	21.51%
3Y (ann.)	12.51%	7.72%
5Y (ann.)	11.15%	5.09%
10Y (ann.)	9.16%	5.85%
All-time (ann.)	5.62%	4.51%
Best Day	10.06%	12.22%
Worst Day	-9.66%	-9.73%
Best Month	12.10%	11.39%
Worst Month	-16.65%	-19.54%
Best Year	34.46%	24.80%
Worst Year	-42.48%	-40.89%
Avg. Drawdown	-2.71%	-2.28%
Avg. Drawdown Days	54	51
Recovery Factor	2.2	1.35
Ulcer Index	1.02	1.02
Avg. Up Month	3.69%	3.14%
Avg. Down Month	-4.40%	-4.48%
Win Days %	52.63%	53.96%
Win Month %	61.90%	61.31%
Win Quarter %	69.64%	69.64%
Win Year %	78.57%	71.43%
Beta	0.89	
Alpha	0.03	

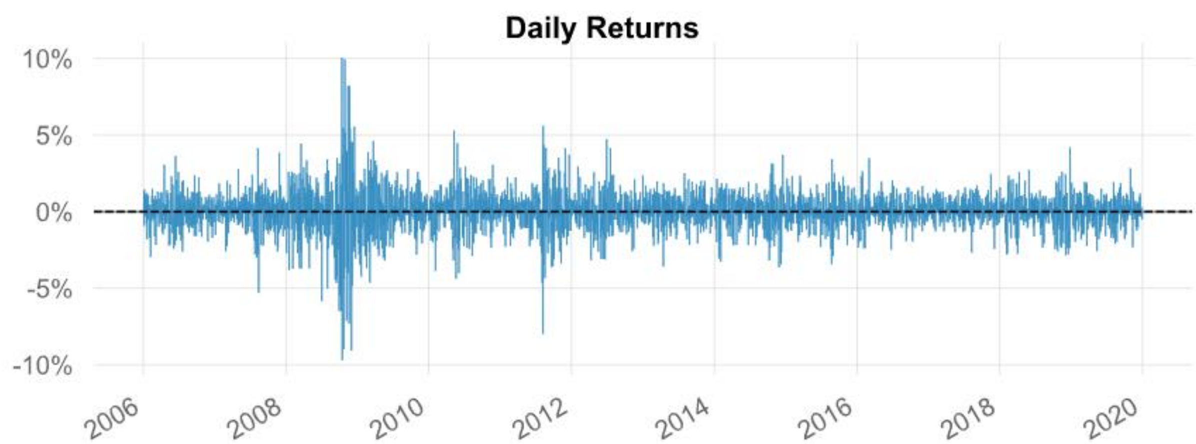

Cumulative Returns vs Index
Index
Model
125%
100%
75%
50%
25%
0%
-25%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

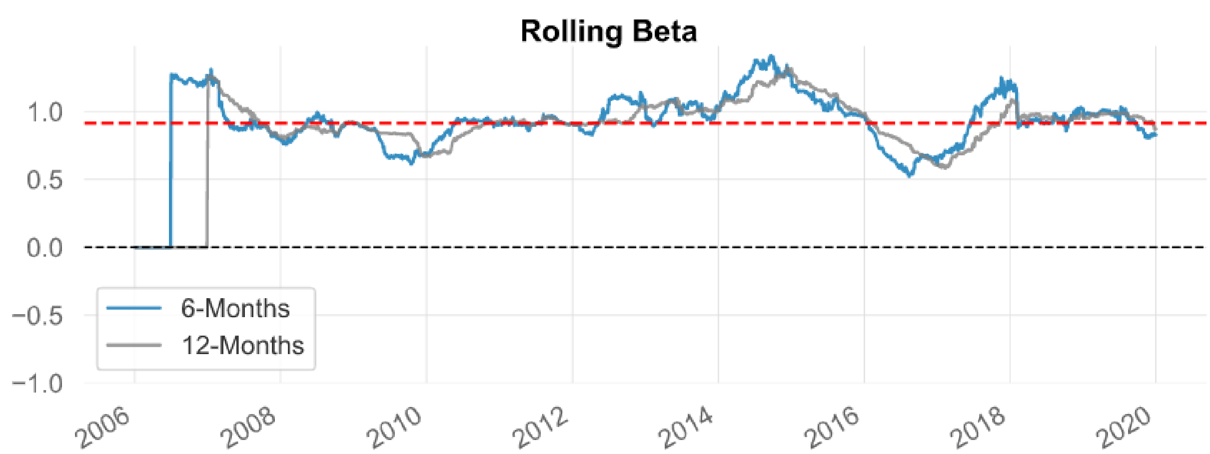

Cumulative Returns vs Index (Log Scaled)
Index
Model
125%
-61%
2006
2008
2010
2012
2014
2016
2018
2020

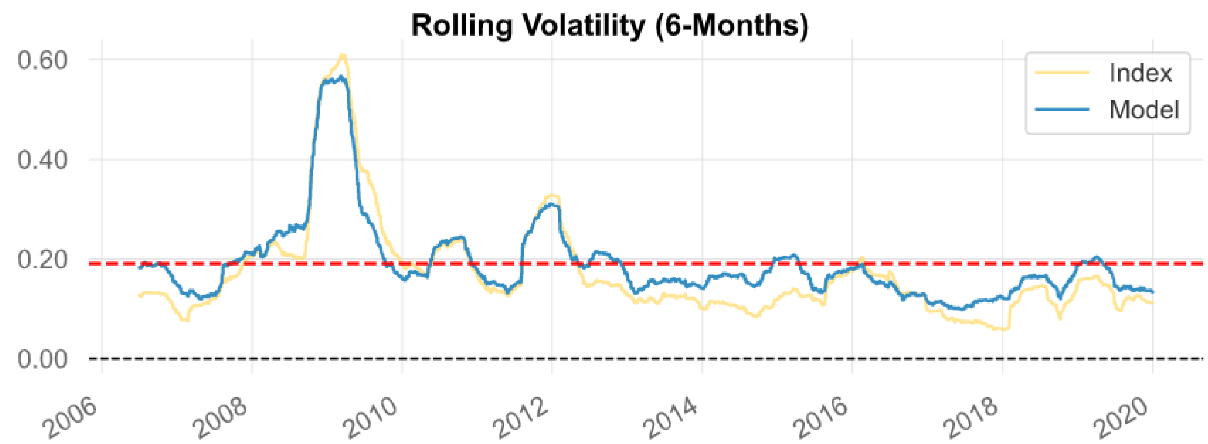

Cumulative Returns vs Index (Volatility Matched)
Index
Model
100%
80%
60%
40%
20%
0%
-20%
-40%
2006
2008
2010
2012
2014
2016
2018
2020

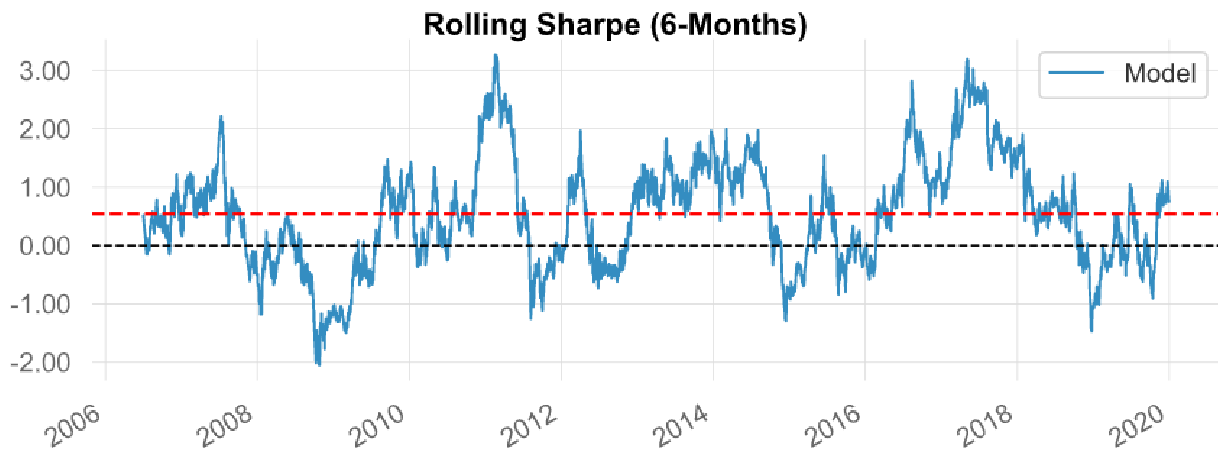

EOY Returns vs Index
30%
20%
10%
0%
-10%
-20%
-30%
-40%
Model Mean
Index
Model
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

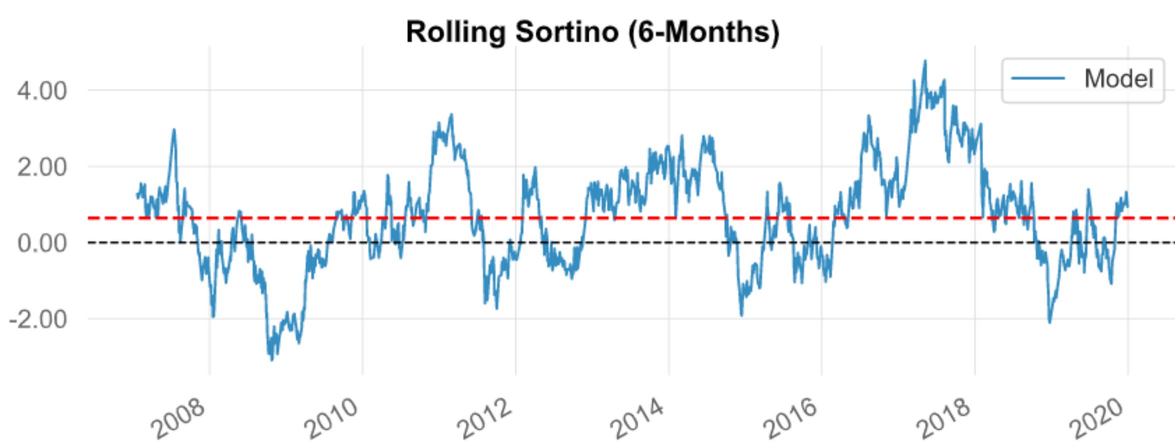

Distribution of Monthly Returns
Average
12
10
8
6
4
2
0
-20%
-15%
-9%
-4%
0%
5%
10%
15%

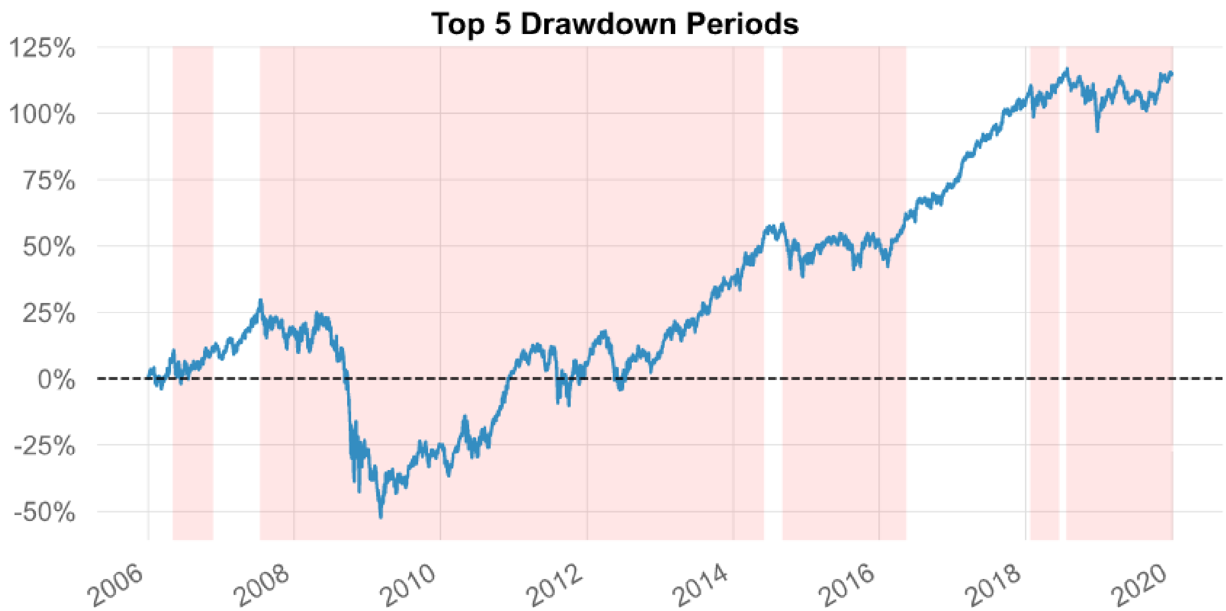

Daily Returns
10%
5%
0%
-5%
-10%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

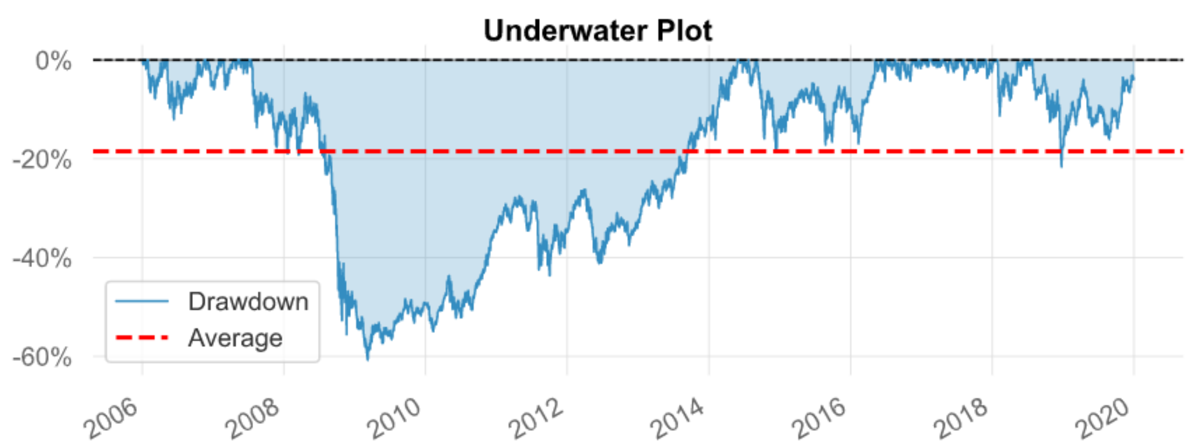

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020

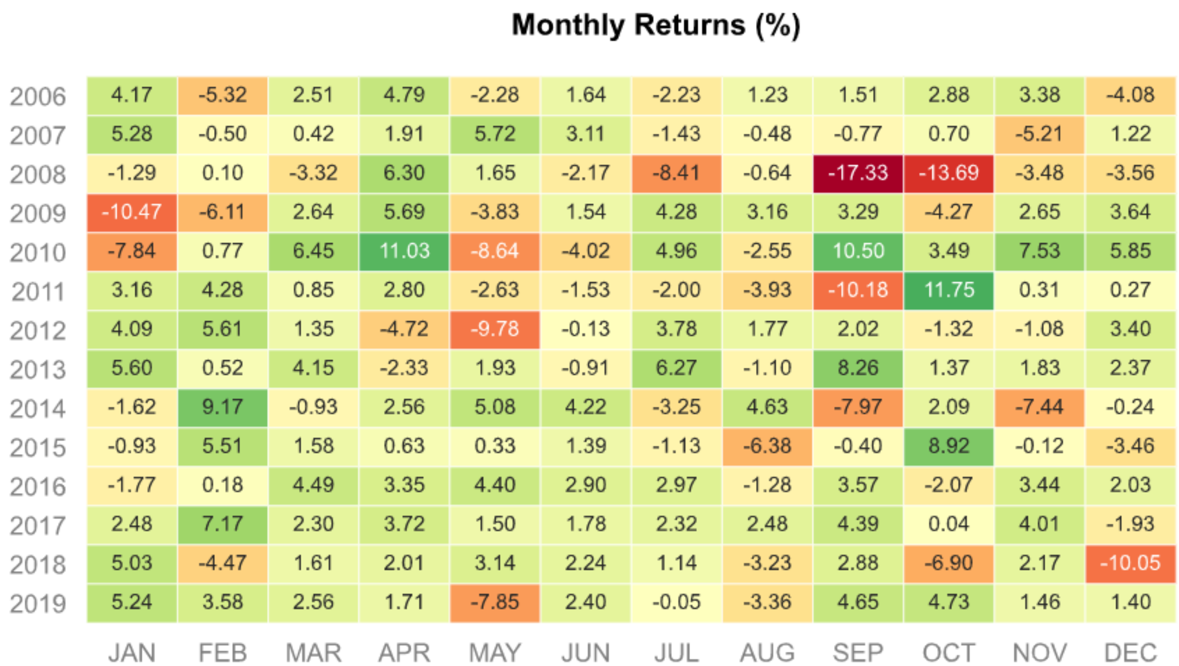

Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020

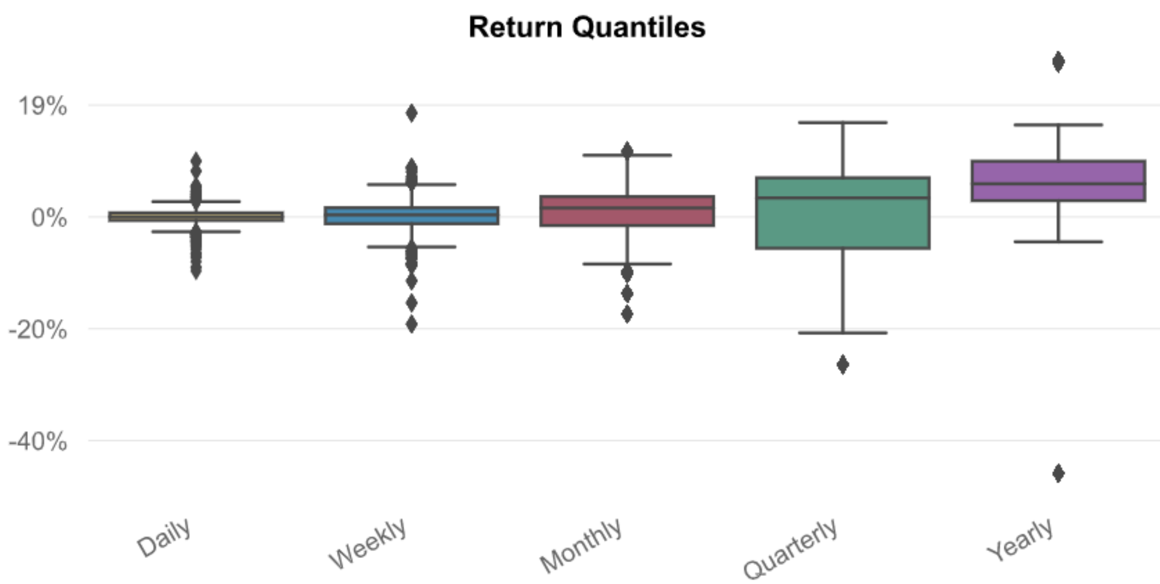

Rolling Sortino (6-Months)
Model
4.00
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020



#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	7/20/2007	3/9/2009	5/29/2014	2505	-60.76	-57.35
2	7/27/2018	12/24/2018	12/31/2019	522	-21.65	-18.07
3	9/8/2014	12/15/2014	5/10/2016	610	-18.61	-17.18
4	5/10/2006	6/13/2006	11/15/2006	189	-12.06	-11.29
5	1/29/2018	2/8/2018	6/12/2018	134	-11.30	-10.65




Monthly Returns (%)
2006 4.17 -5.32 2.51 4.79 -2.28 1.64 -2.23 1.23 1.51 2.88 3.38 -4.08
2007 5.28 -0.50 0.42 1.91 5.72 3.11 -1.43 -0.48 -0.77 0.70 -5.21 1.22
2008 -1.29 0.10 -3.32 6.30 1.65 -2.17 -8.41 -0.64 -17.33 -13.69 -3.48 -3.56
2009 -10.47 -6.11 2.64 5.69 -3.83 1.54 4.28 3.16 3.29 -4.27 2.65 3.64
2010 -7.84 0.77 6.45 11.03 -8.64 -4.02 4.96 -2.55 10.50 3.49 7.53 5.85
2011 3.16 4.28 0.85 2.80 -2.63 -1.53 -2.00 -3.93 -10.18 11.75 0.31 0.27
2012 4.09 5.61 1.35 -4.72 -9.78 -0.13 3.78 1.77 2.02 -1.32 -1.08 3.40
2013 5.60 0.52 4.15 -2.33 1.93 -0.91 6.27 -1.10 8.26 1.37 1.83 2.37
2014 -1.62 9.17 -0.93 2.56 5.08 4.22 -3.25 4.63 -7.97 2.09 -7.44 -0.24
2015 -0.93 5.51 1.58 0.63 0.33 1.39 -1.13 -6.38 -0.40 8.92 -0.12 -3.46
2016 -1.77 0.18 4.49 3.35 4.40 2.90 2.97 -1.28 3.57 -2.07 3.44 2.03
2017 2.48 7.17 2.30 3.72 1.50 1.78 2.32 2.48 4.39 0.04 4.01 -1.93
2018 5.03 -4.47 1.61 2.01 3.14 2.24 1.14 -3.23 2.88 -6.90 2.17 -10.05
2019 5.24 3.58 2.56 1.71 -7.85 2.40 -0.05 -3.36 4.65 4.73 1.46 1.40
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC


Return Quantiles
19%
0%
-20%
-40%
Daily
Weekly
Monthly
Quarterly
Yearly

B: Trading on NASDAQ

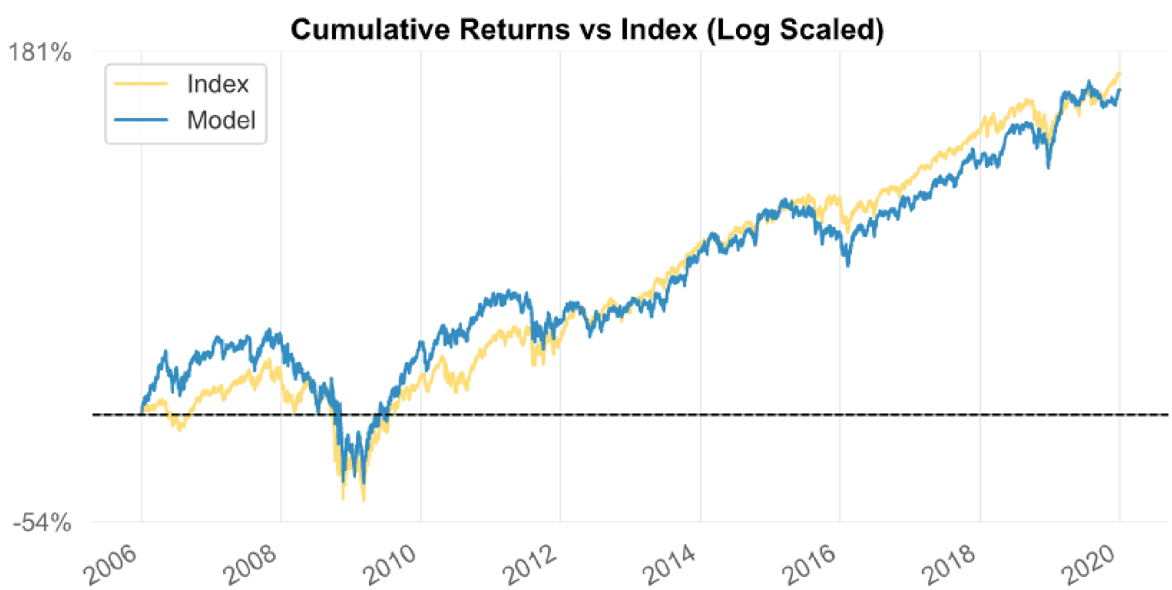
B.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

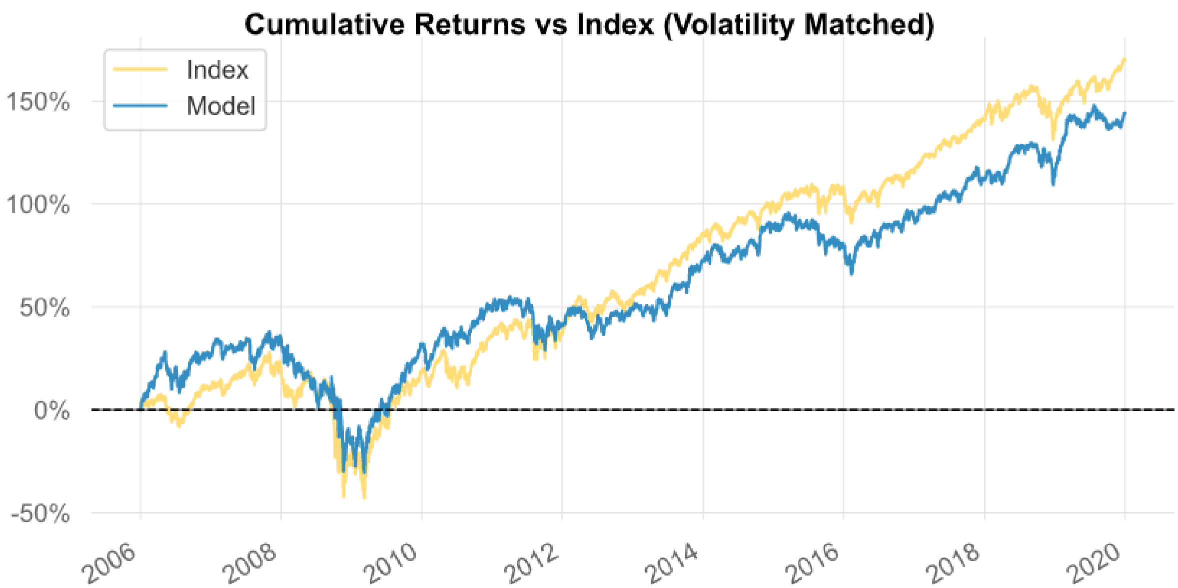
** Performance is benchmarked against NASDAQ Composite Index*

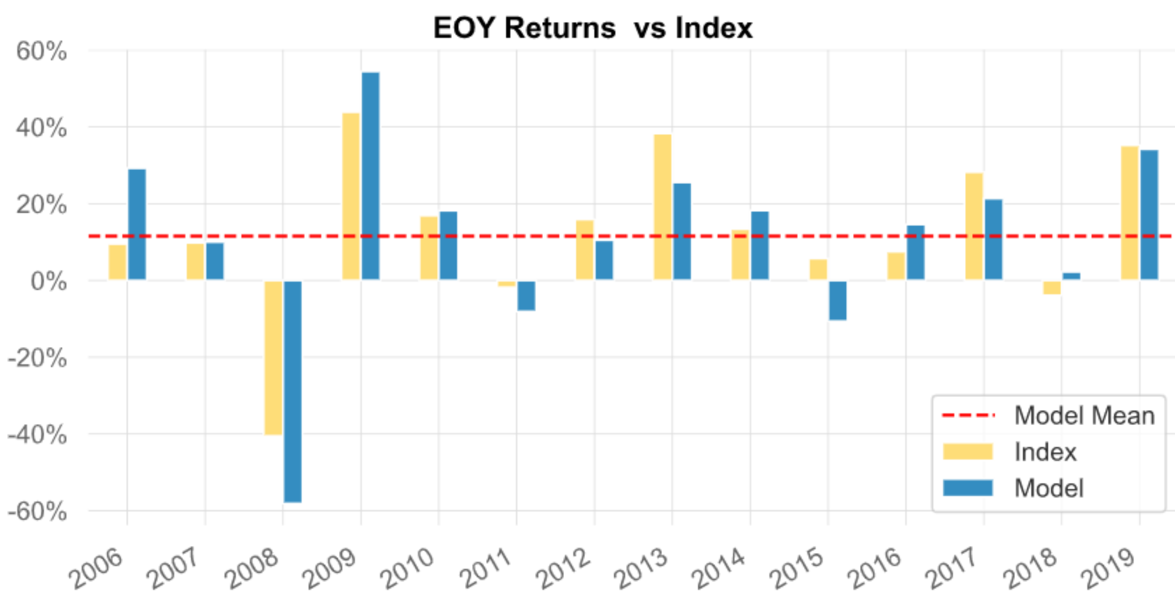
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	161.79%	169.91%
CAGR%	7.12%	7.35%
Sharpe	0.5	0.59
Sortino	0.7	0.83
Max Drawdown	-58.72%	-55.63%
Longest DD Days	1163	1273
Volatility (ann.)	23.10%	20.55%
R^2	0.71	
Calmar	0.16	0.19
Skew	-0.21	-0.12
Kurtosis	3.99	7.48
Expected Daily %	0.04%	0.04%
Expected Monthly %	0.74%	0.84%
Expected Yearly %	9.29%	10.54%
Kelly Criterion	1.91%	4.40%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.35%	-2.08%
Expected Shortfall (cVaR)	-2.35%	-2.08%
Payoff Ratio	0.88	0.88
Profit Factor	1.09	1.12
Common Sense Ratio	1.01	1
CPC Index	0.52	0.54
Tail Ratio	0.93	0.9
Outlier Win Ratio	3.61	4.33
Outlier Loss Ratio	3.64	4.31

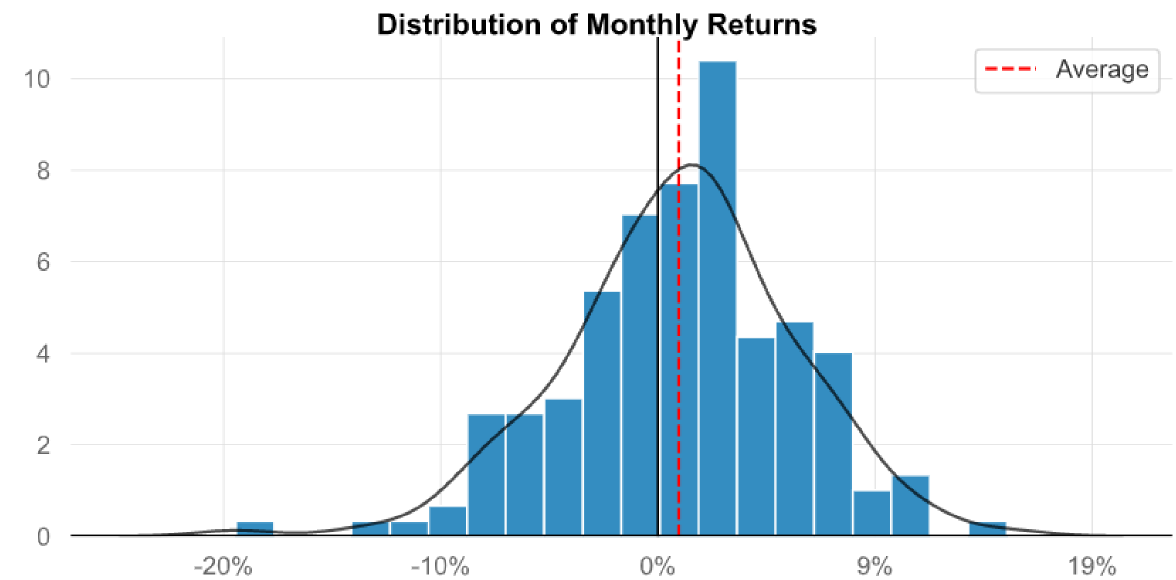
	Model	Index
MTD	4.78%	3.52%
3M	7.77%	12.39%
6M	1.23%	11.95%
YTD	34.22%	31.42%
1Y	35.33%	32.19%
3Y (ann.)	16.48%	15.77%
5Y (ann.)	10.09%	11.14%
10Y (ann.)	8.50%	9.64%
All-time (ann.)	7.12%	7.35%
Best Day	8.36%	11.81%
Worst Day	-10.49%	-9.14%
Best Month	17.19%	12.35%
Worst Month	-19.03%	-17.73%
Best Year	65.04%	43.89%
Worst Year	-49.05%	-40.54%
Avg. Drawdown	-3.80%	-2.37%
Avg. Drawdown Days	53	27
Recovery Factor	4.21	5.52
Ulcer Index	1.02	1.02
Avg. Up Month	4.68%	4.17%
Avg. Down Month	-4.70%	-4.60%
Win Days %	54.13%	55.28%
Win Month %	59.52%	62.50%
Win Quarter %	69.64%	71.43%
Win Year %	78.57%	78.57%
Beta	0.95	
Alpha	0	

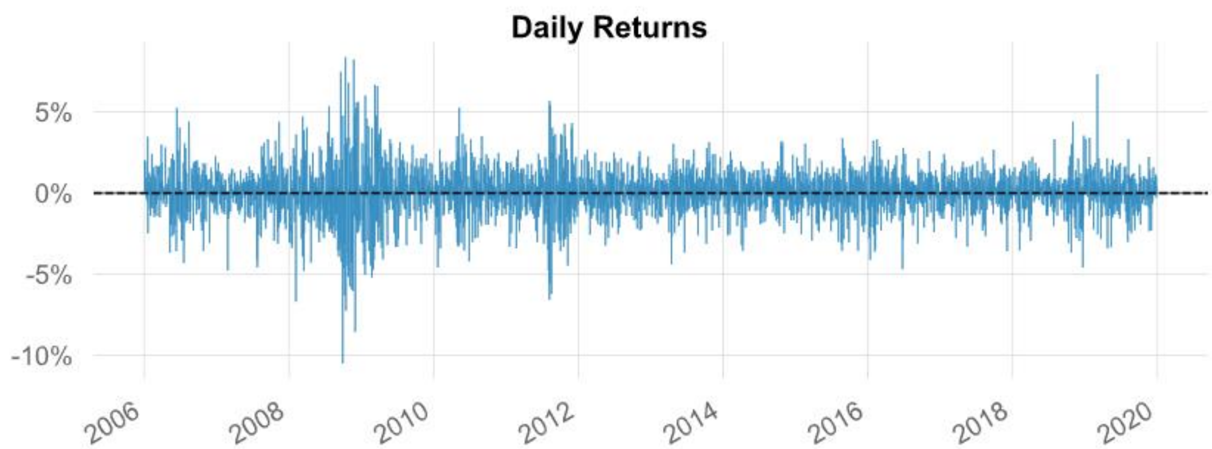

Cumulative Returns vs Index
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

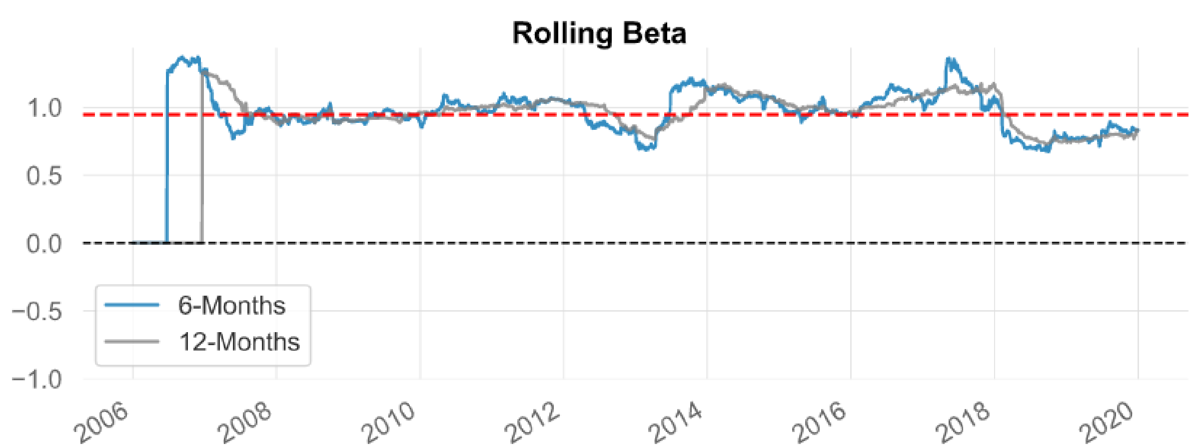

Cumulative Returns vs Index (Log Scaled)
181%
Index
Model
-54%
2006
2008
2010
2012
2014
2016
2018
2020

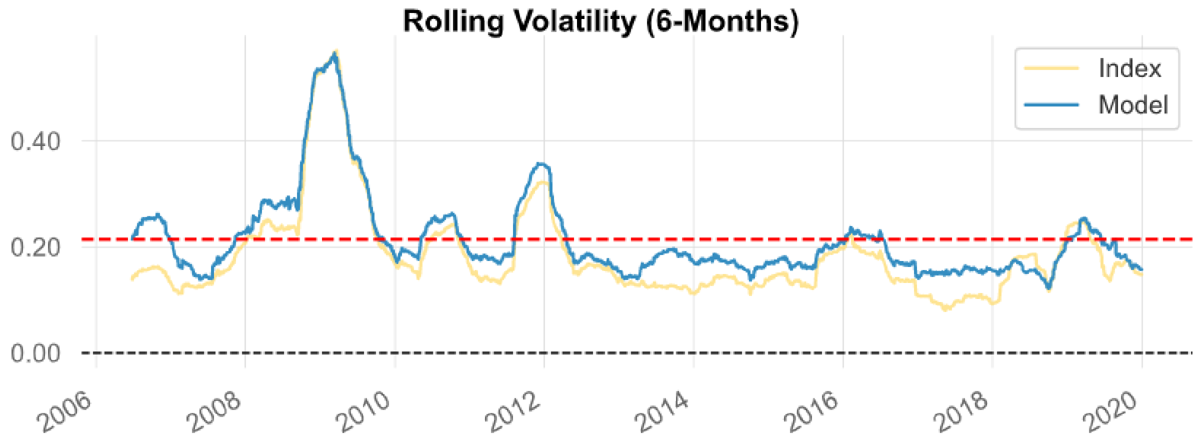

Cumulative Returns vs Index (Volatility Matched)
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

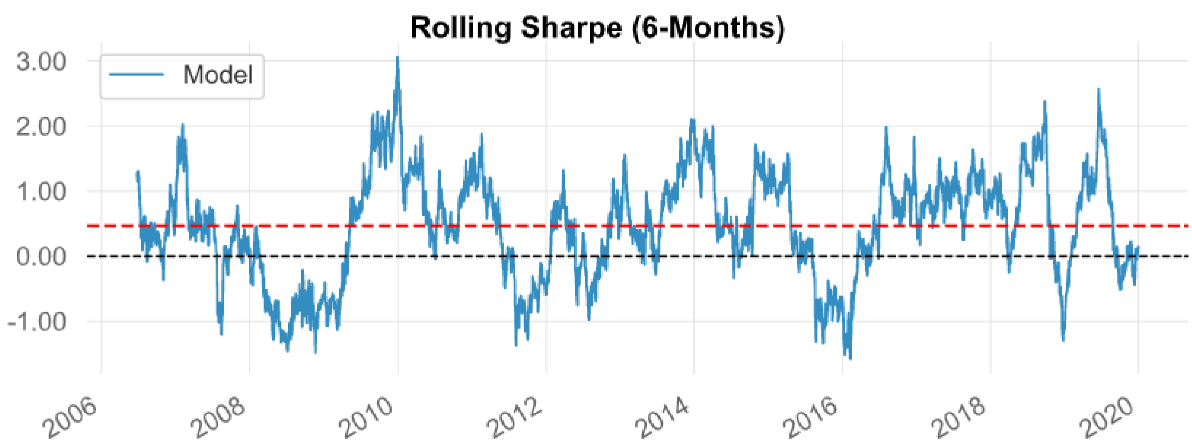

EOY Returns vs Index
60%
40%
20%
0%
-20%
-40%
-60%
Model Mean
Index
Model
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

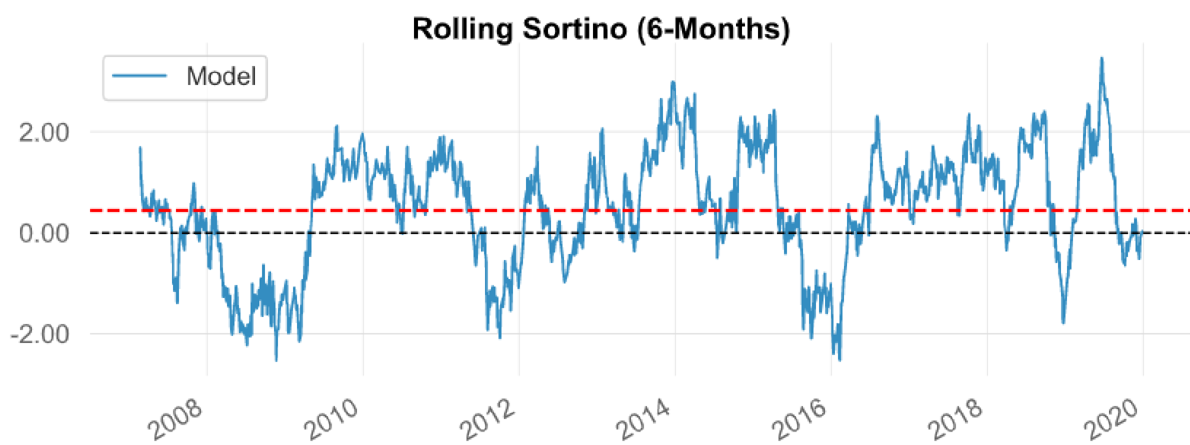

Distribution of Monthly Returns
Average
10
8
6
4
2
0
-20%
-10%
0%
9%
19%

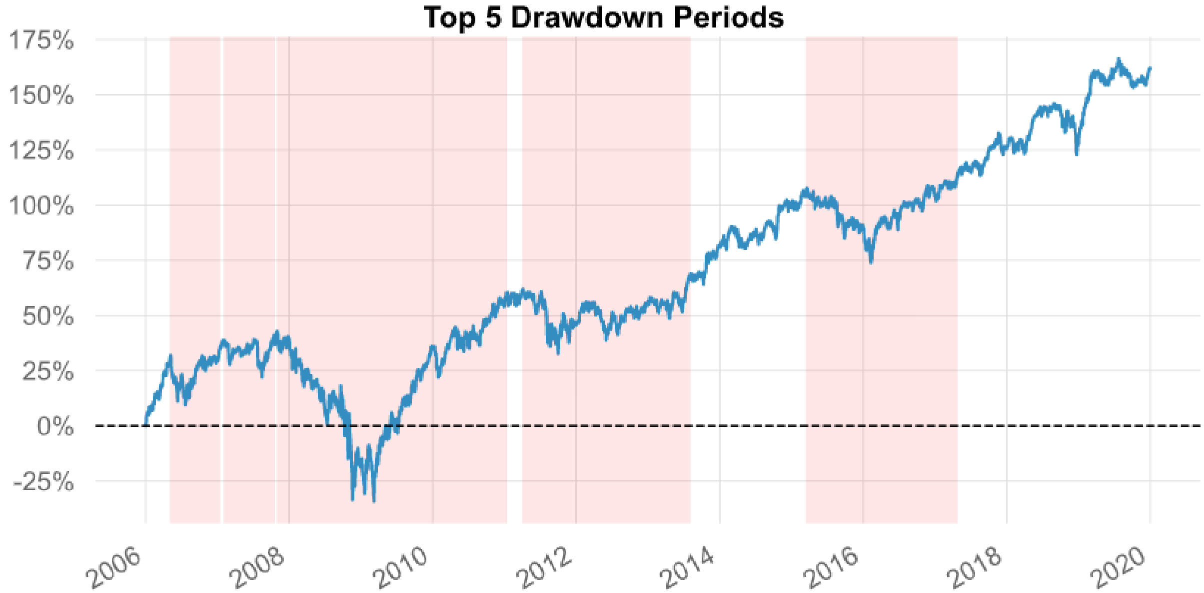

Daily Returns
5%
0%
-5%
-10%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

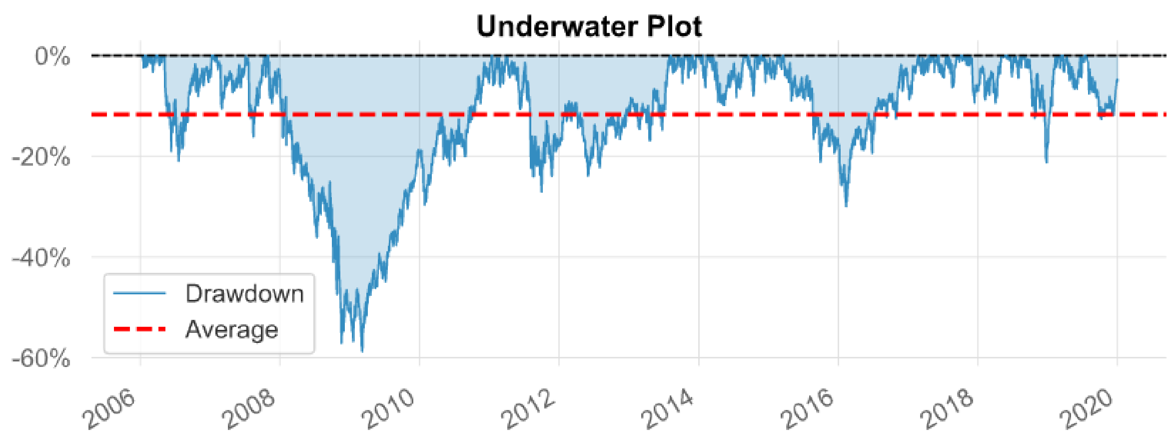

Rolling Volatility (6-Months)
Index
Model
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020

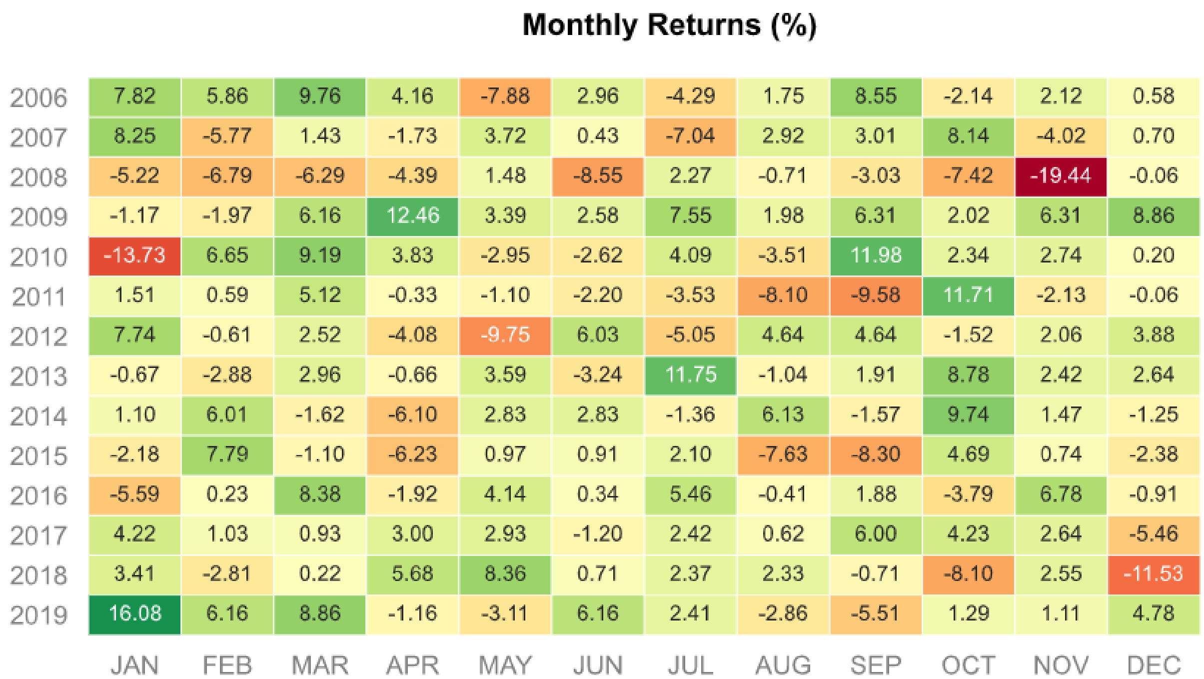

Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
Model
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020



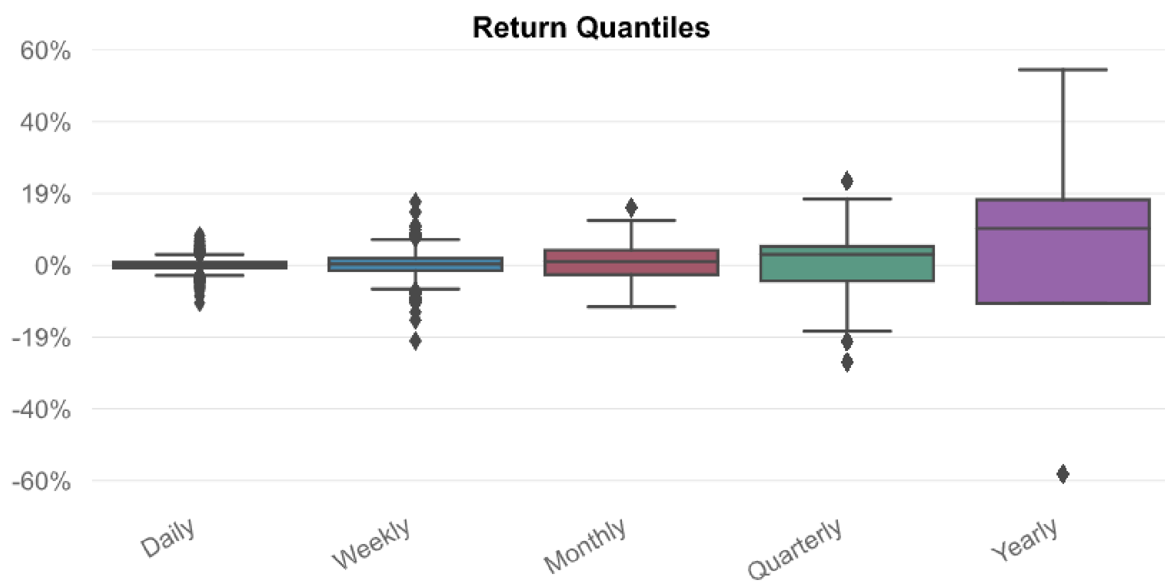
#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	11/5/2007	3/9/2009	1/11/2011	1163	-58.72	-55.42
2	3/20/2015	2/11/2016	4/20/2017	762	-29.97	-26.48
3	4/6/2011	10/3/2011	8/1/2013	848	-27.11	-23.90
4	8/30/2018	12/24/2018	2/12/2019	166	-21.42	-18.69
5	5/10/2006	7/21/2006	1/11/2007	246	-20.93	-19.21





Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	7.82	5.86	9.76	4.16	-7.88	2.96	-4.29	1.75	8.55	-2.14	2.12	0.58
2007	8.25	-5.77	1.43	-1.73	3.72	0.43	-7.04	2.92	3.01	8.14	-4.02	0.70
2008	-5.22	-6.79	-6.29	-4.39	1.48	-8.55	2.27	-0.71	-3.03	-7.42	-19.44	-0.06
2009	-1.17	-1.97	6.16	12.46	3.39	2.58	7.55	1.98	6.31	2.02	6.31	8.86
2010	-13.73	6.65	9.19	3.83	-2.95	-2.62	4.09	-3.51	11.98	2.34	2.74	0.20
2011	1.51	0.59	5.12	-0.33	-1.10	-2.20	-3.53	-8.10	-9.58	11.71	-2.13	-0.06
2012	7.74	-0.61	2.52	-4.08	-9.75	6.03	-5.05	4.64	4.64	-1.52	2.06	3.88
2013	-0.67	-2.88	2.96	-0.66	3.59	-3.24	11.75	-1.04	1.91	8.78	2.42	2.64
2014	1.10	6.01	-1.62	-6.10	2.83	2.83	-1.36	6.13	-1.57	9.74	1.47	-1.25
2015	-2.18	7.79	-1.10	-6.23	0.97	0.91	2.10	-7.63	-8.30	4.69	0.74	-2.38
2016	-5.59	0.23	8.38	-1.92	4.14	0.34	5.46	-0.41	1.88	-3.79	6.78	-0.91
2017	4.22	1.03	0.93	3.00	2.93	-1.20	2.42	0.62	6.00	4.23	2.64	-5.46
2018	3.41	-2.81	0.22	5.68	8.36	0.71	2.37	2.33	-0.71	-8.10	2.55	-11.53
2019	16.08	6.16	8.86	-1.16	-3.11	6.16	2.41	-2.86	-5.51	1.29	1.11	4.78



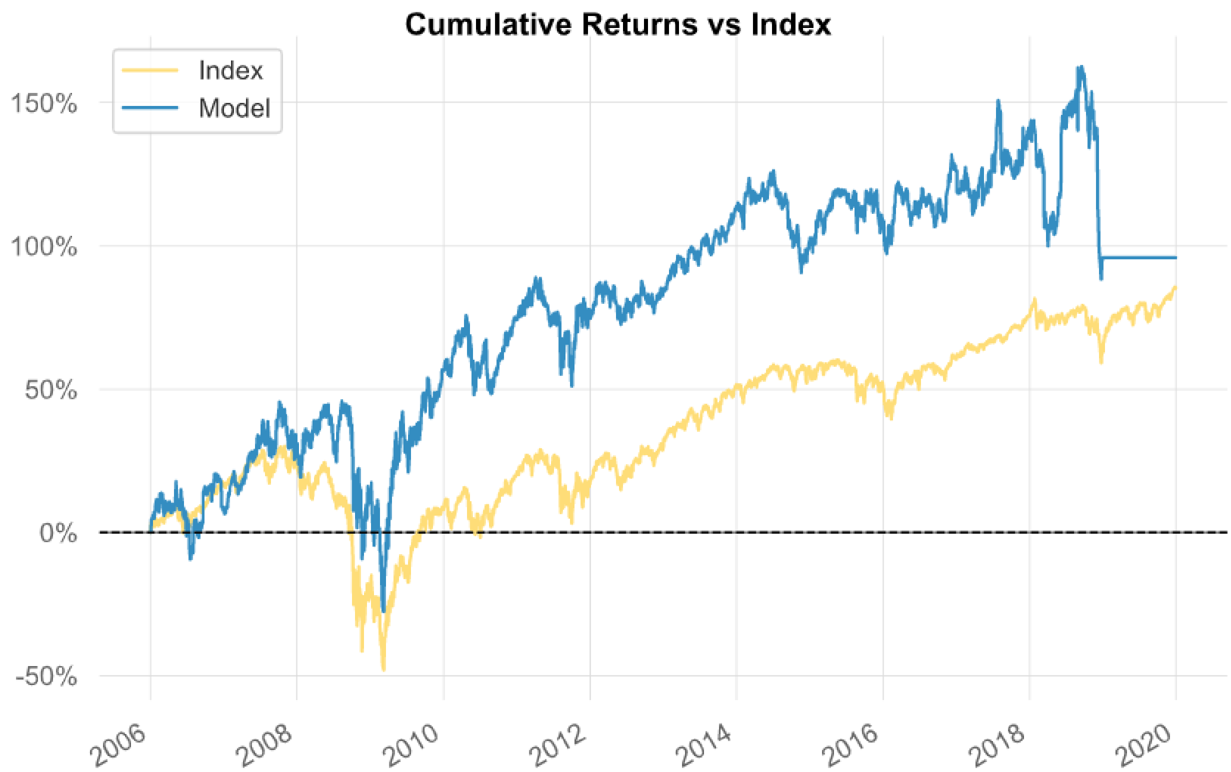
Appendix 3 – Benjamin Graham Defensive Investor Screener Performance
A: Trading on NYSE

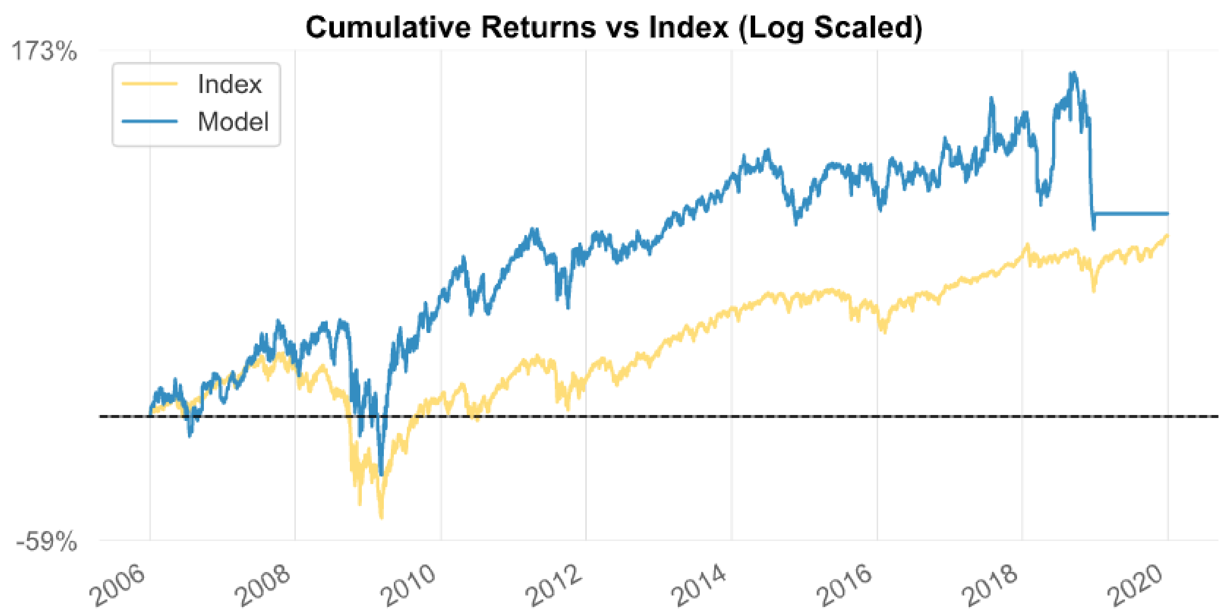
A.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

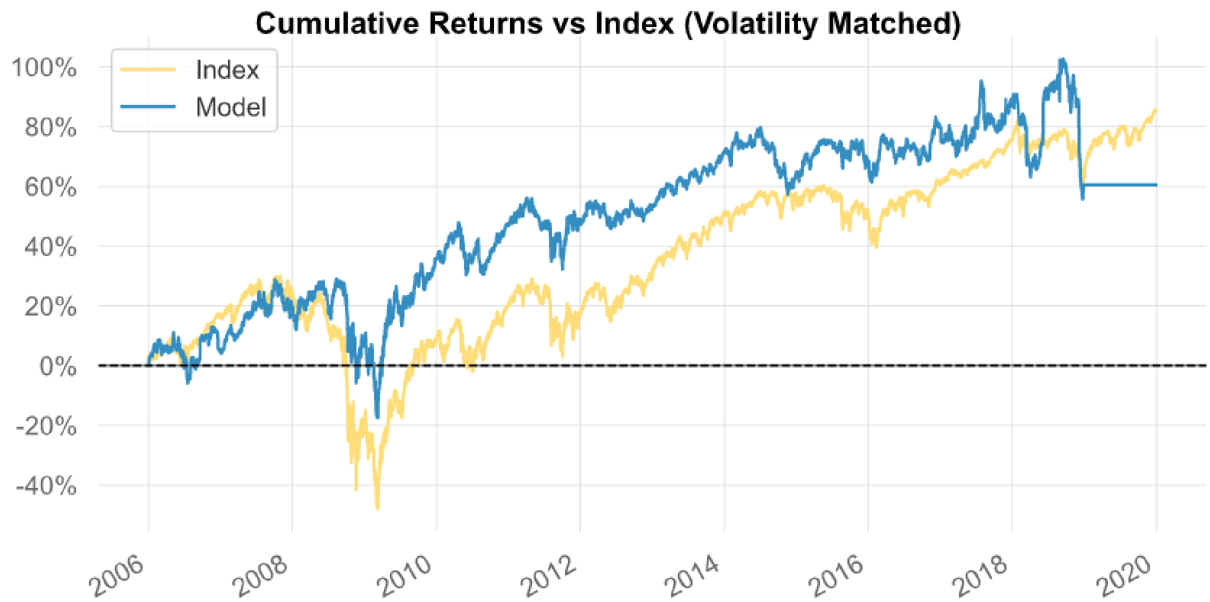
** Performance is benchmarked against NYSE Composite Index*

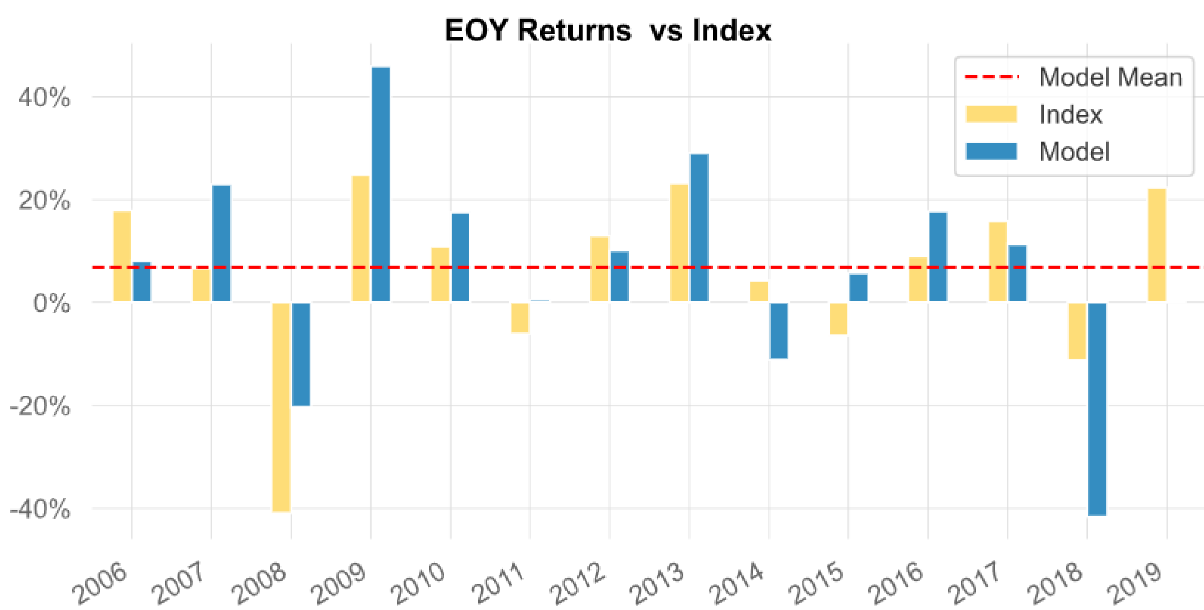
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	92.00%	100.00%
Total Return	95.84%	85.40%
CAGR%	4.92%	4.51%
Sharpe	0.22	0.31
Sortino	0.31	0.43
Max Drawdown	-58.86%	-59.01%
Longest DD Days	1108	2247
Volatility (ann.)	31.05%	19.61%
R^2	0.48	
Calmar	0.03	0.07
Skew	-0.03	-0.2
Kurtosis	13.01	11.69
Expected Daily %	0.01%	0.02%
Expected Monthly %	0.17%	0.35%
Expected Yearly %	2.04%	4.26%
Kelly Criterion	-0.35%	2.52%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-3.19%	-2.01%
Expected Shortfall (cVaR)	-3.19%	-2.01%
Payoff Ratio	0.94	0.9
Profit Factor	1.04	1.06
Common Sense Ratio	1.04	0.94
CPC Index	0.5	0.51
Tail Ratio	0.99	0.88
Outlier Win Ratio	3.73	5.84
Outlier Loss Ratio	3.36	5.69

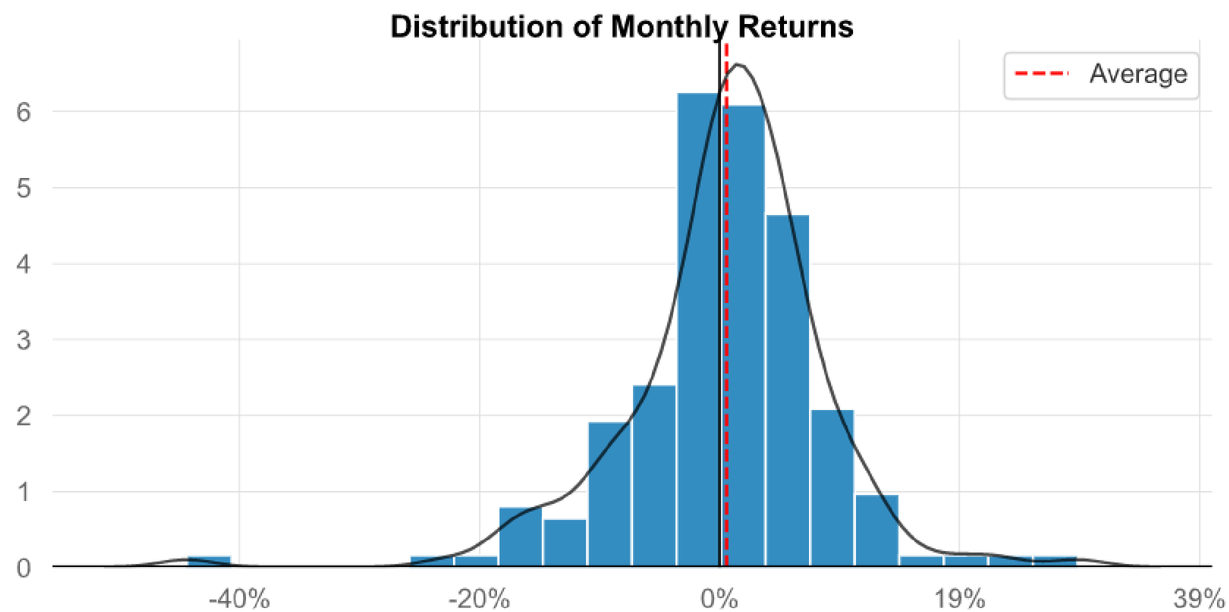
	Model	Index
MTD	0.00%	2.70%
3M	0.00%	7.11%
6M	0.00%	6.72%
YTD	0.00%	20.77%
1Y	1.28%	21.51%
3Y (ann.)	-11.38%	7.72%
5Y (ann.)	-1.13%	5.09%
10Y (ann.)	3.36%	5.85%
All-time (ann.)	4.92%	4.51%
Best Day	22.05%	12.22%
Worst Day	-18.04%	-9.73%
Best Month	32.34%	11.39%
Worst Month	-37.44%	-19.54%
Best Year	40.64%	24.80%
Worst Year	-42.04%	-40.89%
Avg. Drawdown	-6.75%	-2.28%
Avg. Drawdown Days	74	51
Recovery Factor	0.55	1.35
Ulcer Index	1.02	1.02
Avg. Up Month	6.48%	3.53%
Avg. Down Month	-8.45%	-4.63%
Win Days %	51.48%	53.96%
Win Month %	56.41%	61.31%
Win Quarter %	59.62%	69.64%
Win Year %	69.23%	71.43%
Beta	1.1	
Alpha	0	

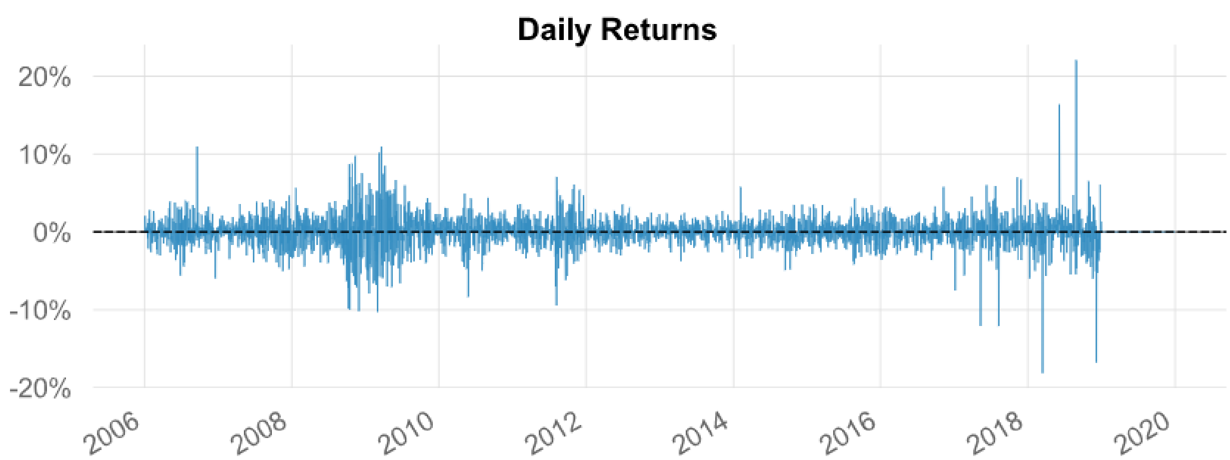

Cumulative Returns vs Index
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

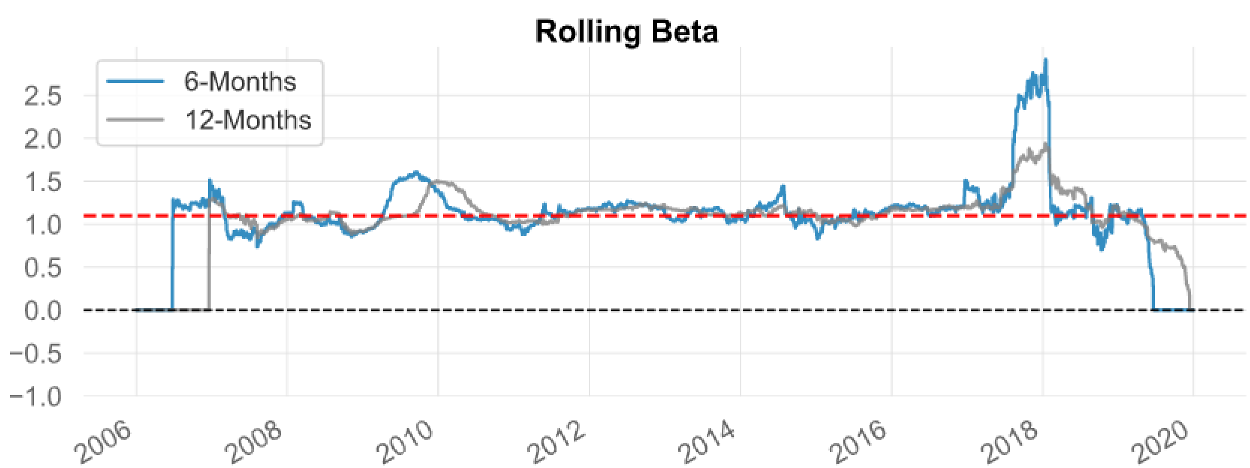

Cumulative Returns vs Index (Log Scaled)
173%
Index
Model
-59%
2006
2008
2010
2012
2014
2016
2018
2020

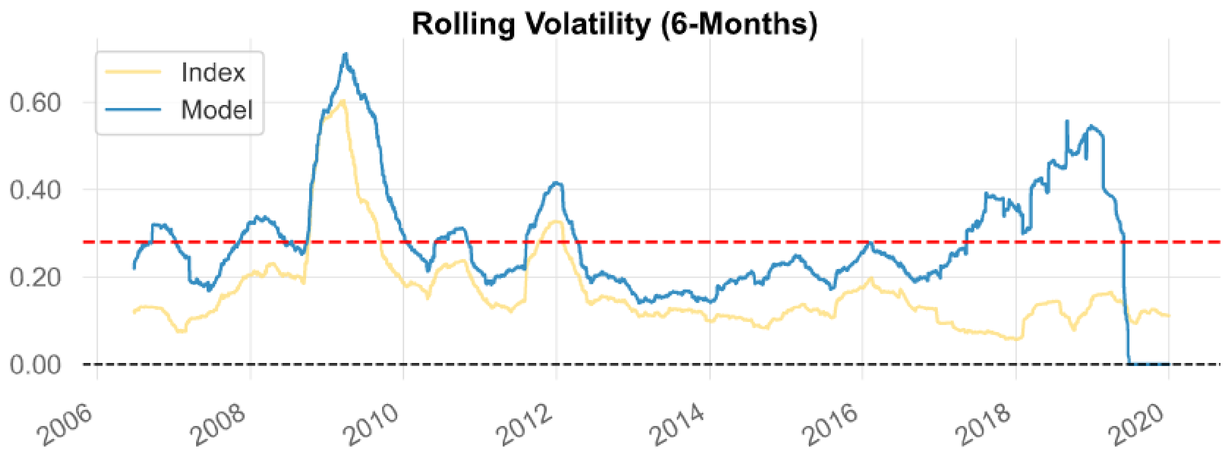

Cumulative Returns vs Index (Volatility Matched)
Index
Model
100%
80%
60%
40%
20%
0%
-20%
-40%
2006
2008
2010
2012
2014
2016
2018
2020

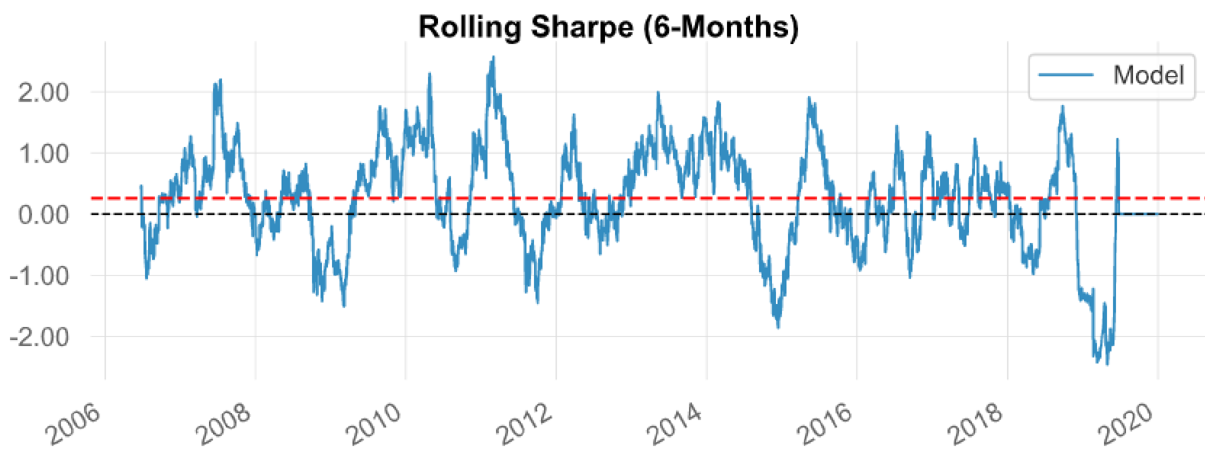

EOY Returns vs Index
Model Mean
Index
Model
40%
20%
0%
-20%
-40%
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

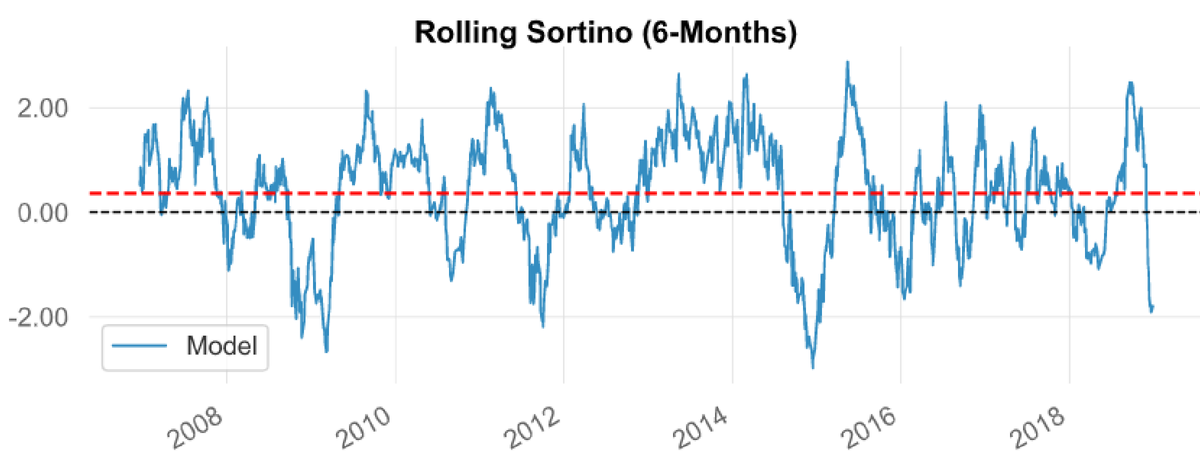

Distribution of Monthly Returns
Average
0
1
2
3
4
5
6
-40%
-20%
0%
19%
39%

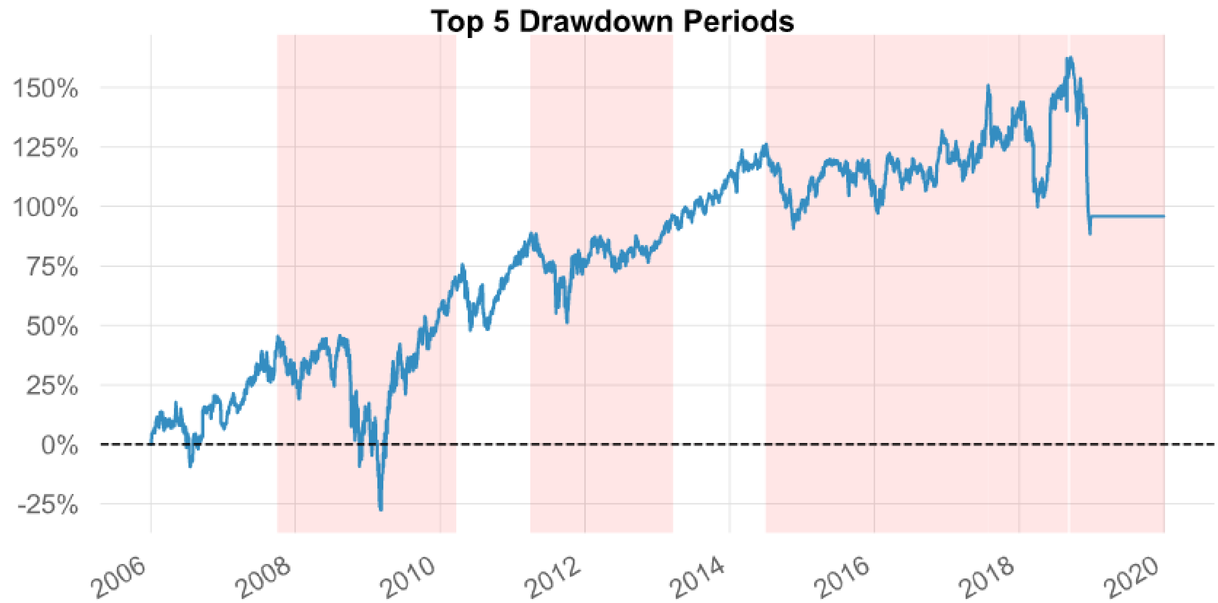

Daily Returns
20%
10%
0%
-10%
-20%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
6-Months
12-Months
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
2006
2008
2010
2012
2014
2016
2018
2020

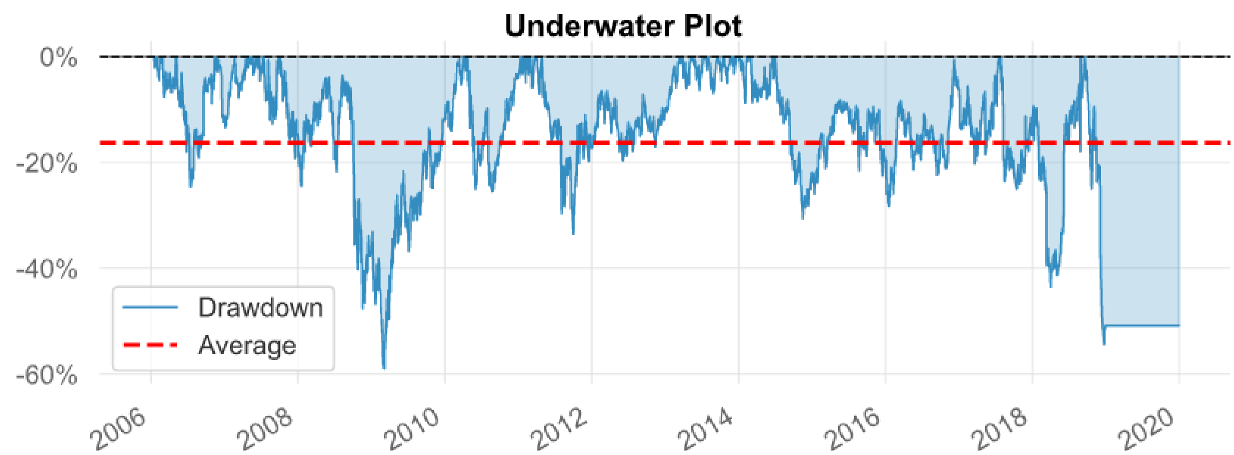

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sharpe (6-Months)
Model
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
2.00
0.00
-2.00
Model
2008
2010
2012
2014
2016
2018

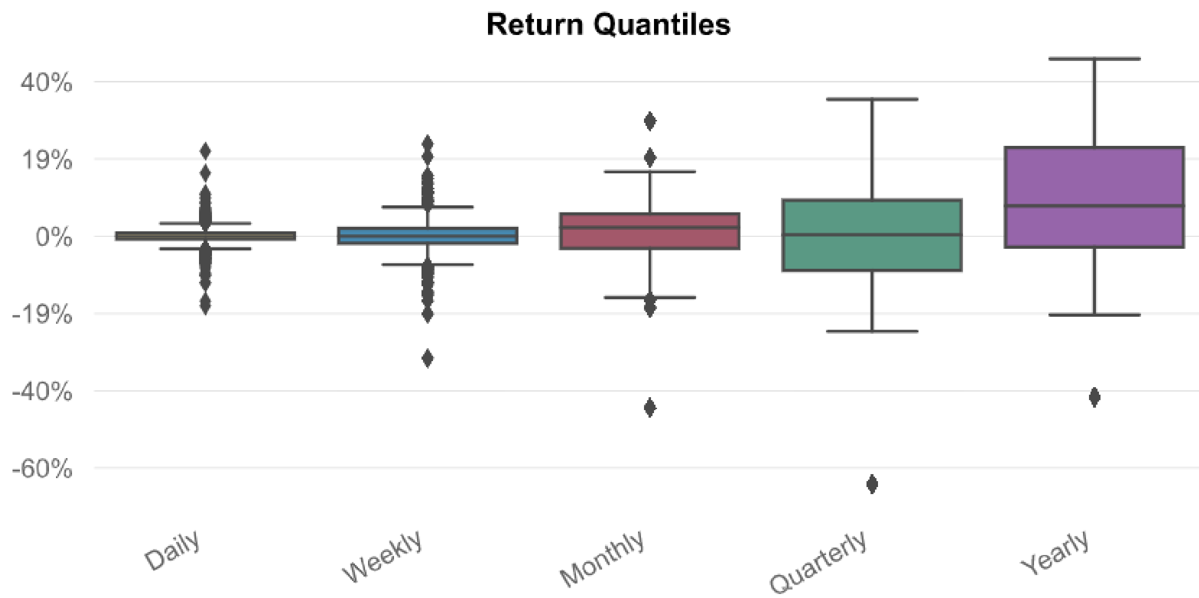


#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	10/8/2007	3/9/2009	3/16/2010	890	-58.86	-54.69
2	9/18/2018	12/24/2018	12/31/2019	469	-54.31	-51.53
3	7/31/2017	4/3/2018	8/30/2018	395	-43.50	-41.34
4	4/6/2011	10/3/2011	3/14/2013	708	-33.48	-29.89
5	7/7/2014	11/19/2014	7/19/2017	1108	-30.64	-28.05



Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	11.07	1.86	-3.69	-0.63	1.85	-8.98	-8.72	8.65	12.55	1.72	2.92	-10.48
2007	5.86	2.98	-0.82	5.12	4.56	3.83	1.17	0.37	8.39	3.19	-9.14	-2.56
2008	0.51	-1.43	5.82	3.83	2.20	-10.37	7.84	3.63	-7.75	-13.83	-17.84	7.05
2009	-9.72	-16.84	10.93	29.82	5.77	-0.10	1.60	2.24	12.28	-6.53	6.61	9.90
2010	-2.04	8.26	3.08	4.02	-18.51	3.30	10.29	-16.54	10.54	5.51	5.15	4.41
2011	3.77	5.69	2.52	2.39	-9.34	-3.09	-0.74	-5.69	-15.86	20.38	7.48	-6.96
2012	4.77	4.95	-0.38	1.56	-9.70	3.71	-0.16	-0.40	4.18	-3.07	2.50	2.13
2013	3.31	3.02	4.92	-2.25	3.88	-1.81	5.16	-3.52	6.34	-0.69	5.95	4.72
2014	-4.46	12.50	-4.18	-0.10	0.90	4.25	-8.06	2.74	-13.60	3.30	-12.64	8.31
2015	-0.92	8.22	1.95	5.48	0.04	1.10	-3.66	-0.13	-5.06	6.83	0.27	-8.45
2016	-1.38	6.70	6.76	-1.63	-8.01	3.69	2.21	-4.12	2.30	-4.59	14.44	1.33
2017	-4.82	-0.53	-3.28	6.29	-3.46	9.00	16.72	-12.82	-3.83	-4.42	12.67	-0.26
2018	-1.33	-6.35	-22.82	0.78	9.87	23.47	4.00	12.54	2.48	-14.90	-4.93	-44.40
2019	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00



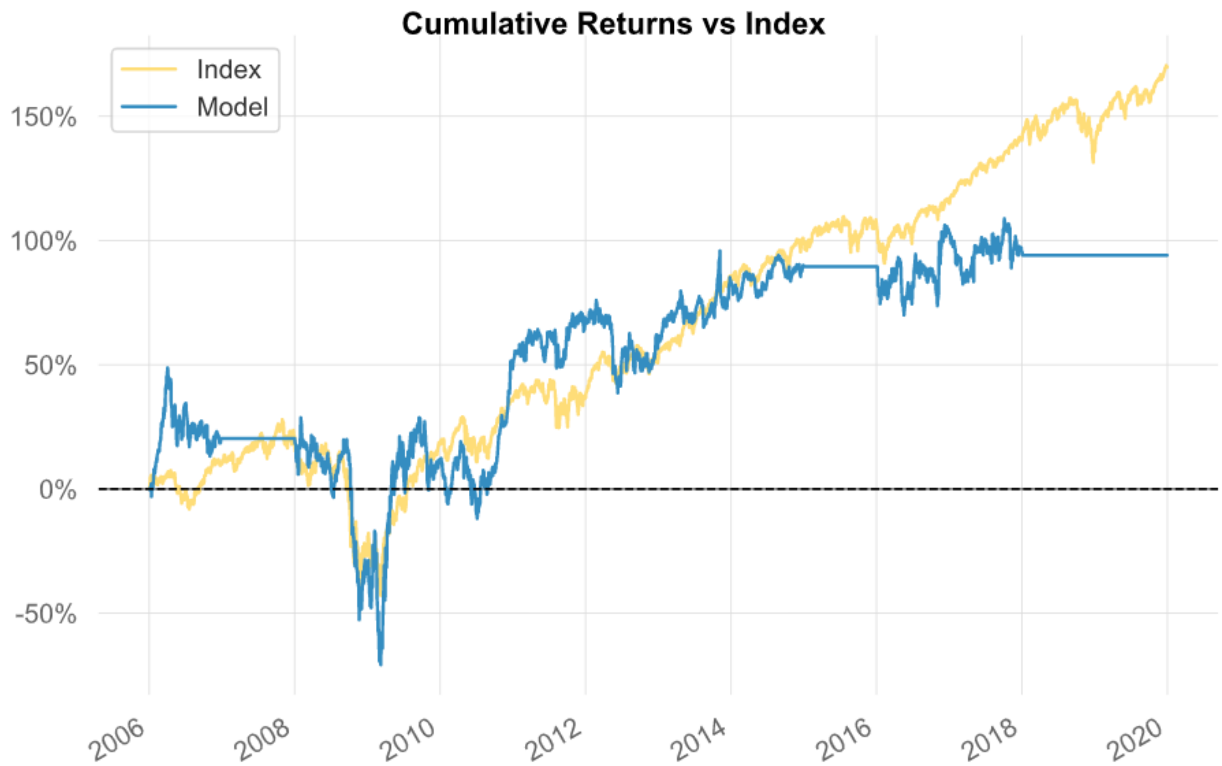
B: Trading on NASDAQ

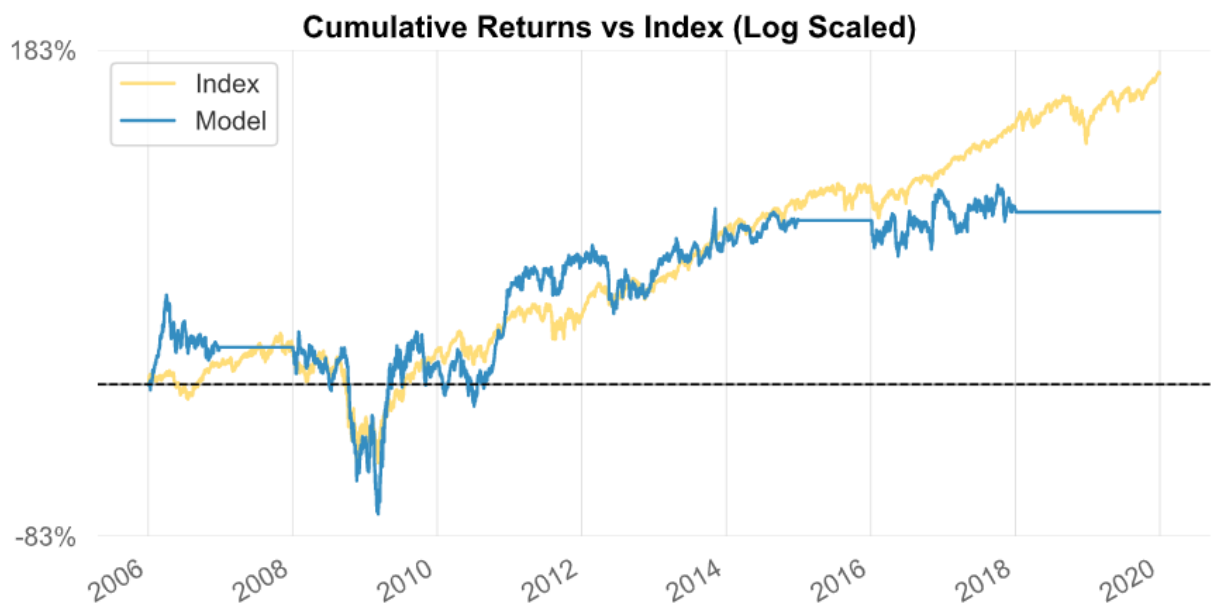
B.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

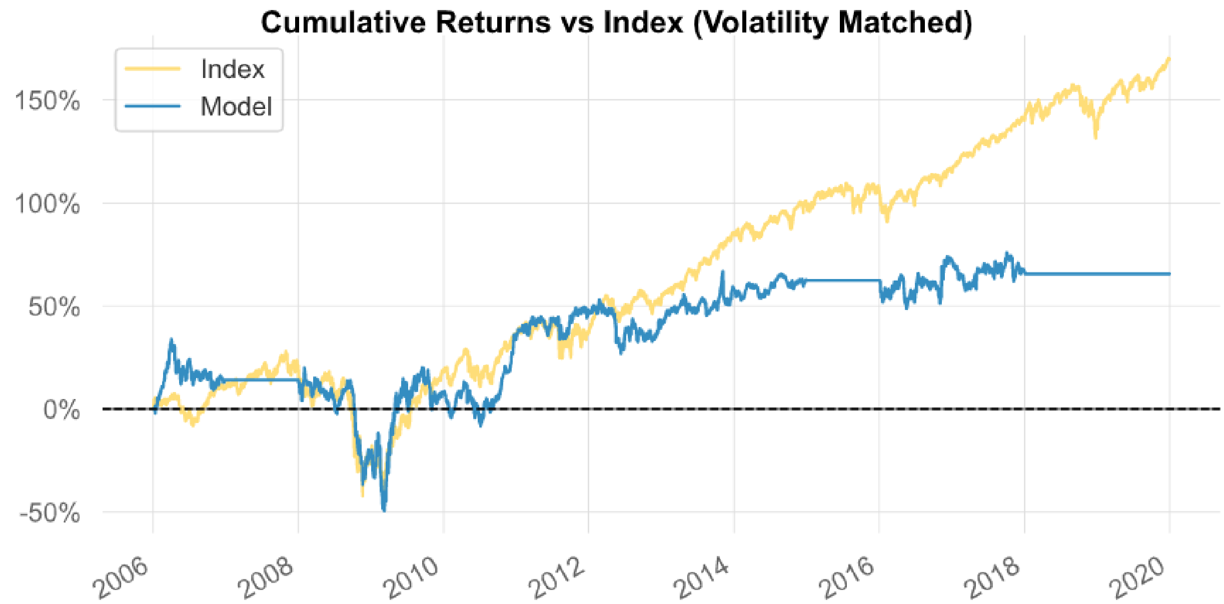
** Performance is benchmarked against NASDAQ Composite Index*

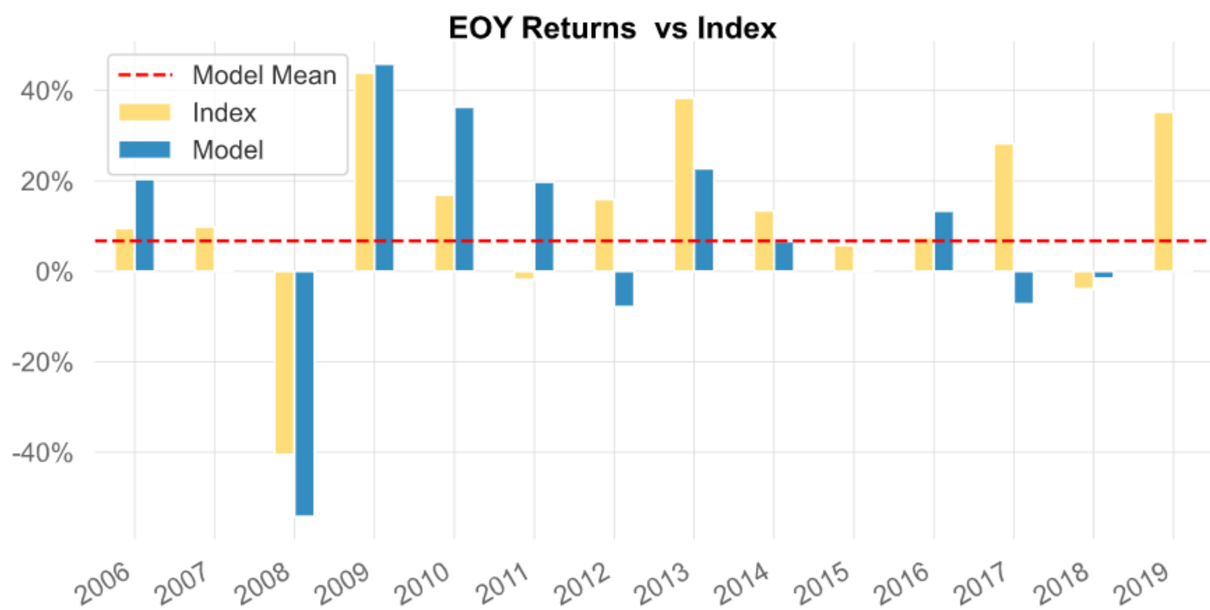
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	71.00%	100.00%
Total Return	94.05%	169.91%
CAGR%	4.85%	7.35%
Sharpe	0.23	0.59
Sortino	0.32	0.83
Max Drawdown	-75.36%	-55.63%
Longest DD Days	3899	1273
Volatility (ann.)	29.49%	20.55%
R^2	0.23	
Calmar	0.03	0.19
Skew	-0.24	-0.12
Kurtosis	9.38	7.48
Expected Daily %	0.01%	0.04%
Expected Monthly %	0.20%	0.84%
Expected Yearly %	2.39%	10.54%
Kelly Criterion	0.57%	3.94%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-3.03%	-2.08%
Expected Shortfall (cVaR)	-3.03%	-2.08%
Payoff Ratio	0.93	0.87
Profit Factor	1.05	1.12
Common Sense Ratio	1.09	1
CPC Index	0.51	0.54
Tail Ratio	1.04	0.9
Outlier Win Ratio	5.26	5.24
Outlier Loss Ratio	3.1	5.18

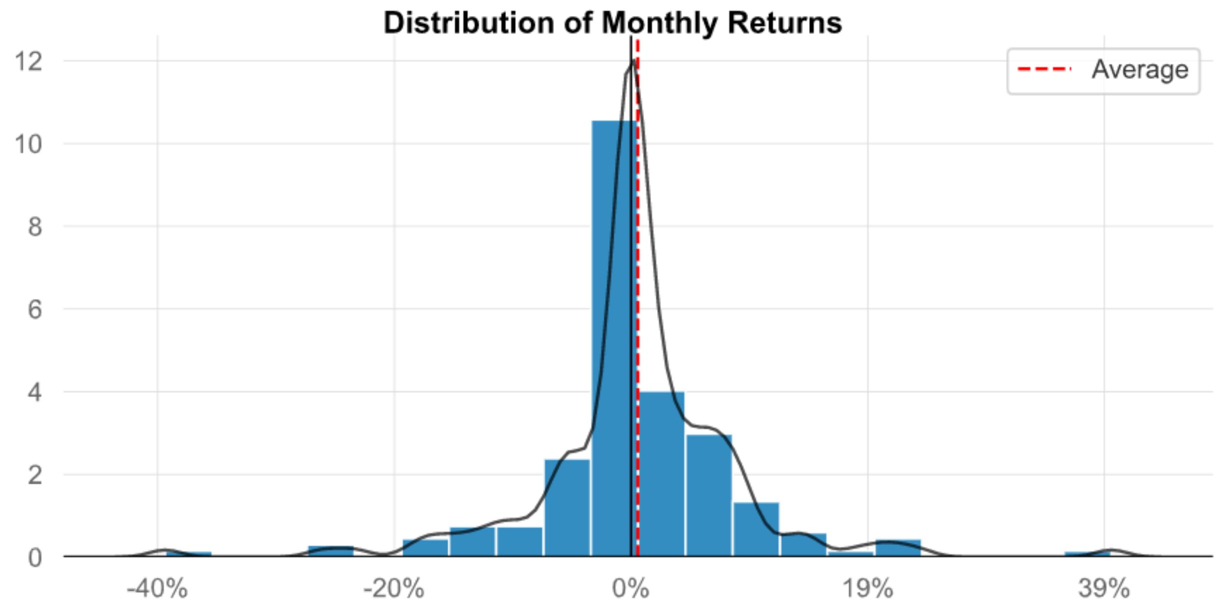
	Model	Index
MTD	0.00%	3.52%
3M	0.00%	12.39%
6M	0.00%	11.95%
YTD	0.00%	31.42%
1Y	0.00%	32.19%
3Y (ann.)	-3.03%	15.77%
5Y (ann.)	0.81%	11.14%
10Y (ann.)	6.17%	9.64%
All-time (ann.)	4.85%	7.35%
Best Day	12.40%	11.81%
Worst Day	-13.79%	-9.14%
Best Month	45.67%	12.35%
Worst Month	-33.69%	-17.73%
Best Year	36.30%	43.89%
Worst Year	-46.67%	-40.54%
Avg. Drawdown	-8.81%	-2.37%
Avg. Drawdown Days	389	27
Recovery Factor	0.52	5.52
Ulcer Index	1.02	1.02
Avg. Up Month	7.64%	4.27%
Avg. Down Month	-8.34%	-4.96%
Win Days %	52.17%	55.28%
Win Month %	53.72%	62.50%
Win Quarter %	53.66%	71.43%
Win Year %	63.64%	78.57%
Beta	0.69	
Alpha	-0.02	

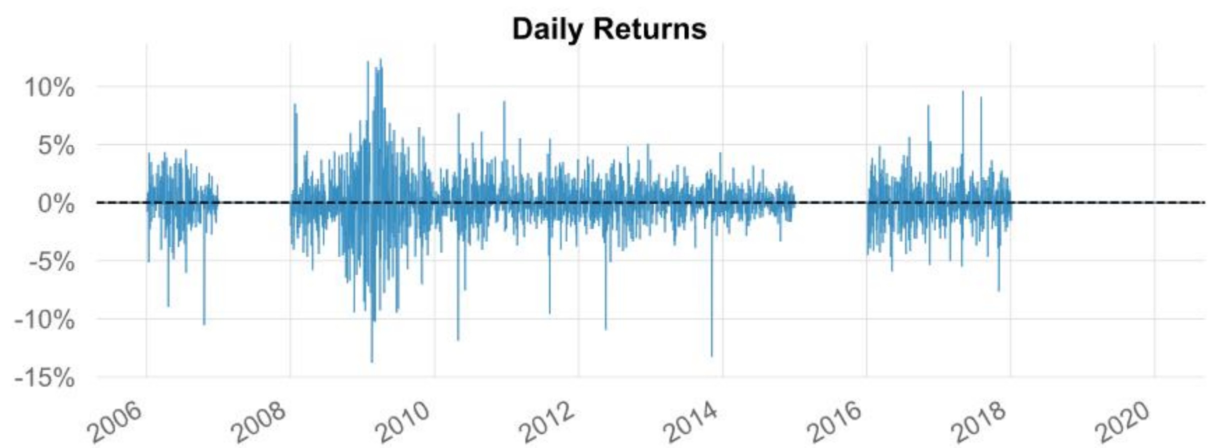

Cumulative Returns vs Index
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

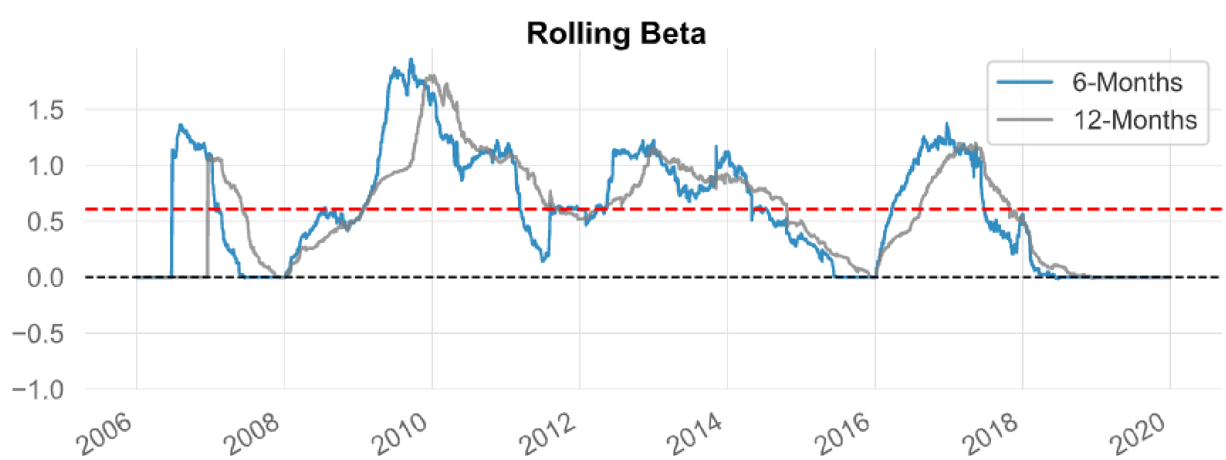

Cumulative Returns vs Index (Log Scaled)
183%
Index
Model
-83%
2006
2008
2010
2012
2014
2016
2018
2020

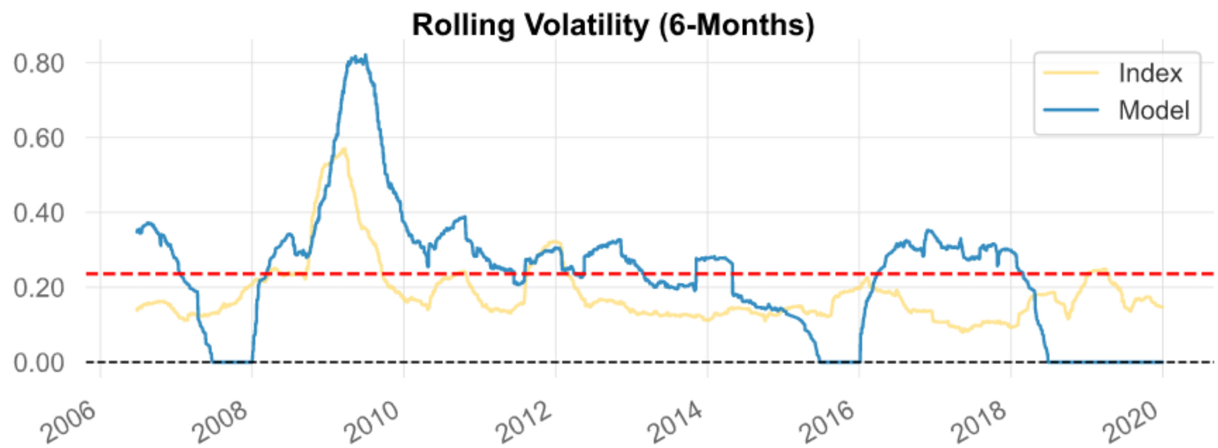

Cumulative Returns vs Index (Volatility Matched)
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

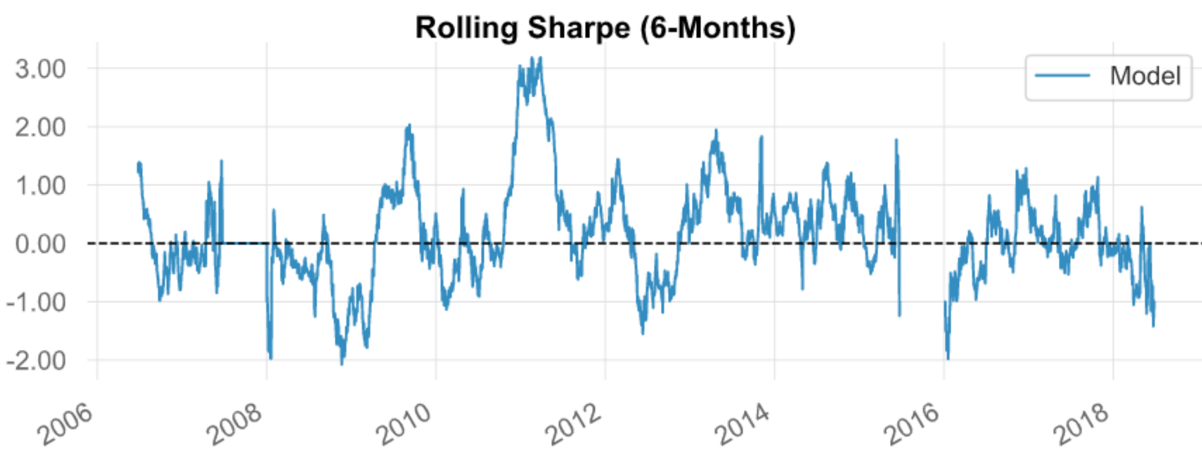

EOY Returns vs Index
Model Mean
Index
Model
40%
20%
0%
-20%
-40%
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

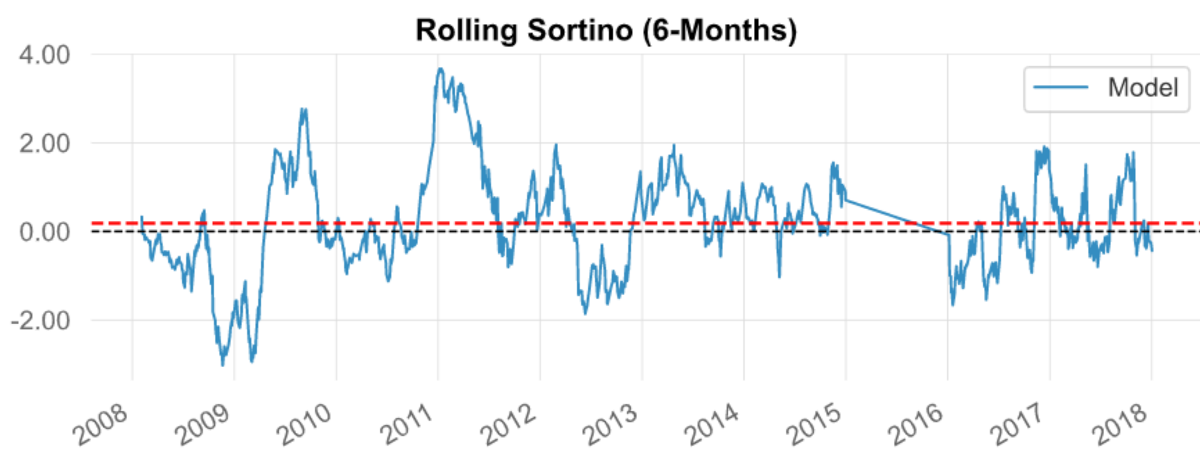

Distribution of Monthly Returns
Average
12
10
8
6
4
2
0
-40%
-20%
0%
19%
39%

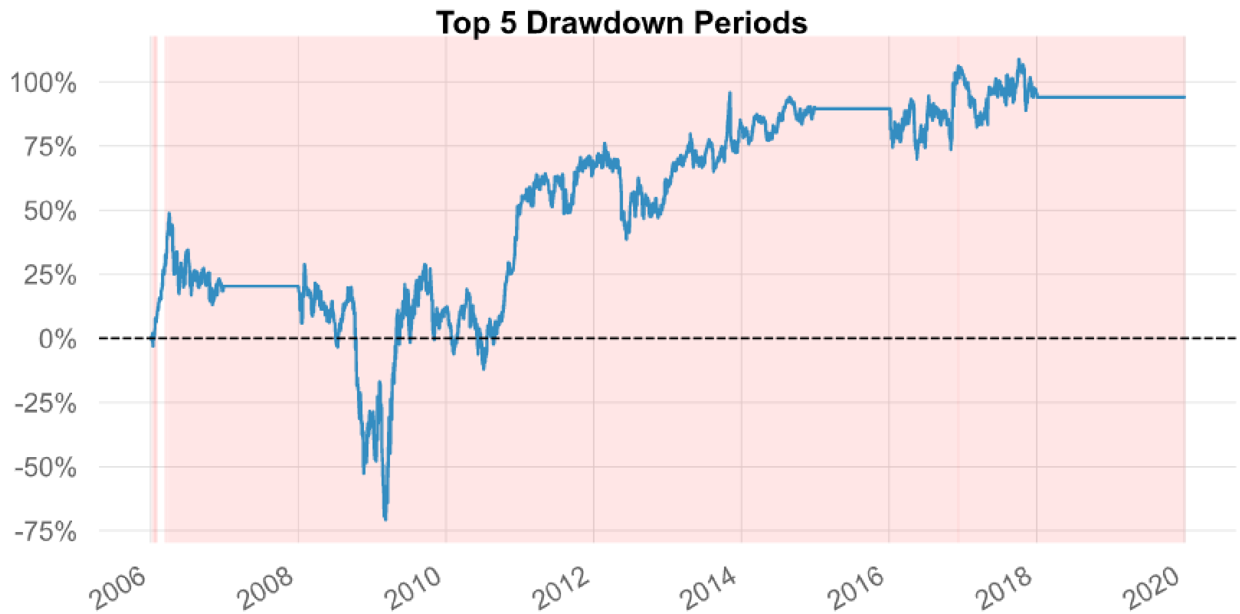

Daily Returns
10%
5%
0%
-5%
-10%
-15%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
6-Months
12-Months
1.5
1.0
0.5
0.0
−0.5
−1.0
2006
2008
2010
2012
2014
2016
2018
2020

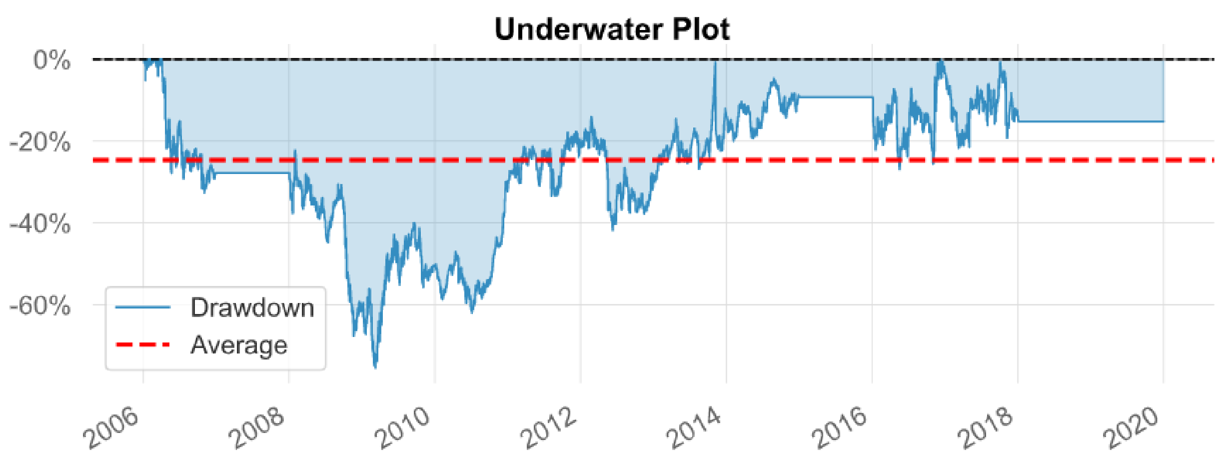

Rolling Volatility (6-Months)
Index
Model
0.80
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018


Rolling Sortino (6-Months)
Model
4.00
2.00
0.00
-2.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018

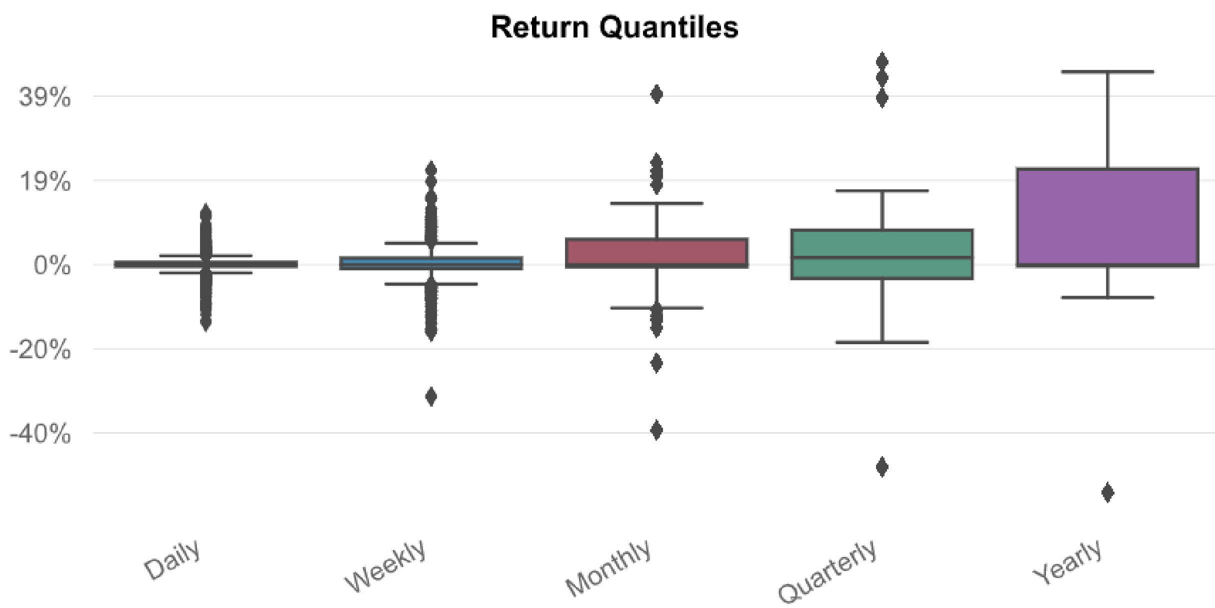


#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	4/4/2006	3/9/2009	12/6/2016	3899	-75.36	-66.92
2	12/12/2016	3/10/2017	12/31/2019	1114	-21.71	-20.44
3	1/12/2006	1/12/2006	1/23/2006	11	-5.12	-2.50
4	3/16/2006	3/16/2006	3/22/2006	6	-4.06	-1.98
5	1/25/2006	1/27/2006	1/31/2006	6	-1.78	-1.62



Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	9.03	11.21	24.20	-17.34	0.46	6.65	-9.89	-0.29	-1.50	-5.38	4.48	-1.30
2007	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008	6.33	-10.74	1.13	-5.51	-4.36	-1.14	-0.28	8.95	-0.50	-39.36	-16.43	7.68
2009	0.66	-26.03	18.97	40.56	9.89	-2.27	7.76	5.36	-0.62	-18.17	1.96	7.77
2010	-14.26	2.84	9.06	-5.14	-0.17	-13.14	12.92	-1.48	6.09	15.40	3.21	21.00
2011	6.55	-3.23	8.86	1.57	-5.06	6.22	-0.69	-12.20	14.53	2.35	3.02	-2.18
2012	0.59	3.80	-5.50	2.28	-23.40	4.74	1.58	-4.25	4.20	-1.15	0.86	8.40
2013	6.46	3.22	1.04	6.68	-8.79	-1.53	7.68	-6.59	5.88	14.27	-11.58	5.98
2014	-2.95	3.07	1.87	-0.73	-5.35	4.11	6.82	3.74	-7.03	-0.95	3.20	0.84
2015	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2016	-5.17	-6.23	8.23	5.17	-15.07	4.69	9.45	-4.58	2.23	-10.32	22.26	2.67
2017	-6.48	-8.55	-0.54	-1.16	10.03	2.95	-6.55	8.61	1.06	1.09	-3.16	-4.53
2018	-1.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00



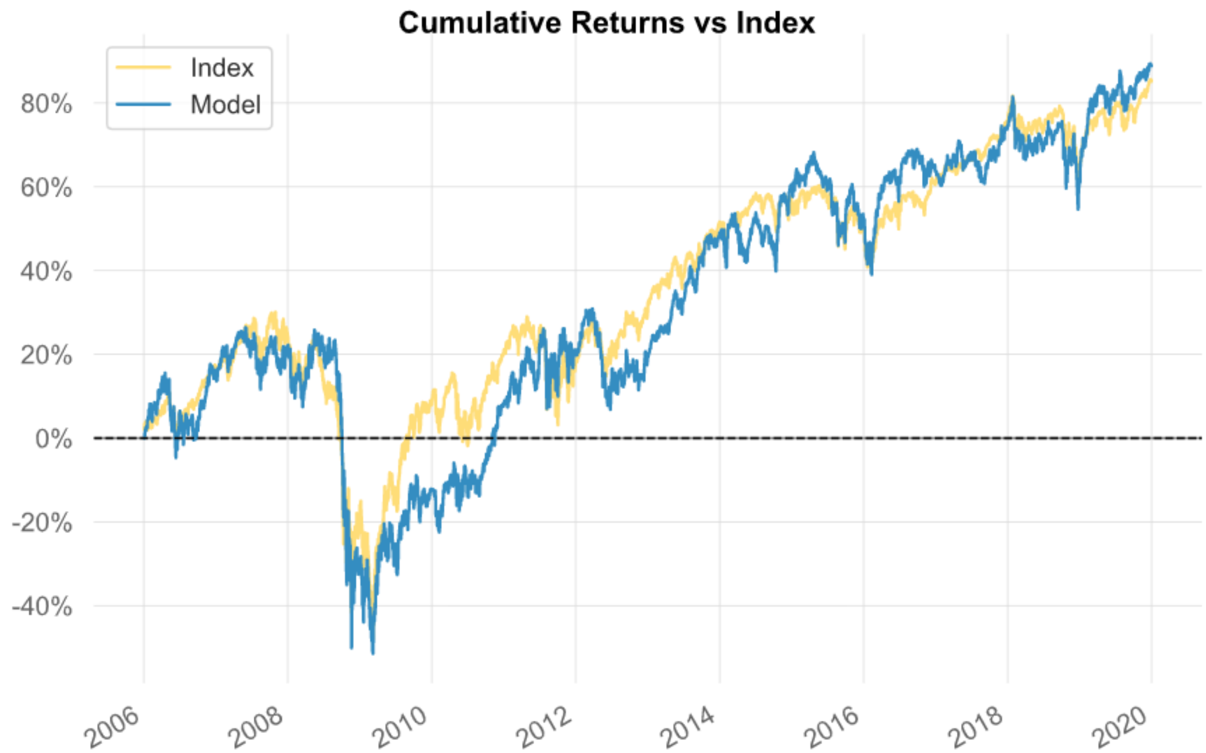
Appendix 4 – Piotroski F-Score Screener Performance
A: Trading on NYSE

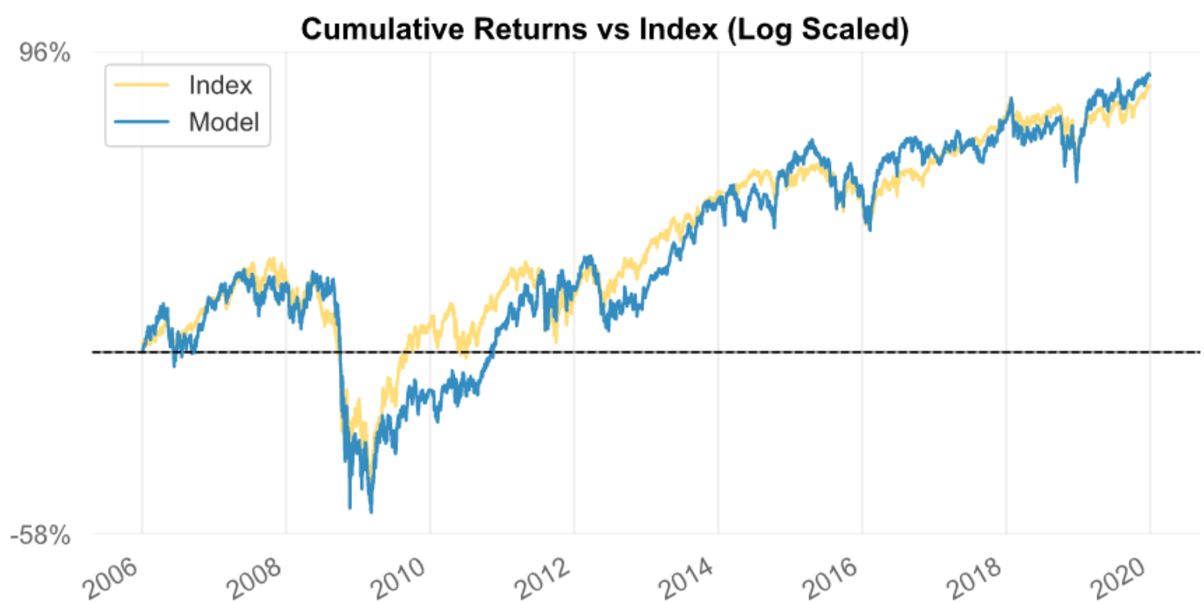
A.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

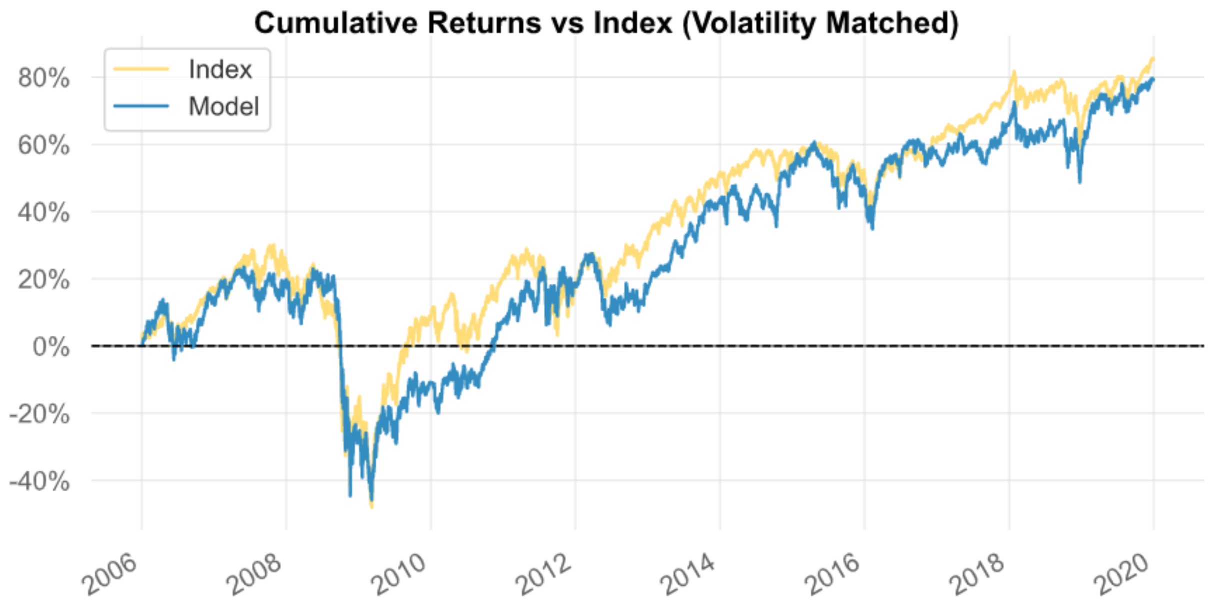
** Performance is benchmarked against NYSE Composite Index*

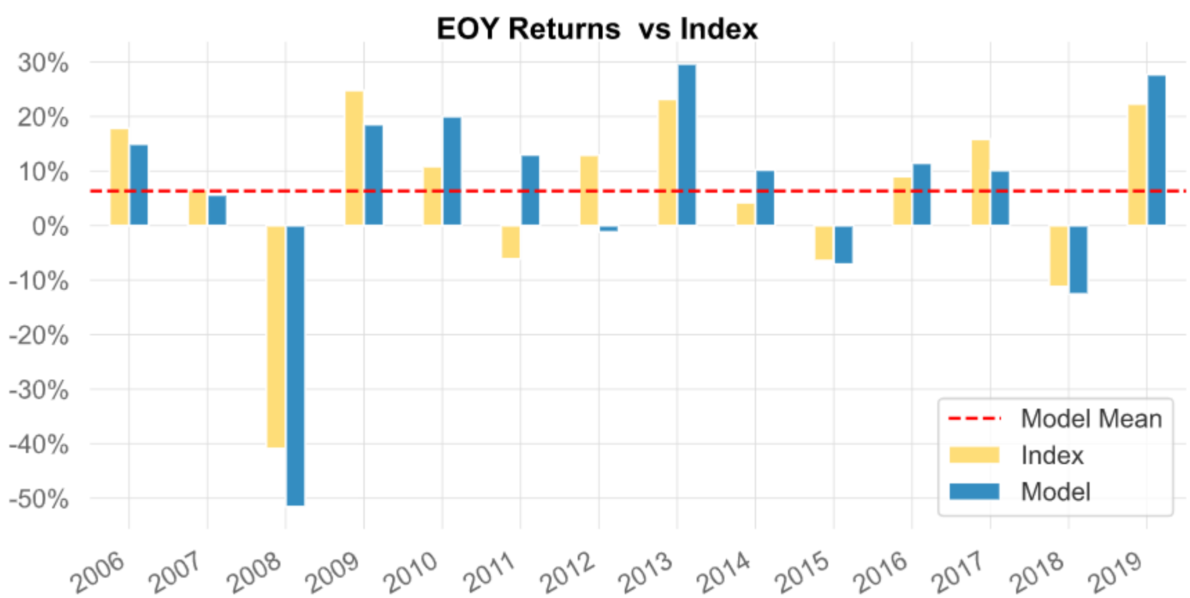
	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	88.86%	85.40%
CAGR%	4.65%	4.51%
Sharpe	0.29	0.31
Sortino	0.4	0.43
Max Drawdown	-59.40%	-59.01%
Longest DD Days	2446	2247
Volatility (ann.)	22.02%	19.61%
R^2	0.77	
Calmar	0.07	0.07
Skew	-0.31	-0.2
Kurtosis	7.27	11.69
Expected Daily %	0.02%	0.02%
Expected Monthly %	0.33%	0.35%
Expected Yearly %	4.00%	4.26%
Kelly Criterion	1.25%	1.19%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.26%	-2.01%
Expected Shortfall (cVaR)	-2.26%	-2.01%
Payoff Ratio	0.9	0.87
Profit Factor	1.05	1.06
Common Sense Ratio	1	0.94
CPC Index	0.5	0.5
Tail Ratio	0.95	0.88
Outlier Win Ratio	3.9	4.71
Outlier Loss Ratio	3.93	4.74

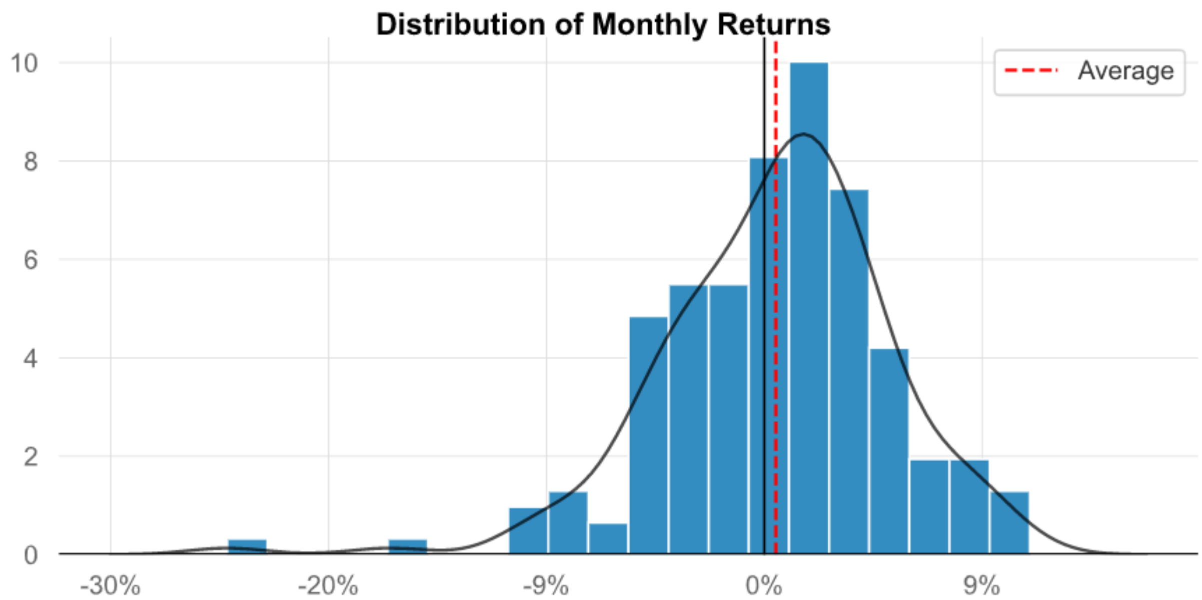
	Model	Index
MTD	1.66%	2.70%
3M	6.17%	7.11%
6M	7.33%	6.72%
YTD	27.69%	20.77%
1Y	29.04%	21.51%
3Y (ann.)	7.82%	7.72%
5Y (ann.)	5.25%	5.09%
10Y (ann.)	7.24%	5.85%
All-time (ann.)	4.65%	4.51%
Best Day	11.03%	12.22%
Worst Day	-11.04%	-9.73%
Best Month	12.39%	11.39%
Worst Month	-24.05%	-19.54%
Best Year	33.60%	24.80%
Worst Year	-45.58%	-40.89%
Avg. Drawdown	-4.41%	-2.28%
Avg. Drawdown Days	92	51
Recovery Factor	1.23	1.35
Ulcer Index	1.02	1.02
Avg. Up Month	4.22%	3.45%
Avg. Down Month	-5.48%	-4.51%
Win Days %	53.34%	53.96%
Win Month %	58.93%	61.31%
Win Quarter %	66.07%	69.64%
Win Year %	71.43%	71.43%
Beta	0.99	
Alpha	0	

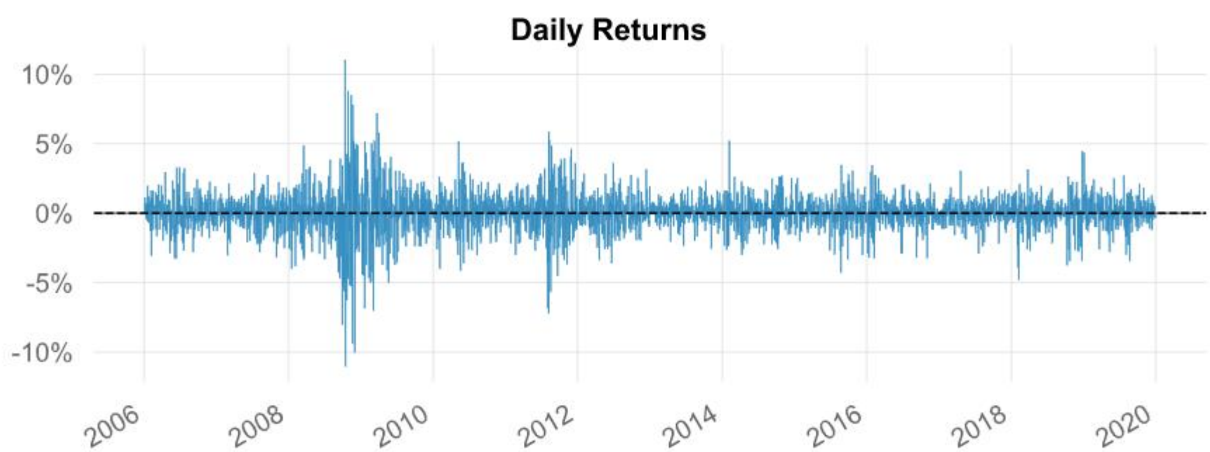

Cumulative Returns vs Index
Index
Model
80%
60%
40%
20%
0%
-20%
-40%
2006
2008
2010
2012
2014
2016
2018
2020

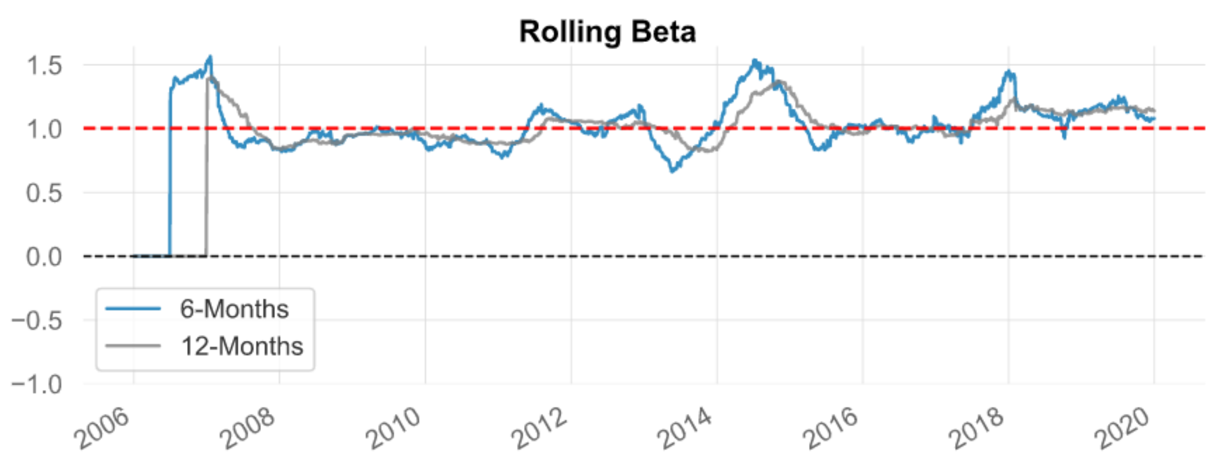

Cumulative Returns vs Index (Log Scaled)
96%
Index
Model
-58%
2006
2008
2010
2012
2014
2016
2018
2020

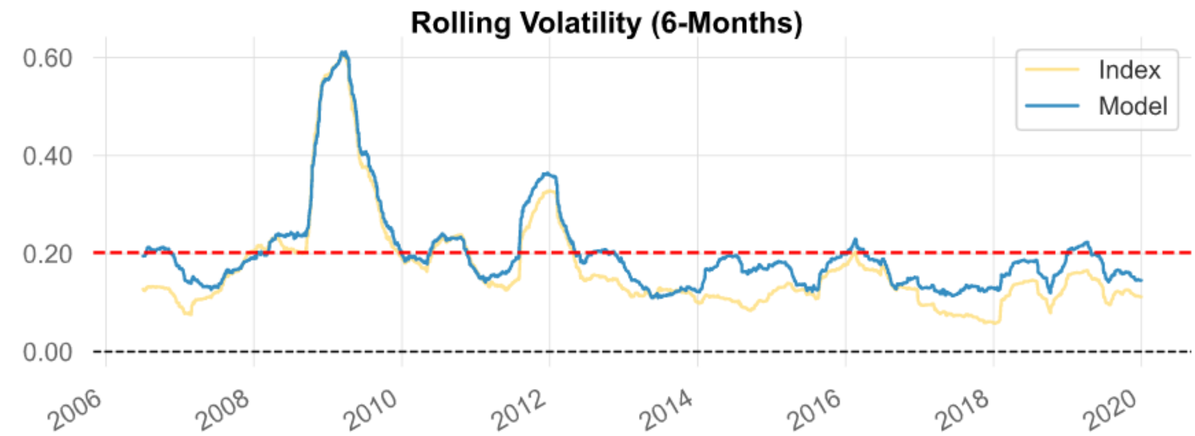

Cumulative Returns vs Index (Volatility Matched)
Index
Model
80%
60%
40%
20%
0%
-20%
-40%
2006
2008
2010
2012
2014
2016
2018
2020

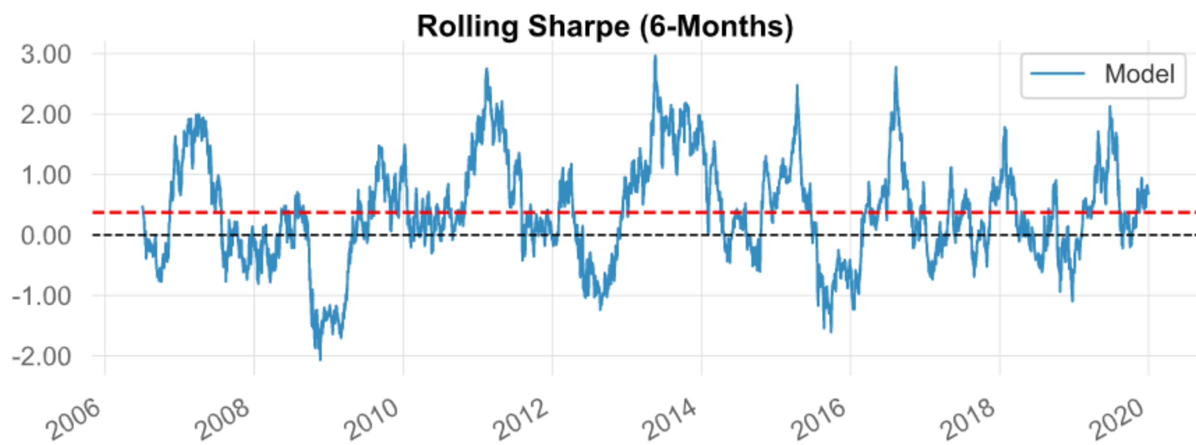

EOY Returns vs Index
30%
20%
10%
0%
-10%
-20%
-30%
-40%
-50%
Model Mean
Index
Model
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

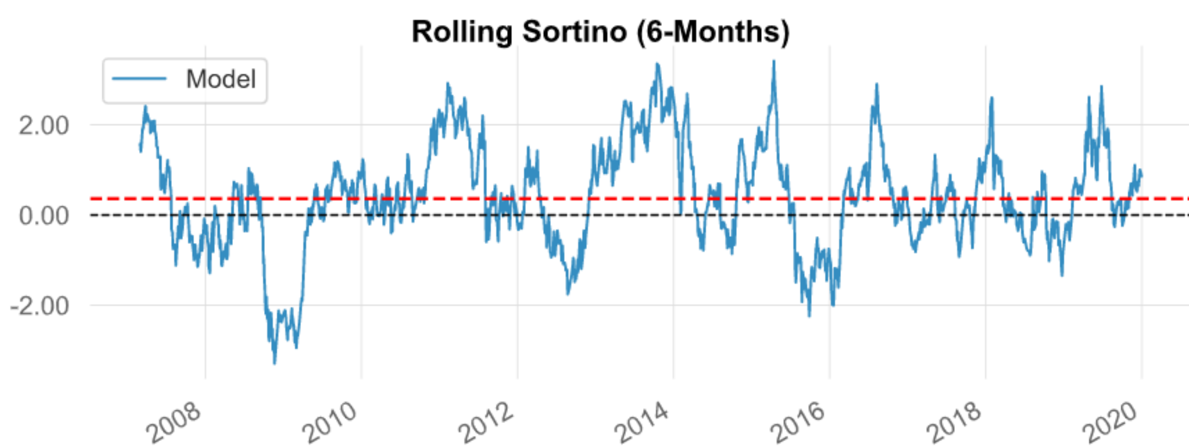

Distribution of Monthly Returns
Average
10
8
6
4
2
0
-30%
-20%
-9%
0%
9%

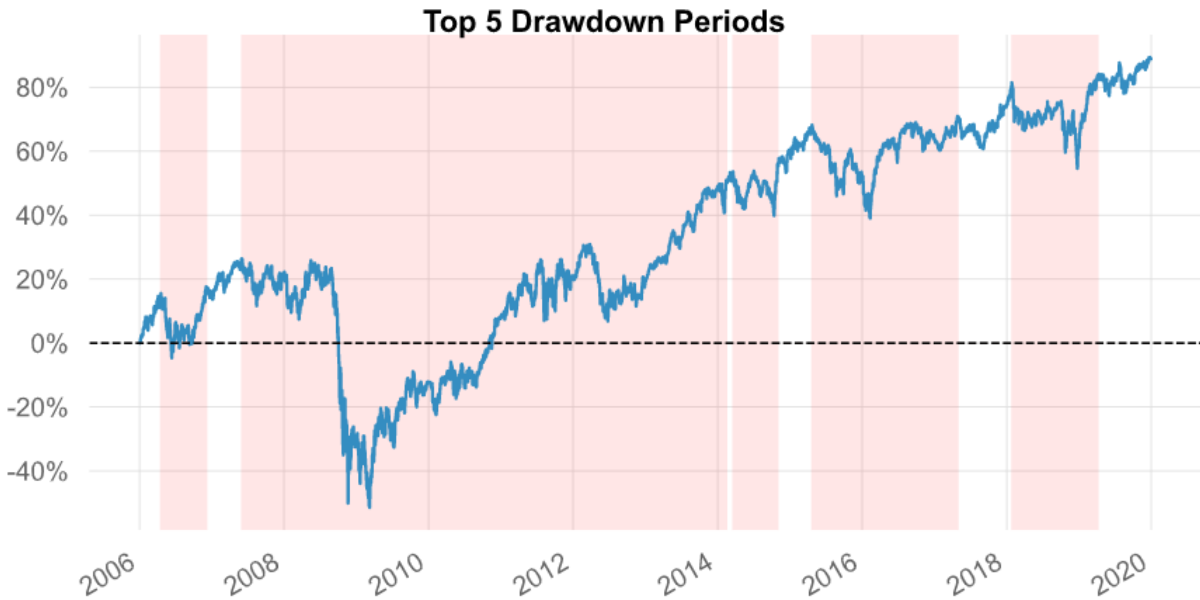

Daily Returns
10%
5%
0%
-5%
-10%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
1.5
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

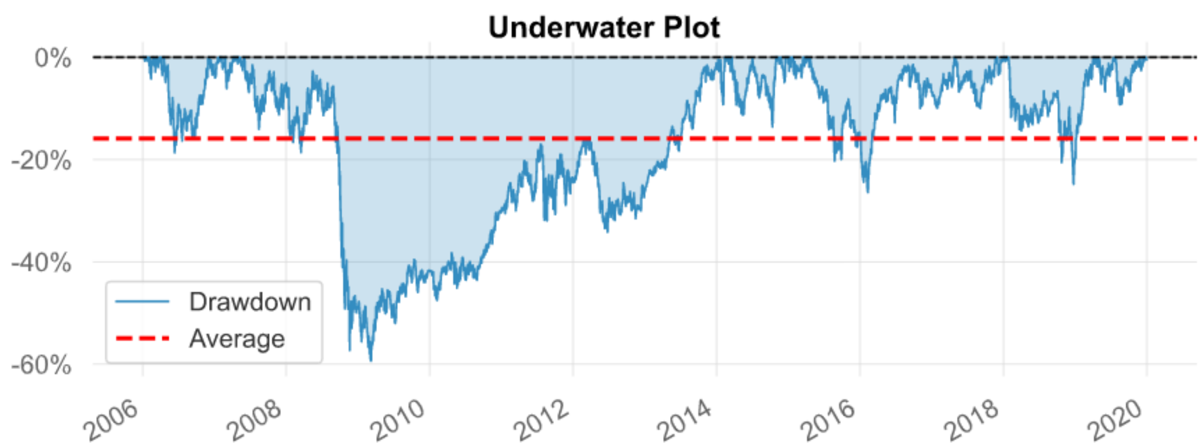

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
Model
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020

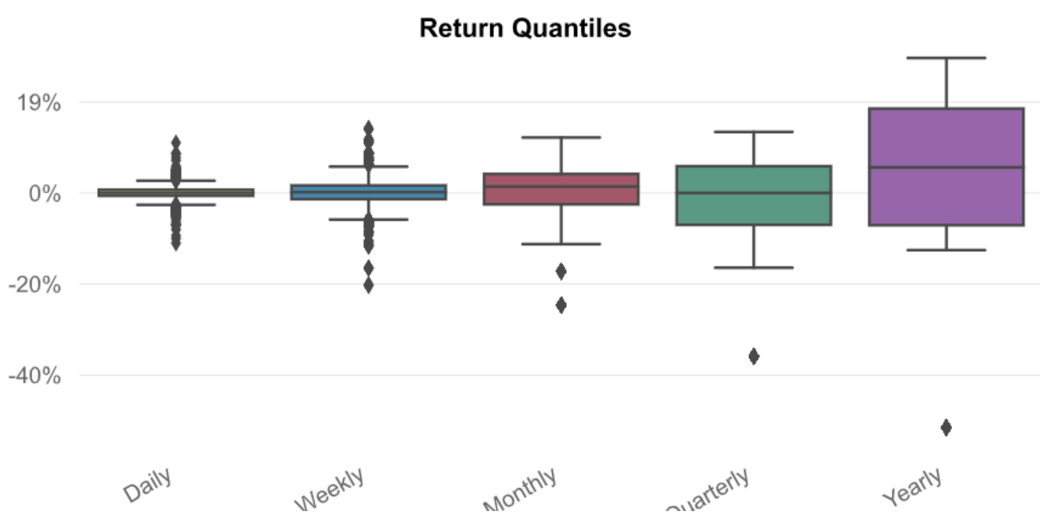


#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	6/4/2007	3/9/2009	2/13/2014	2446	-59.40	-55.14
2	4/24/2015	2/11/2016	4/27/2017	734	-26.43	-23.71
3	1/29/2018	12/24/2018	4/5/2019	431	-24.83	-21.23
4	4/20/2006	6/13/2006	12/4/2006	228	-18.65	-17.24
5	3/21/2014	10/13/2014	10/30/2014	223	-13.61	-12.26



Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	7.31	-0.48	6.04	-1.71	-5.87	0.57	-2.14	0.52	-0.75	4.18	8.77	-1.50
2007	4.85	-0.59	0.85	3.88	2.38	-4.89	-5.09	2.39	2.69	2.69	-5.30	1.78
2008	-8.03	2.75	-2.50	4.74	6.06	-2.22	0.83	-0.03	-17.22	-24.65	-9.65	-1.61
2009	-6.58	-5.94	7.74	10.54	0.95	-2.59	5.03	1.33	7.05	-5.44	3.30	3.15
2010	-8.48	5.17	3.80	2.68	-3.51	-0.25	2.59	-3.24	7.98	4.13	4.43	4.71
2011	2.13	3.08	3.68	5.19	-3.47	1.60	3.93	-3.64	-8.30	12.19	-2.68	-0.71
2012	3.35	4.94	0.09	-5.23	-11.24	0.58	-0.73	0.56	4.18	-2.79	0.76	4.35
2013	4.29	1.83	1.31	3.44	1.27	1.08	5.98	-3.72	7.18	5.31	-0.65	2.34
2014	-6.07	9.12	-2.03	-4.65	1.49	5.43	-5.39	3.42	-4.28	10.06	1.64	1.48
2015	1.59	0.71	3.57	0.23	-3.03	-3.01	-3.01	-5.85	-1.40	10.63	-4.44	-3.08
2016	-5.66	2.51	10.39	2.31	1.26	-1.50	5.20	0.98	0.88	-3.49	-1.45	0.03
2017	-2.76	4.76	2.12	1.79	-4.60	2.84	-2.26	-4.02	6.22	-1.68	8.52	-0.79
2018	5.50	-8.48	-2.38	0.24	-0.05	1.21	4.11	-0.69	1.07	-10.47	7.90	-10.51
2019	9.76	9.09	1.06	2.51	-5.76	3.69	3.63	-3.68	1.58	2.34	1.79	1.66



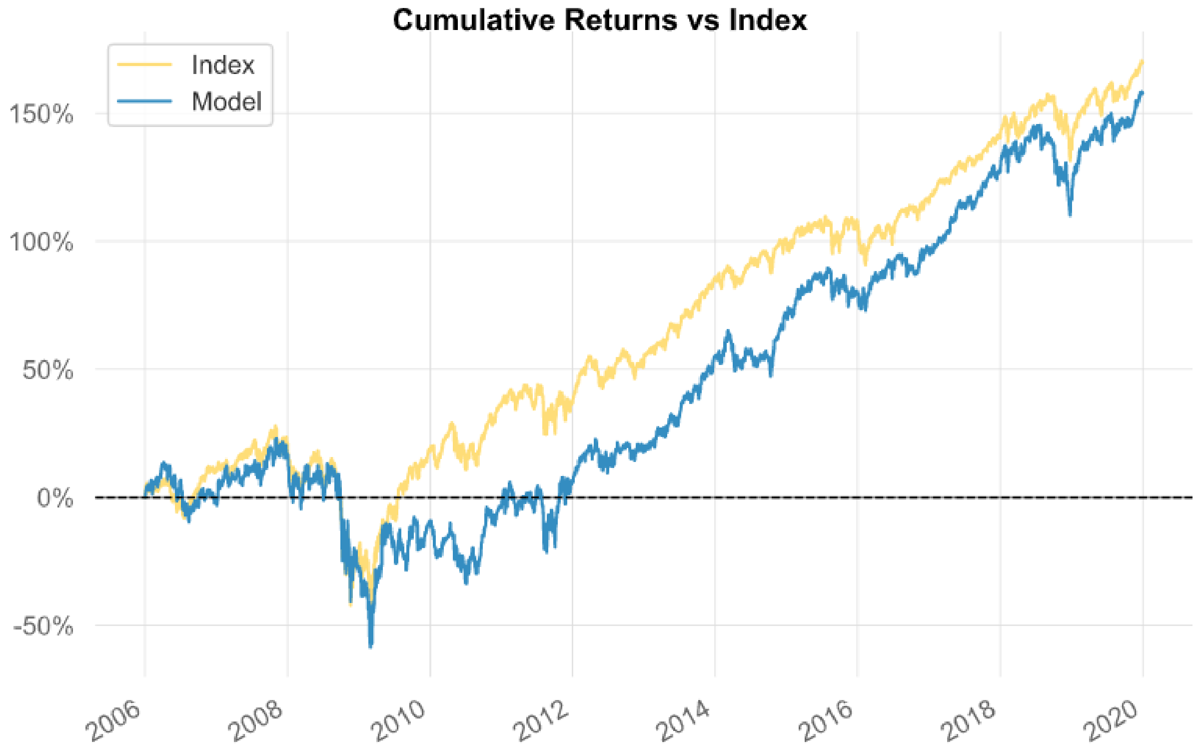
B: Trading on NASDAQ

B.1 Summary of Strategy Performance from Jan 2006 till Dec 2019:

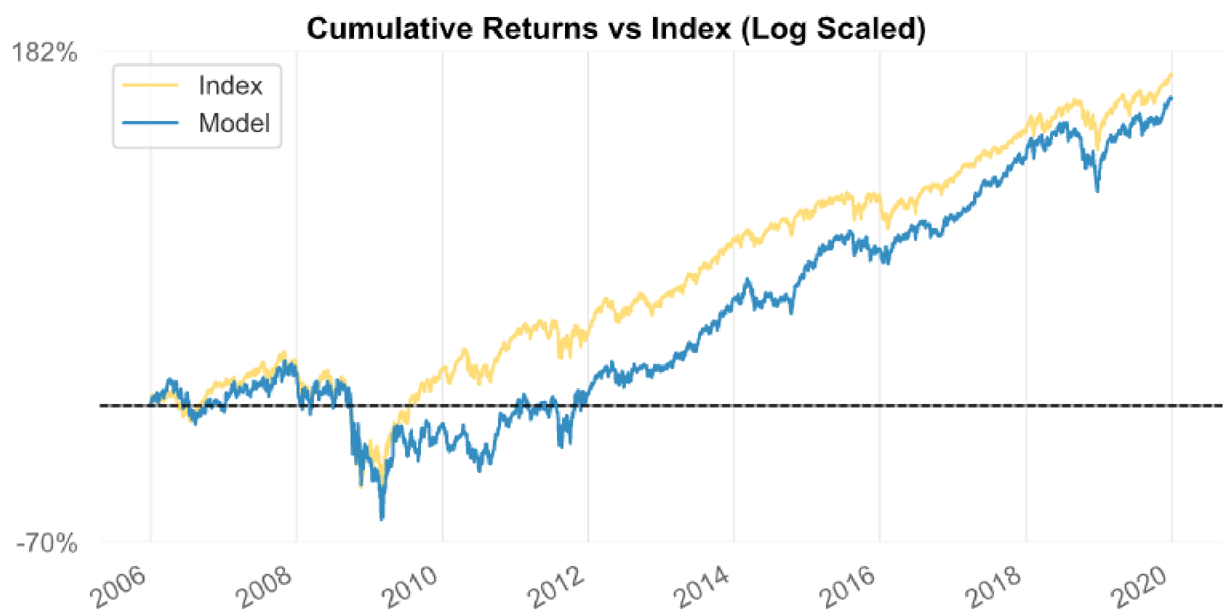
** Performance is benchmarked against NASDAQ Composite Index*

	Model	Index
Start Period	1/3/2006	1/3/2006
End Period	12/31/2019	12/31/2019
Risk-Free Rate	0.00%	0.00%
Time in Market	100.00%	100.00%
Total Return	157.24%	169.91%
CAGR%	6.98%	7.35%
Sharpe	0.47	0.59
Sortino	0.66	0.83
Max Drawdown	-61.20%	-55.63%
Longest DD Days	2212	1273
Volatility (ann.)	24.16%	20.55%
R^2	0.67	
Calmar	0.14	0.19
Skew	0.02	-0.12
Kurtosis	6.89	7.48
Expected Daily %	0.03%	0.04%
Expected Monthly %	0.70%	0.84%
Expected Yearly %	8.67%	10.54%
Kelly Criterion	2.02%	3.65%
Risk of Ruin	0.00%	0.00%
Daily Value-at-Risk	-2.46%	-2.08%
Expected Shortfall (cVaR)	-2.46%	-2.08%
Payoff Ratio	0.87	0.87
Profit Factor	1.09	1.12
Common Sense Ratio	1	1
CPC Index	0.52	0.53
Tail Ratio	0.92	0.9
Outlier Win Ratio	3.8	4.55
Outlier Loss Ratio	3.62	4.32

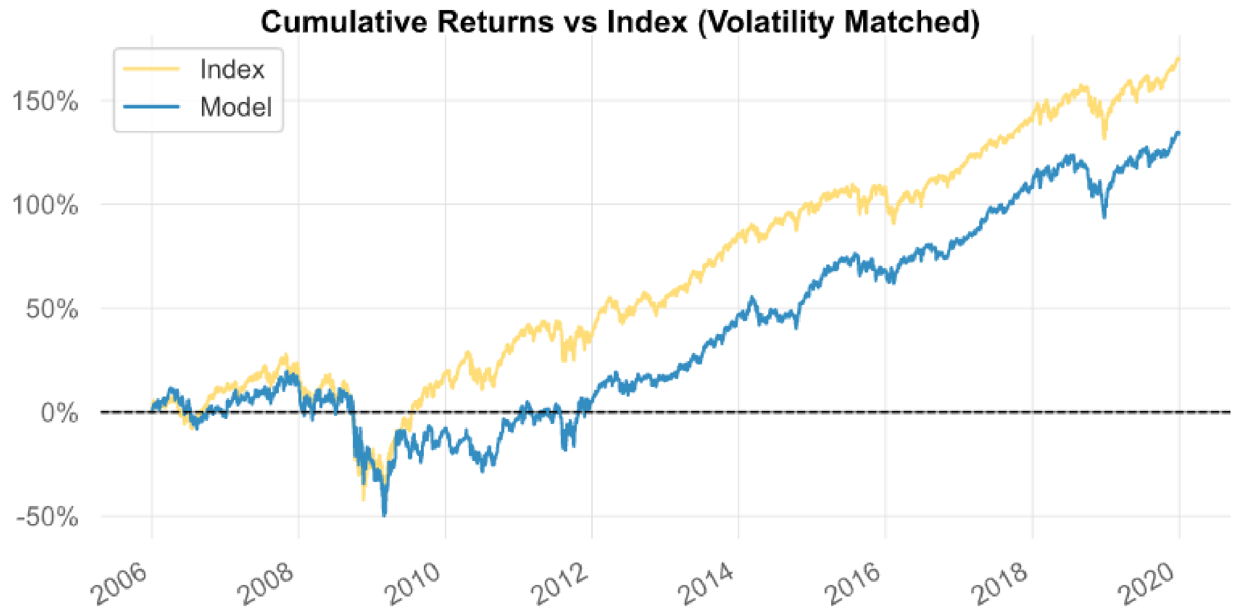
	Model	Index
MTD	3.68%	3.52%
3M	12.13%	12.39%
6M	11.07%	11.95%
YTD	41.77%	31.42%
1Y	41.84%	32.19%
3Y (ann.)	17.43%	15.77%
5Y (ann.)	13.23%	11.14%
10Y (ann.)	10.29%	9.64%
All-time (ann.)	6.98%	7.35%
Best Day	13.96%	11.81%
Worst Day	-10.78%	-9.14%
Best Month	22.41%	12.35%
Worst Month	-18.00%	-17.73%
Best Year	49.54%	43.89%
Worst Year	-43.00%	-40.54%
Avg. Drawdown	-3.53%	-2.37%
Avg. Drawdown Days	52	27
Recovery Factor	3.6	5.52
Ulcer Index	1.01	1.02
Avg. Up Month	5.26%	4.19%
Avg. Down Month	-5.21%	-4.21%
Win Days %	54.30%	55.28%
Win Month %	56.55%	62.50%
Win Quarter %	60.71%	71.43%
Win Year %	78.57%	78.57%
Beta	0.96	
Alpha	0	

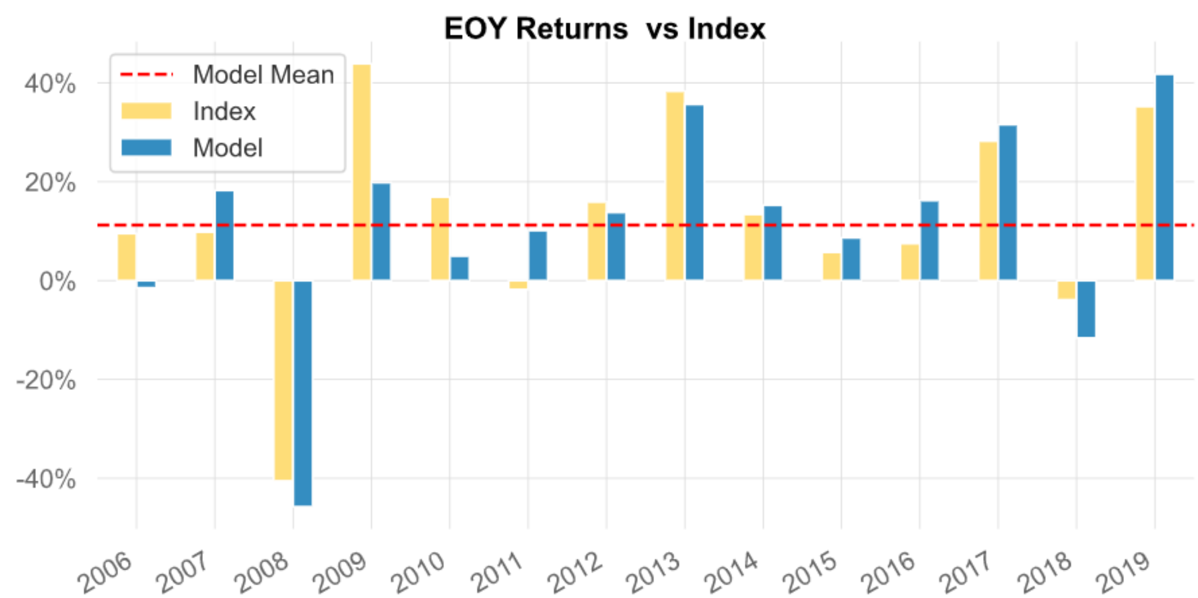


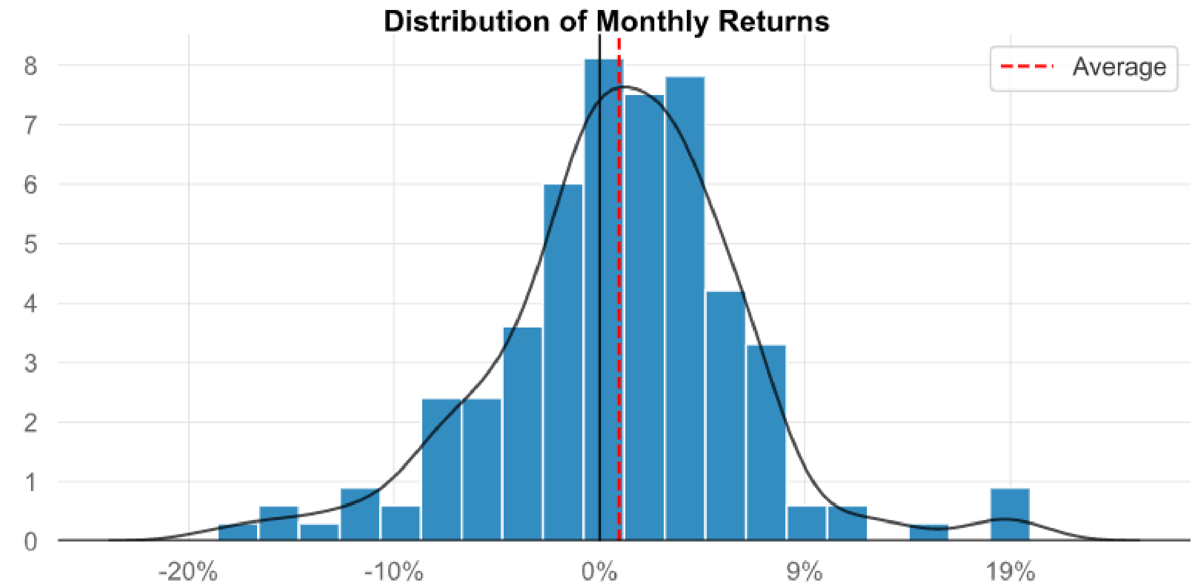
Cumulative Returns vs Index
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020



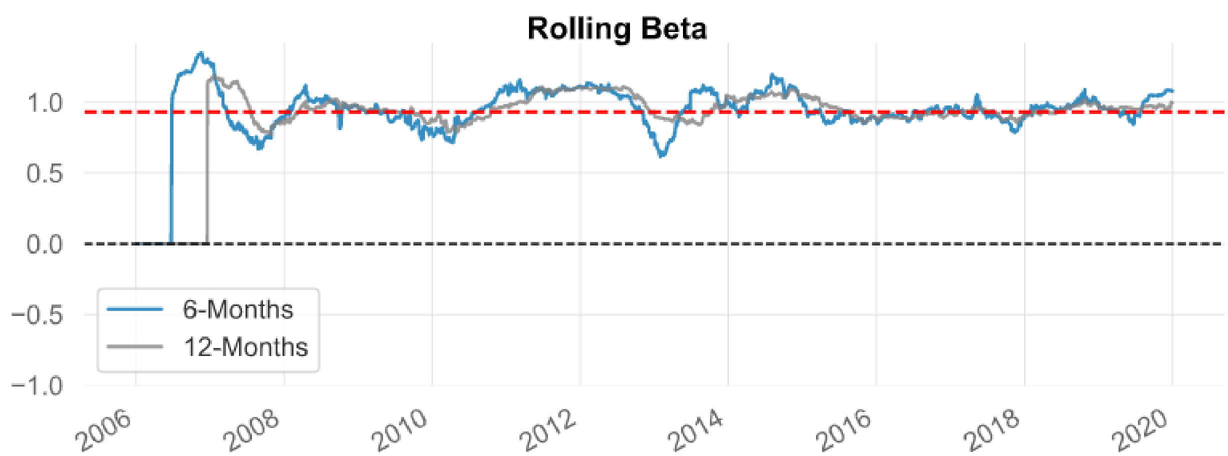
Cumulative Returns vs Index (Log Scaled)
182%
Index
Model
-70%
2006
2008
2010
2012
2014
2016
2018
2020

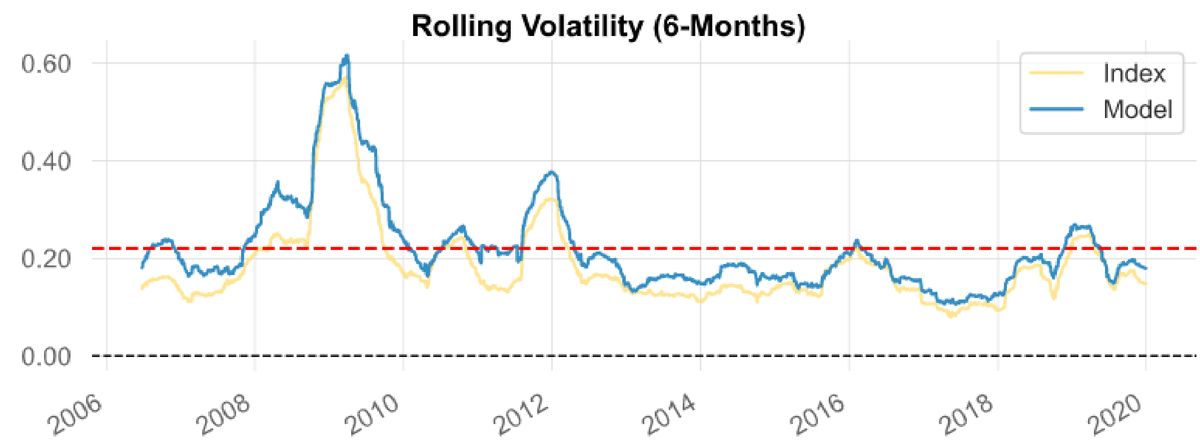

Cumulative Returns vs Index (Volatility Matched)
Index
Model
150%
100%
50%
0%
-50%
2006
2008
2010
2012
2014
2016
2018
2020

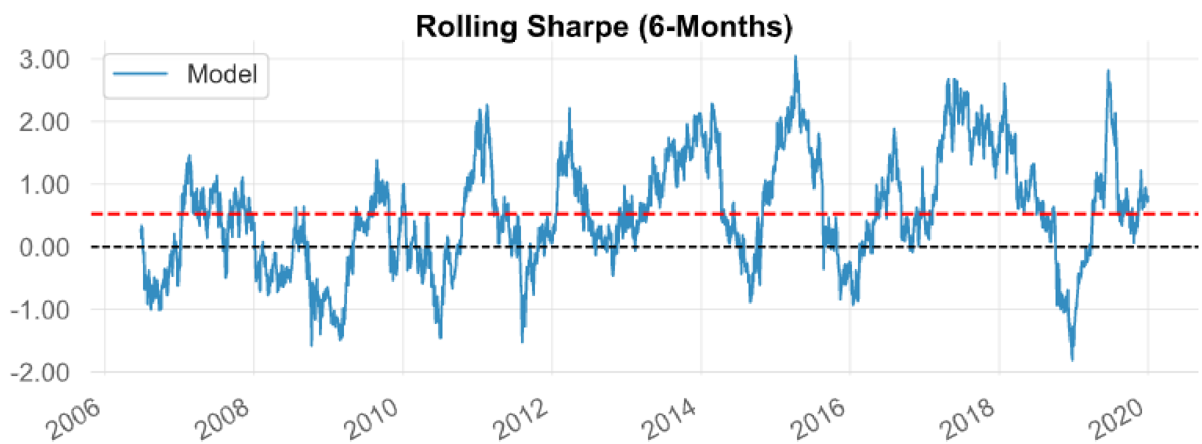

EOY Returns vs Index
Model Mean
Index
Model
40%
20%
0%
-20%
-40%
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

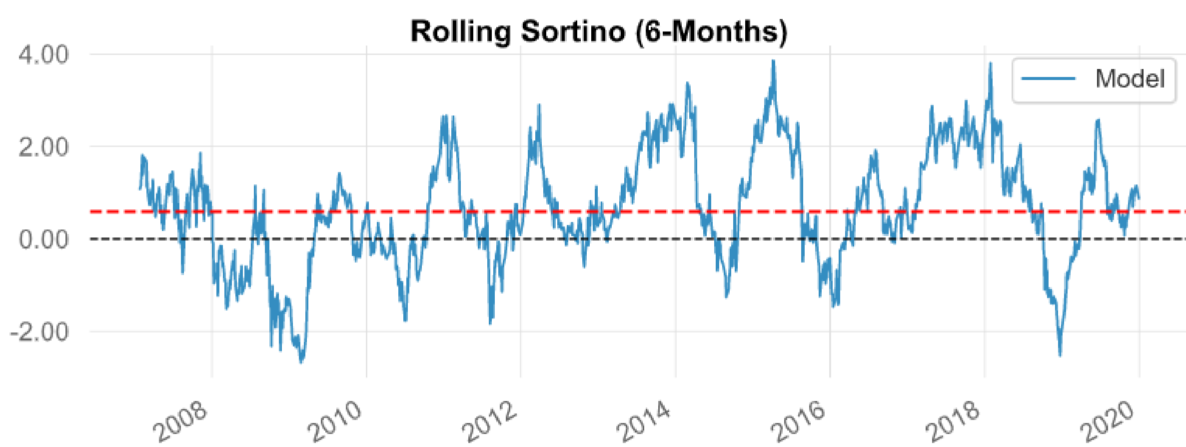

Distribution of Monthly Returns
Average
8
7
6
5
4
3
2
1
0
-20%
-10%
0%
9%
19%

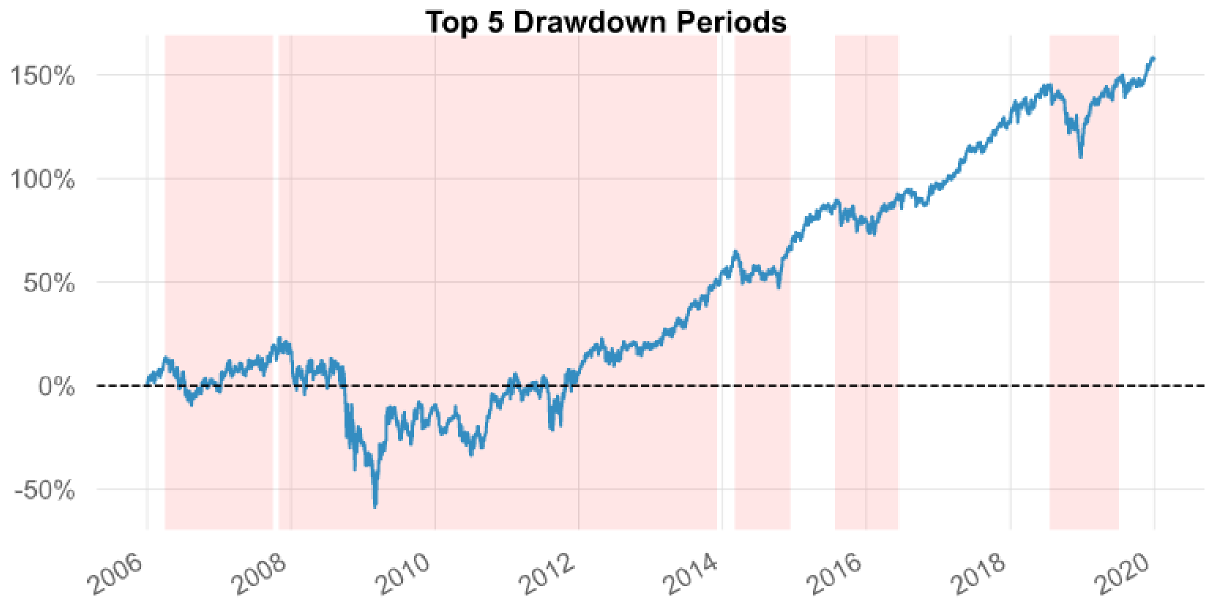

Daily Returns
15%
10%
5%
0%
-5%
-10%
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Beta
1.0
0.5
0.0
−0.5
−1.0
6-Months
12-Months
2006
2008
2010
2012
2014
2016
2018
2020

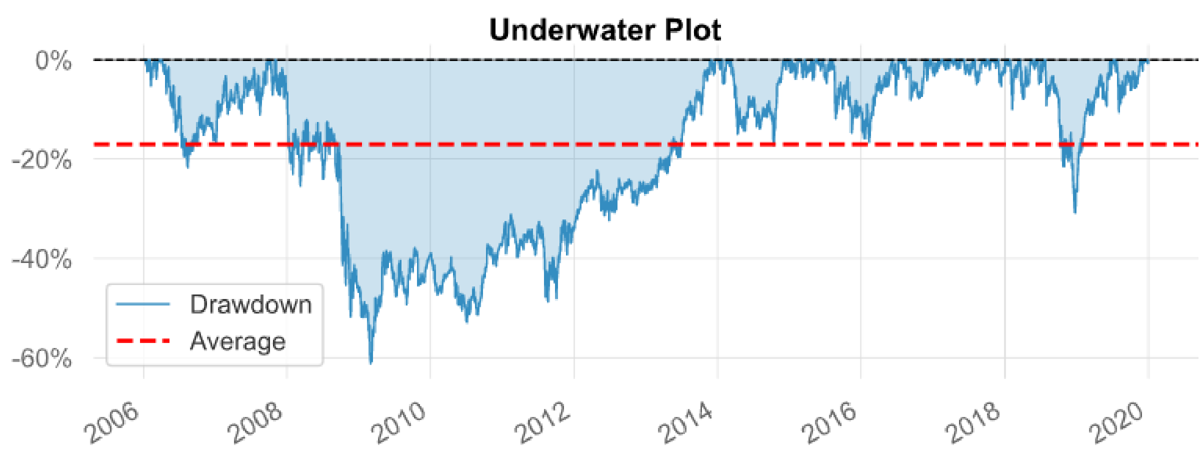

Rolling Volatility (6-Months)
Index
Model
0.60
0.40
0.20
0.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sharpe (6-Months)
Model
3.00
2.00
1.00
0.00
-1.00
-2.00
2006
2008
2010
2012
2014
2016
2018
2020


Rolling Sortino (6-Months)
Model
4.00
2.00
0.00
-2.00
2008
2010
2012
2014
2016
2018
2020

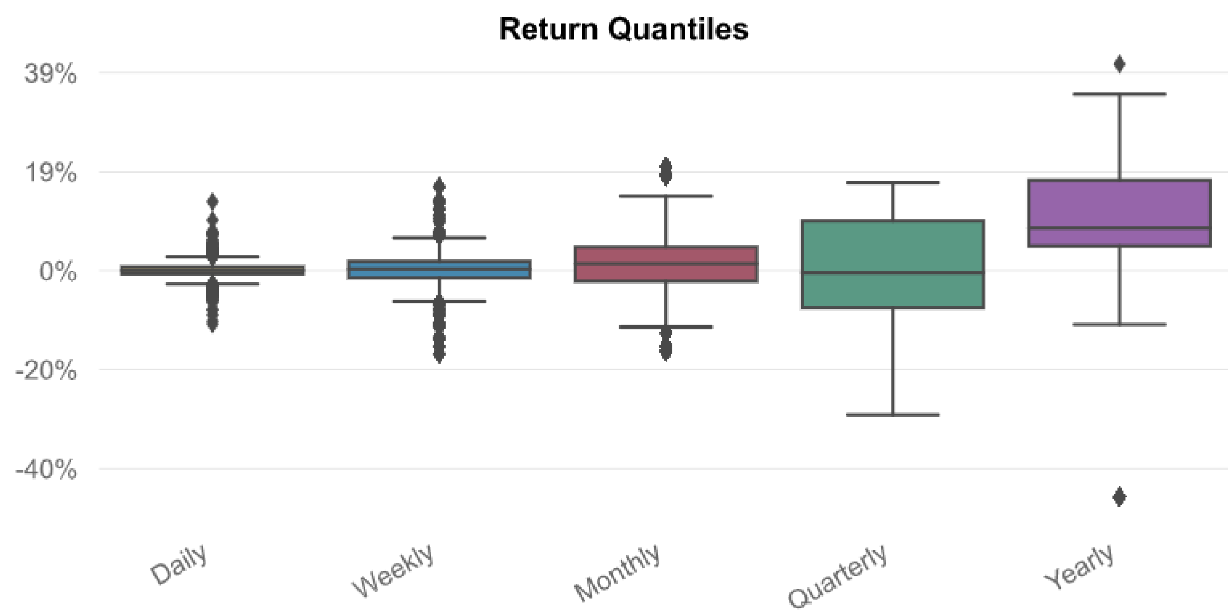


#	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	11/7/2007	3/2/2009	11/27/2013	2212	-61.20	-54.69
2	7/26/2018	12/24/2018	7/10/2019	349	-31.27	-27.67
3	4/7/2006	8/14/2006	9/26/2007	537	-21.69	-19.53
4	3/10/2014	10/13/2014	12/5/2014	270	-17.24	-16.22
5	7/31/2015	2/11/2016	6/7/2016	312	-16.57	-15.86



Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2006	6.60	-0.27	6.68	-4.17	-3.62	0.27	-10.73	1.42	2.14	2.46	1.42	-3.65
2007	6.11	4.14	-1.64	0.56	3.58	-0.29	-3.04	2.54	7.30	4.92	-2.32	-3.60
2008	-16.29	3.18	3.25	-0.30	3.49	-6.90	5.96	0.25	-9.26	-15.32	-8.17	-5.64
2009	-7.16	-18.59	19.43	20.99	1.93	-5.09	-0.30	-7.33	12.57	-8.10	1.37	10.10
2010	-13.16	-0.34	7.22	-0.81	-8.83	-6.53	7.90	-6.13	15.07	7.82	-4.04	6.81
2011	0.56	5.90	-3.79	1.55	1.83	-0.37	-4.16	-4.17	-8.35	19.13	2.54	-0.53
2012	5.99	3.81	2.89	2.43	-7.00	-1.60	2.37	2.42	2.43	-2.88	3.91	-1.00
2013	0.39	1.20	5.41	0.76	2.93	0.16	7.70	-0.78	4.83	5.13	3.92	4.02
2014	-1.48	7.72	-3.06	-6.47	1.20	3.24	-5.10	3.07	0.27	6.56	4.68	4.63
2015	-0.24	7.24	3.22	-0.37	6.12	-1.91	4.79	-8.53	0.68	-0.38	-0.74	-1.21
2016	2.25	-2.23	7.56	-1.06	4.06	0.58	4.24	-2.40	-2.23	-1.60	6.39	0.64
2017	1.92	2.62	3.73	4.37	5.63	0.02	3.32	-0.79	4.68	3.89	3.85	-1.68
2018	7.99	-0.95	0.13	0.18	4.42	2.53	-5.46	6.16	-3.79	-12.55	1.84	-11.37
2019	12.76	8.70	-0.19	6.40	-5.20	8.22	-1.44	-0.79	2.46	-2.10	9.25	3.68



Appendix 5 – Details of the Financial Metrics computed in the assessment report

Metric Name	Details
Start Period	First day of trading
End Period	Last day of trading
Time in Market	% of the time the portfolio was not being traded
Total Return	Total holding period return
CAGR%	Compound annual growth rate
Sharpe	Measure of risk Adjusted return, calculated as: mean(Returns)/std(Returns)
Sortino	Measure of risk Adjusted return, calculated according to: www.redrockcapital.com/Sortino__A__Sharper__Ratio_Red_Rock_Capital.pdf
Max Drawdown%	Maximum loss from peak to trough, calculated as: (trough-peak)/peak
Longest DD Days	The longest duration of drawdown, calculated as the maximum count of days between two peaks
Volatility (ann.)	Annualized Volatility of returns, calculated as: std(Returns)*sqrt(252)
R^2	Coefficient of determination, measures the straight line fit between the returns of the model and the index
Calmar	Measure of risk Adjusted return, calculated as: (CAGR%)/(Max Drawdown%)
Skew	The degree of asymmetry of returns distribution around its mean
Kurtosis	A statistical measure that describes the similarity of the tails of a distribution compared to a normal distribution
Expected Daily %	The geometric mean of the daily returns
Expected Monthly %	The geometric mean of the Monthly returns
Expected Yearly %	The geometric mean of the Yearly returns
Kelly Criterion	A measure of the recommended daily maximum amount of capital to be allocated to a given strategy, calculated as: (((win-to-loss ratio) * (win probability)) – (loss probability)) / (win-to-loss ratio)
Risk of Ruin	A measure of likelihood of a total investment loss
Daily Value-at-Risk	Maximum daily loss expected
Expected Shortfall (cVaR)	A measure of expected loss that would occur after the daily Value-at-Risk threshold
Payoff Ratio	Calculated as (win probability)/(loss probability)
Profit Factor	A measure of profit ratio, calculated as: sum(positive returns)/sum(negative returns)
Common Sense Ratio	Calculated as (profit factor) * (Tail Ratio)
CPC Index	Calculated as (profit factor) * (win probability) * (win-to-loss ratio)
Tail Ratio	A measure of the ratio of right tail to left tail
Outlier Win Ratio	Calculated as: mean(returns | conf =0.99) / mean(positive returns)

Outlier Loss Ratio	Calculated as: mean(returns | conf =0.01) / mean(negative returns)
MTD	Month to date returns
3M	Quarter to date returns
6M	Six Month to date returns
YTD	Year to date returns
1Y	The last annual return
3Y (ann.)	3 Years CAGR%
5Y (ann.)	5 Years CAGR%
10Y (ann.)	10 Years CAGR%
All-time (ann.)	Full-Period CAGR%
Best Day	Best Daily return
Worst Day	Worst Daily return
Best Month	Best Month return
Worst Month	Worst Month return
Best Year	Best Year return
Worst Year	Worst Year return
Avg. Drawdown	Average Drawdown % over the whole investment period
Avg. Drawdown Days	Average Drawdown days over the whole investment period
Recovery Factor	A measure of recovery from drawdowns, calculated as: (Total Return) / abs(Max drawdown)
Ulcer Index	A measure of downside risk, calculation is down over the total period
Avg. Up Month	Average monthly profit%
Avg. Down Month	Average monthly loss%
Win Days %	Percentage of days with positive returns
Win Month %	Percentage of Months with positive returns
Win Quarter %	Percentage of Quarters with positive returns
Win Year %	Percentage of Years with positive returns
Beta	A measure of volatility against an index, calculated as: covariance(model returns, index returns) / variance(index returns)
Alpha	A measure of return performance against an index, calculated as: (mean(Model Returns) – Beta * mean(Index Returns)) * 252