

STEVENS INSTITUTE OF TECHNOLOGY

FINANCIAL ENGINEERING

Robo - Advisor on U.S. ETF Market

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May 12, 2017

Abstract

Taking advantages of technology into financial industry has been a growing trend among financial companies. Robo Advisor is a typical FinTech (Finance and Technology) product in this tendency. It is a digital platform that provides automated, algorithm-driven financial planning services with little to no human supervision. Our product is based on the extension of Black-Litterman model, and we use machine learning method to predict views which can be added into Black-Litterman model. Tax loss harvesting is also implemented to maximized after-tax returns. Furthermore, there are two interfaces are built –client interface and manager interface.

Keywords: Robo-Advisor, Tax Loss Harvesting, Black-Litterman Model, ARIMA

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1 Introduction

Robo Advisor has gained its popularity in wealth management service. It aims to provide automated, algorithm-based portfolio management service that have low charges and low account minimums, provide unbiased, transparent and customized financial solutions, and provide comfortable user experience. The goal of this projects is to build a Robo Advisor with interfaces for both clients and managers.

In this project, we invest in equity market to maximize long-term returns. Each of the selected asset classes is represented by a low expense ratio ETF. And the portfolio is constantly monitored and will be rebalanced once the given drift is reached. By this means, the chance of investment success can be maximized for the long run. Additionally, taxes are minimized by analyzing the taxes likely to be generated by any given asset class.

Black-Litterman Model are used to combine equilibrium return and views in this research. Currently, Auto Regressive Integrated Moving Average (ARIMA) Model are applied to predict views of each ETF. Whats more, the manager can adjust views for clients according to their personal investment styles. Our product also provides opportunity to experienced investors to change views if they have highly confidence of their views.

Modern Portfolio Theory (MPT) is what we used to identify the ideal portfolio for each client. Today, MPT is the most widely accepted framework for managing diversified investment portfolios. MPT has its limitations, especially in the area of very low probability significant downside scenarios, but it is still the best framework on which to build a compelling investment management service.

Tax Loss Harvesting is implemented through switch back strategy. Tax Loss Harvesting is an essential method to increase after-tax returns. The switch back strategy is designed to maintain the optimal asset allocation and the expected return.

2 Data

The portfolio of the Robo-Advisor is always globally diversified mix of stock and bond index ETFs, Our objective is to help investors achieve the best possible allocation of highest return under specific risk level. As a result, we select the ETFs with low expense ratio and high liquidity to minimize the holding and transaction cost to improve our return. We choose 3 ETFs from each asset classes and we choose 8 ETFs in our back-testing result. The result is showed below:

Table 1: ETF selection

ASSET TYPE	EXPLANATION	ETFs
US STOCKS	represent an ownership share in U.S.-based corporations	VTI ITOT MGC
FOREIGN DEVELOPED STOCKS	represent an ownership share in companies headquartered in developed economies	VEA IXUS SCHF
EMERGING MARKET STOCKS	represent an ownership share in foreign companies in developing economies	VWO IEMG SCHE
DIVIDEND GROWTH STOCKS	represent an ownership share in U.S. companies that have increased their dividend payout each year for the last ten or more consecutive years	VIG DVY SCHD
US GOVERNMENT BONDS	are debt issued by the U.S. federal government and agencies to fund various spending programs	VGSH IEF TLT
MUNICIPAL BONDS	are debt issued by U.S. state and local governments	MUB TFI PZA
TREASURY INFLATION-PROTECTED SECURITIES (TIPS)	are inflation-indexed bonds issued by the U.S. federal government	SCHP TIP IPE
NATURAL RESOURCES	reflect the prices of energy (e.g., natural gas and crude oil)	XLE DJP VDE

3 Methodology

We use Black-Litterman model as our basic model to build our portfolio and integrate ARIMA model for prediction market price as a subjective view, we also use the report from Research Affiliate to stabilize our portfolio.

We set our project into several steps as follows:

- Step 1: Data Collection
- Step 2: Calculate the capital weighted equilibrium excess return.
- Step 3: Predict investors subjective views by ARIMA model
- Step 4: Combine the views from ARIMA model and Research Affiliate
- Step 5: Use Black-Litterman model to calculate the combined expected return and covariance matrix.
- Step 6: Use mean-variance optimization to calculate the optimal weights
- Step 7: Do the rebalance based on the strategy we discussed before
- Step 8: Generate the portfolio back-testing result and performance analysis.

We will give thorough introduction about Black-Litterman model, prediction of subjective view, Mean-Variance Optimization and rebalance method.

3.1 Black-Litterman Model

The Black-Litterman Model (Black and Litterman (1992)) is a well-known asset allocation model created by Fischer Black and Robert Litterman, which provides the flexibility of combining the market equilibrium with additional market view of the investor. The model is based on Bayesian methodology which effectively updates currently held opinions with historical data to form a new opinion on expected return and covariance matrix for each asset. This model can allow the manager to avoid certain problems or issues inherent in Markowitz's mean-variance optimization framework, such as the concentration of portfolio assets in only a handful of the asset under optimization. In this project, we basically follow the steps of the paper "A step-by-step guide to the Black-Litterman model" (Idzorek (2002)).

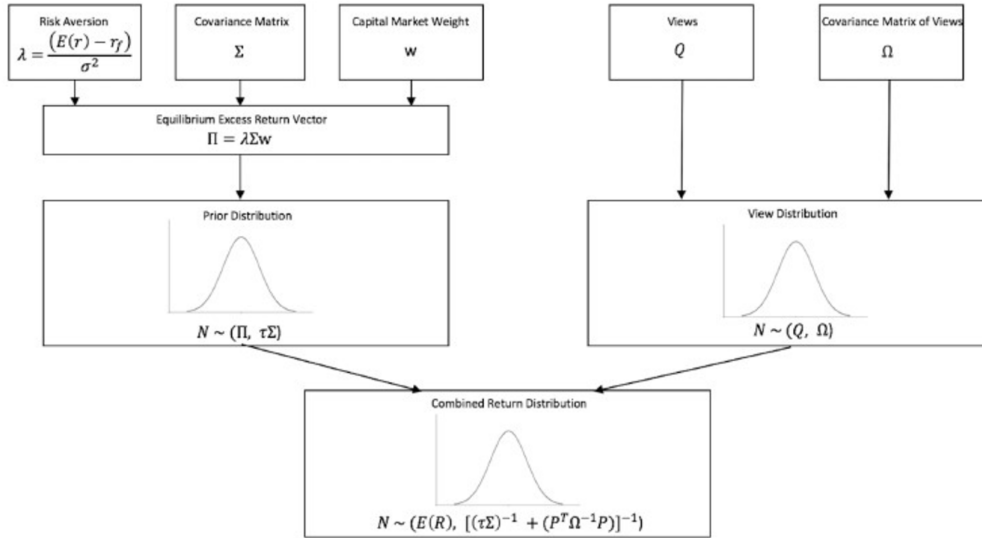


Figure 1: Black-Litterman Model

3.1.1 Equilibrium Returns

The Black-Litterman model uses “equilibrium” returns as a neutral starting point. Equilibrium returns are the set of returns that clear the market. To get the unconstrained maximization problem, we need the maximization condition. Here we set up a quadratic utility function:

$$U = \omega^T \Pi - \frac{\lambda \omega^T \Sigma \omega}{2}$$

Where ω is the allocation of each asset, and λ is the risk aversion parameter. Since the convexity of the utility function, we can derive the utility function and set the result to 0 and get the global minimum

$$\frac{dU}{d\omega} = \Pi - \lambda \Sigma \omega = 0$$

Thus, the equilibrium returns are derived using a reverse optimization method in which the vector of implied excess equilibrium return as extracted from known information using the formula below:

$$\Pi = \lambda \Sigma \omega_{mkt}$$

Where:

Π is the Implied Excess Equilibrium Return Vector;
 λ is the risk aversion coefficient;
 Σ is the covariance matrix of excess returns; and,
 ω_{mkt} is the market capitalization weight of the assets.

The risk-aversion coefficient (λ) characterized the expected risk-return trade-off. In the optimization process, risk aversion coefficient acts as a scaling factor for the reverse optimization estimate of excess returns. The weight reverse optimized excess returns equal the specified marked risk premium. We can solve λ by giving the Sharpe Ratio which is described by [Bevan and Winkelmann \(1998\)](#):

$$\lambda = \frac{SharpeRatio}{\sigma_m}$$

And the optimal portfolio weight is solved by:

$$\omega = (\lambda \Sigma)^{-1} \Pi$$

3.1.2 Combined Expected Return

In the real practice, the investors always have their specific views regarding the expected return of some of the assets in the portfolio. The Black-Litterman model provide the way to calculate new expected return by Bayesian method([Bernardo and Smith \(2001\)](#)). The formula for the new combined return vector is:

$$E[R] = [(\tau \Sigma)^{-1} + P' \Omega^{-1} P]^{-1} [(\tau \Sigma)^{-1} \Pi + P' \Omega^{-1} Q]$$

Where:

$E[R]$ is the new (posterior) Combined Return Vector;
 τ is a scalar;
 Σ is the covariance matrix of excess returns;
 P is a matrix that identifies the assets involved in the views;
 Ω is a diagonal covariance matrix of error terms from the expressed views representing the uncertainty in each view;
 Π is the Implied Equilibrium Return Vector; and,
 Q is the View Vector.

With the covariance matrix equals to:

$$\Sigma_r = [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}$$

3.2 Prediction of Subjective View

The Black-Litterman model allows such views to be expressed in either absolute or relative terms. Below are tree sample views expressed and summarized using the format of black and Litterman (1990)

View 1: Stock A have an absolute excess return of 5.25%

View 2: Stock B will outperform Stock C by 2%

That will generate the example of the model input below:

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 5.25 \\ 2 \end{bmatrix}$$

Basically, in this project, we use absolute views in general.

3.2.1 ARIMA Model

ARIMA stands for Autoregressive Integrated Moving Average models. It is a forecasting technique that project the future value of a series based entirely on its own inertia. it works best when the data exhibits a stable or consistent pattern over time with a minimum number of outliers. It is usually superior to exponential smoothing techniques when the data is reasonably long and correlation between past observation is stable.([Pai and Lin \(2005\)](#))

The first step to apply ARIMA model is to check for stationarity. Stationarity implies that the series remains at a constant level over time. If a trend exists, as in most economic or business applications, then your data is not stationary. The data should also show a constant variance in its fluctuations over time. We can use ADF method for testing. If the result indicates the time-series date is non-stationary, then we should difference the series. Differencing is a great way to transform a non-stationary series to a stationary one. This process essentially eliminates the trend if your series is growing

at a constant rate. You can keep differencing it until it becomes stationary.

ARIMA methodology allows model to be built that incorporate both autoregressive and moving average parameters together. An ARIMA model is usually states as ARIMA (p, d, q) where p represents the order of the autoregressive components, d stand for the number of differencing times, and q stand for the highest order of the moving average term. The general mixed model equation is given by:

$$(\Delta)^d y_t = \sum_{i=1}^p \Phi_i(\Delta)^d y_{t-1} + \sum_{j=1}^q \Theta_j \epsilon_{t-j} + \epsilon_t$$

Where Δ here is the lag operator.

3.2.2 Long-Term Fundamental Analysis

Research Affiliates, LLC, is a global leader in smart beta and asset allocation. They are seeking a profound impact on the global investment community through our insights and products, focus on long-term horizon investment. They calculated the historical data of global asset classes and get the 10-year expected returns and corresponding volatilities. And result is shows as follows:

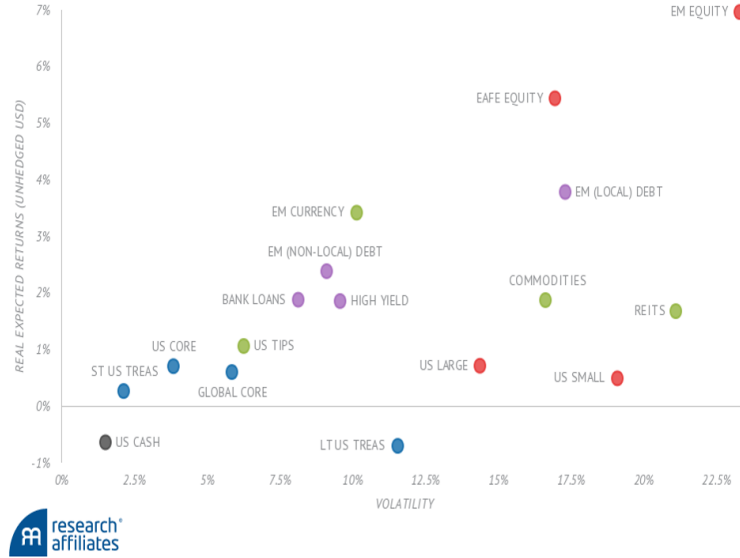


Figure 2: 10-Year Expected Returns of Global Asset Classes, source: [Affiliate \(2017\)](#)

We use it as a fundamental analysis result into the Black-Litterman model aiming to generate a long-term profit and stabilize our portfolio to avoid huge transaction cost.

3.2.3 Confidence Level

For the Q Matrix(??) discussed before. The model assumes that there is a random, independent, normally-distributed error term with a mean of 0 associated with each view. Thus, a view has the form $Q + \epsilon$ as follows:

$$Q + \epsilon = \begin{bmatrix} Q_1 \\ \vdots \\ Q_k \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_k \end{bmatrix}$$

The error term ϵ will not directly enter the Black-Litterman Formula. However, the variance of each error term does enter the formula. The variance of each error term is equal to the reciprocal of the level of confidence (LC) of the view multiplied by a calibration factor (CF). The variances of the error terms form Ω , where Ω is a diagonal covariance matrix with 0s in all of the off-diagonal positions. The larger the variance of the error term, the greater the relative uncertainty of the view. The off-diagonal elements of Ω are assumed to be 0 because the error terms are residuals, which are assumed to be independent of one another. The general case is showed below with each diagonal element $\omega = \frac{1}{LC} * CF$.

$$\Omega = \begin{bmatrix} \omega_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \omega_k \end{bmatrix}$$

The final and most subjective value that enters the Black-Litterman formula is the scalar τ . Unfortunately, there is very little guidance in the literature for setting the scalar's value. Both [Black and Litterman \(1992\)](#) and [Lee \(2000\)](#) address this issue: since the uncertainty in the mean is less than the uncertainty in the return, the scalar is close to zero. Conversely, [Satchell and Scowcroft \(2000\)](#) say the value is often set to 1.

[He and Litterman \(1999\)](#) calibrate the confidence so that the ratio of ω/τ is equal to the variance of the view portfolio. Views with significant confidence result in relatively small ω . Low levels of confidence can have a significant impact on the model if the sum of the diagonal elements of the covariance matrix of the error term is used to set the value of the scalar. For this reason, greater stability is achieved by setting the value of ω equal to the average value of the diagonal elements of the covariance of the error term as the formula below:

$$\omega = \frac{\sum_{i=1}^k 1/LC_i * CF}{k}$$

And the initial value of the scalar should equal the average value of the variance of the error terms divided by the variance of the view portfolio:

$$\tau = \frac{\frac{\sum_{i=1}^k 1/LC_i * CF}{k}}{P\Sigma P'}$$

We set the baseline as recommended at 50% level of confidence and get the calibration factor:

$$CF = \frac{P\Sigma P'}{\frac{1}{50\%}}$$

Then we can get the confidence level from the formula.

3.3 Mean-Variance Optimization

A mean-variance analysis is the process of trade-off between risk and expected return. As giving an expected return and variance of an asset, investors want to find the most efficient investment combination of the assets, which is getting the highest return at a given risk level. Our destination is to maximize our utility function:

$$U = \tau\mu - \frac{1}{2}\sigma^2$$

With the budget constraint:

$$\sum_{j=1}^N h_j = 1$$

And boundary weights for each $\mu \in (0.05, 0.35)$

By Lagranges Method, we can write the mean-variance portfolio problem with quadratic programming:

$$\mathcal{L}(h, \lambda) = \tau\mu^T h - \frac{1}{2}h^T Q h - \lambda^T (\beta^T h - 1)$$

with solution:

$$\begin{bmatrix} h \\ \lambda \end{bmatrix} = \begin{bmatrix} Q & \beta \\ \beta^T & 0 \end{bmatrix}^{-1} \begin{bmatrix} \tau\mu \\ 1 \end{bmatrix}$$

3.4 Rebalance Method

A portfolio created using MPT-based techniques will not stay optimized over time. The composition of any investment portfolio will naturally drift as capital markets move and certain holdings outperform others. This typically results in two adverse outcomes: (1) portfolio risk increases as the equity portion of the portfolio grows beyond its original allocation, and (2) allocations become sub-optimally mixed. To maintain the intended risk level and asset allocations, a portfolio must be periodically rebalanced back to its original targets. Sophisticated algorithms are required to optimize rebalancing subject to tax and trading expense effects.

We define portfolio drift as the total absolute deviation of each asset class from its target. However, deviations are zero-sum, so including both overweights and underweights would be double-counting. Therefore, we divide by 2. Then we set a drift-threshold. When the daily drift beyond the limitation, we will execute the rebalance to keep the portfolio optimized. Here is an example of calculation of the drift:

	Target	Current	Deviation	Absolute Deviation
US Bonds	25%	30%	5%	5%
Intl Bonds	25%	20%	-5%	5%
US Stocks	25%	30%	5%	5%
Intl Stocks	25%	20%	-5%	5%
			Total	20%
			Total / 2	10%

Figure 3: Drift Calculation

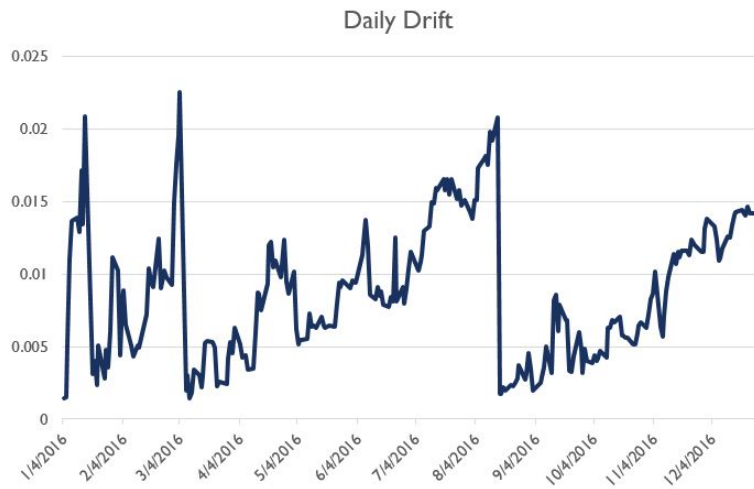


Figure 4: Daily Drift Example

In Figure 4, We daily track and record the drift and set the drift threshold into 2.5 as our rebalance strategy.

3.5 Tax Loss Harvesting

There are diversified ways in Robo Advisor can be used to increase returns, like better diversification, better asset choosing for investors with different risk tolerances. In this

project, Tax Loss Harvesting is implemented to maximize after-tax returns.

In common, once an investor sells a capital asset for a price that is higher than the purchase price, the investor realizes capital gains and needs to pay tax for the capital gains. As a result, how much tax is paid effects the returns directly.

3.5.1 What is Tax Loss Harvesting

Tax loss harvesting is a strategy of selling securities at a loss to offset a capital gains tax liability. It is an efficient way to make your investment portfolio work harder not just in generating investment returns, but by also in generating tax savings.

Tax loss harvesting is primarily a tax deferral strategy, and its benefit depends entirely on individual circumstances, through which you can defer tax liabilities, not avoid them. So it has very little value if applied over a short investment horizon (*i.e.* less than two years), but can be extremely valuable if executed over a long period of time. Most of all, it combines the need to respect the asset allocation constraints at any point in time with the restrictions of the tax code (*i.e.* wash sale rules).

3.5.2 Wash Sale Rule

Wash Sale Rule is at the core of any TLH strategy. It disallows a loss from selling a security if a substantially identical security is purchased 30 days after or before the sale. Substantially identical security means two securities are too similar that the IRS cannot distinguish between them.

3.5.3 Tax Alpha

Tax Alpha refers to the additional performance benefit gained from your investments through tax savings. It is a measurement of tax efficiency. Here is the equation,

$$TaxAlpha = \frac{CL_{ST}X_{ST} + CL_{LT}X_{LT}}{V_{PORT}}$$

where CL_{ST} is the short-term capital loss, CL_{LT} is the long-term capital loss, and X_{ST} and X_{LT} are the corresponding short-term and long-term federal and state capital gains tax rates.([Sironi \(2016\)](#)) V_{PORT} is the beginning value of portfolio.

3.5.4 Switch Back Strategy

Since Robo-Advisor cannot freely dispose of declined losses, the switch back strategy systematically replace declined assets with correlated ones, that is assets which are not substantially identical for the tax code but whose returns are highly correlated to the original ones from a portfolio management perspective. That could be the case for ETFs which are in the same category but formally track different index. For example, the iShares 7-10 Year Treasury Bond ETF (IEF) seeks to track the investment results of an index composed of U.S. Treasury bonds with remaining maturities between seven and ten years, and the iShares 20+ Year Treasury Bond ETF (TLT) tracks a market-weighted index of debt issued by the US Treasury with remaining maturities of 20 years

or more.

In this Robo Advisor, the switch back strategy shares the same basic goal: maximizing a portfolios after-tax returns while minimizing the negative impact of wash sales. Here is an example of 6-years investment horizon. This strategy scans portfolio at the end of every year during the first three years to realize losses. It can systematically sell ETFs which experienced a loss then use highly correlated ETFs to replace them. So the losses are harvested while the optimal asset allocation and expected returns are maintained. And the harvested losses can be carried over to subsequent years to be deducted against capital gains. At the end of year 4, ETFs are switched back to the original ones. We hold the portfolio for 2 years, then sell it at the end of year 6. This strategy has another advantage, which can be attributed to the difference in the tax rate between short and long term.

The average tax alpha for the whole investment period is 0.57%. (*Under the assumption that the combined federal and state tax rate for short term and long term capital gain is 40% and 25% respectively.*)

Table 2: 6-years investment horizon result

	YEAR1	YEAR2	YEAR3	YEAR4	YEAR5	YEAR6
Beginning Portfolio Value(\$)	100000.00	101553.52	108172.70	115515.07	120685.88	112439.19
Ending Portfolio Value(\$)	101553.52	108172.70	115515.07	120685.88	112439.19	133555.58
Harvested Loss(\$)	676.24	0	4716.05	2469.14	0	-
Ending Value After Tax(\$)	101553.52	108172.70	115515.07	120685.88	112439.19	132303.52
Tax Alpha(%)	0.27	0	1.74	0.86	0	-

And the annualized after-tax return of portfolio with Tax loss harvesting is 0.39% more than which without Tax loss harvesting. As can be seen from the graph, the differences between these two portfolios is fluctuating. The reason may because of tracking errors for each ETF.

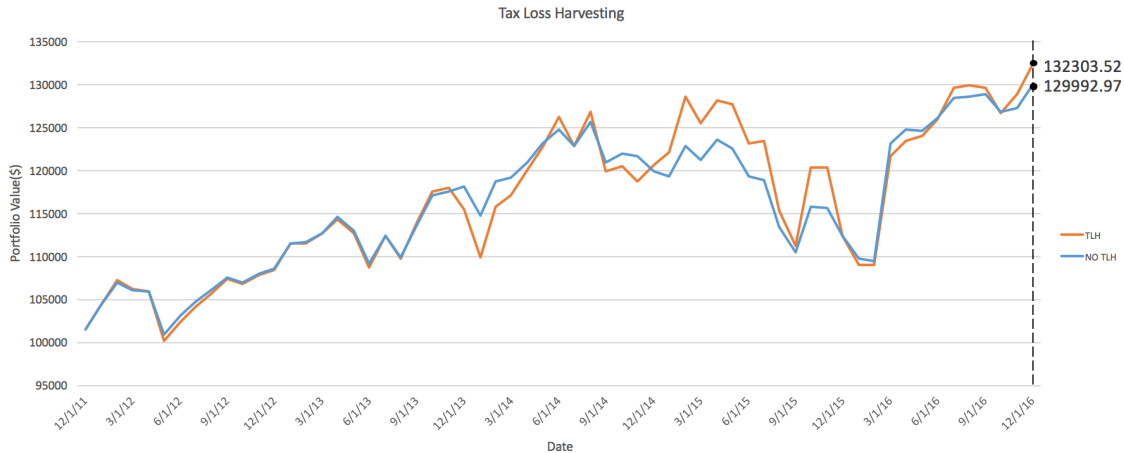


Figure 5: Tax loss harvesting result

4 Database Design

This project uses MongoDB to store data in JSON-like documents which vary in structure. Embedded data models (deformalized models) are implemented and related information is stored together. Thus, applications may need to issue fewer queries and updates to complete common operations so that speed up query access and save users online waiting time.

Robo-Advisor, the database of this project, has four collections: ETFs, Views, Backtest and Parameter. These four collections work for clients interface or managers interface. The database can be updated manually or automatically on a regular basis if a server is always available.

Collection ETFs stores the ETFs asset type, summary data, and historical data. It provides the raw materials for generating views for Black-Litterman model and implementing MVO. This collection contains 24 objects and each object presents an ETFs. Each kind of asset type maps three ETFs, which has been previously showed at Table 1.

Summary data are crawled from ETF.com using python package Beautiful Soup. For each ETF, summary data includes tracking difference, average spread, expense ratio, average daily volume and inception date. Those three values are important indicators to decide which ETF should be in the portfolio. The target portfolio is designed to contain the ETFs that has low tracking difference, low average spread, low expense ratio, high average daily volume and early and inception date.

Historical data is downloaded by Yahoo Finance API. Historical data for each ETF contains daily adjusted closing price since the inception date of that ETF. The adjusted closing price reflects the dividends and splits so that represents a more accurate reflection of a fund's value than closing price.

Collection Views is used for Black-Litterman model and includes views from ARIMA model and views from Research Affiliates.

Collection Backtest stores test parameters and back-testing results. It can be only accessed by portfolio managers. Managers can test their new strategies through managers interface and store the testing results into this collection. If the managers are satisfied with the new strategy, they can confirm the test parameter of the new strategy to collection Parameter.

Collection Parameter stores a unique set of parameters which are read by clients interface and only can be changed through managers interface. Every client will use the same set of parameters.

5 User Interfaces and Results

There are two web-based user interfaces in this project: one is for managers who have the knowledge to test new strategies, do the back-testing and conduct portfolio analy-

sis; another is for clients who are not professional in the financial field.

The interfaces are built with Django, incorporated with tools such as HTML, JavaScript, CSS, Bootstrap and Plotly. Django is a free and open-source python web framework. HTML describes and defines the content of a web page and it is the most basic building block of the Web. JavaScript adds functionality to a web page. CSS describes a webpage's appearance and presentation. Bootstrap develops responsive, mobile-first websites. Plotly is an online analytic and data visualization tool which draws stunning and informative graphics.

The product is named CGM Intelligent Portfolios, or CGM for short. C, G and M are the initials of each team members' last names. CGM's logo is on every web page of the two interfaces.



Figure 6: CGM Logo

5.1 User Interface for Clients

In this interface, the **home** page will firstly show up. It contains a head with two buttons and a long body of introductions of CGM. The two buttons are “Build now” and “Explore CGM”. When click “Build now”, it will navigate to web page `show_plan.html`. Clicking “Explore CGM” will stay on the same web page but it will jump to the location of “ABOUT THE PRODUCT”, which introduces the key features of the product. Scrolling down the web page, clients can see more information about the product, such as methodology, team and contact. Clients can also use the navbar links (on top in big screens, or slide left in small screens) to direct them to target locations.

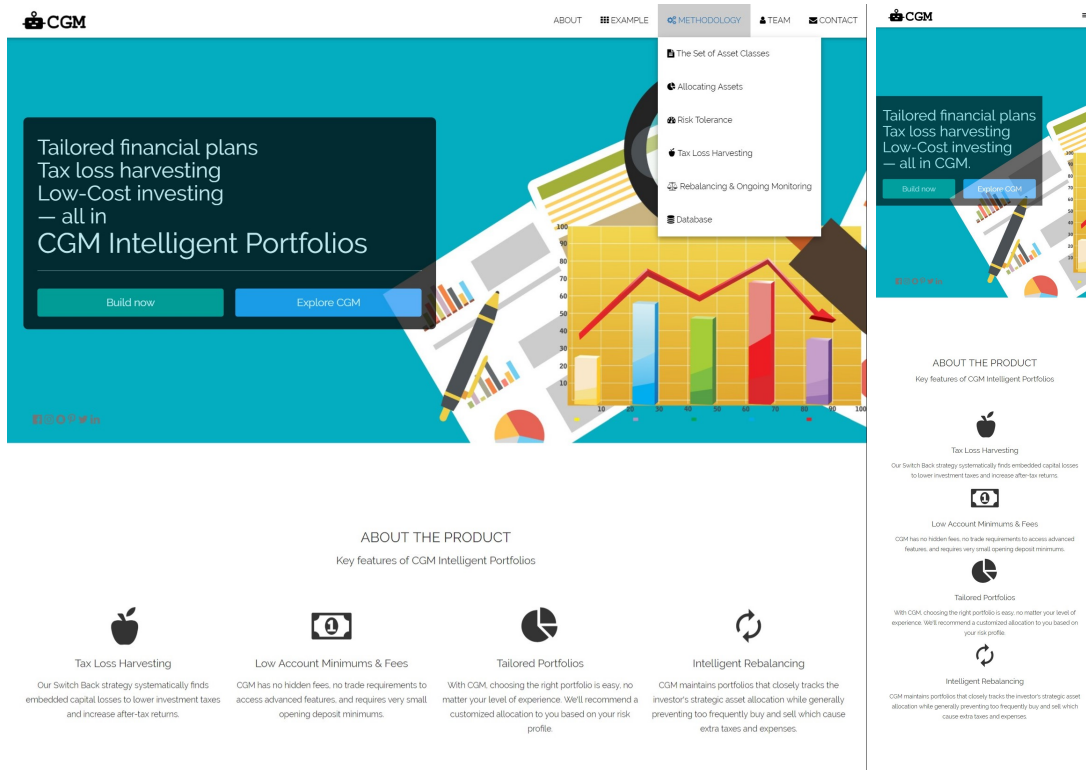


Figure 7: Part of Home Page on Large and Small Screens

In **show plan** page, CGM provides five portfolios with different risk tolerance. They are portfolios of very conservative, conservative, moderate, aggressive and very aggressive. Clients are free to explore the five portfolios by clicking the buttons of risk tolerances. For each portfolio, the asset allocation is shown in table and pie chart, the historical performance and tax loss harvesting are shown in a line chart.

Your financial plan

Start with: \$100000

Assess your risk tolerance [click here](#)

Frequently Asked Questions

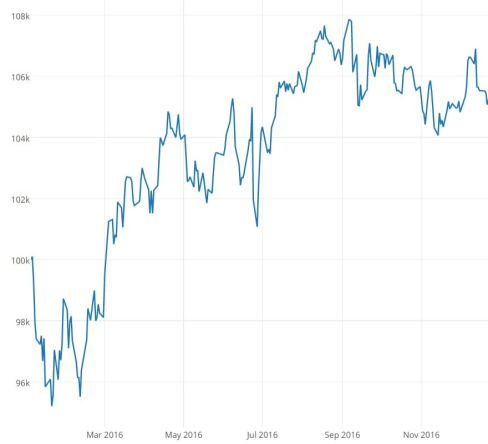
[What is Robo-Advisor?](#)[What is risk tolerance?](#)[What models does CGM use?](#)[What is Tax Loss Harvesting?](#)[How does CGM rebalance its portfolio?](#)Very Conservative Conservative **Moderate** Aggressive Very Aggressive

	labels	text	values
1	US STOCKS	VTI	0.0883744822949
2	FOREIGN DEVELOPED STOCKS	VEA	0.153632661382
3	EMERGING MARKET STOCKS	VWO	0.174303400664
4	DIVIDEND GROWTH STOCKS	VIG	0.0773249049815
5	US GOVERNMENT BONDS	VGSH	0.189296655199
6	MUNICIPAL BONDS	MUB	0.15338824815
7	TREASURY INFLATION-PROTECTED SECURITIES (TIPS)	SCHP	0.113679070664
8	NATURAL RESOURCES	XLE	0.05



Historical Performance

CGM Portfolio



EDIT CHART

Tax Loss Harvesting

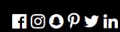
[To the top](#)Powered by [w3css](#)

Figure 8: Show Plan

Risk tolerance is the emotional capacity to withstand losses without panicking. Before the investing, the clients should have a realistic understanding of their risk tolerance. For their convenience, CGM provides a **online questionnaire** (the source of the questionnaire is [Morningstar \(2012\)](#), which is a Chicago-based investment research firm.) to assess the risk tolerance. On their finishing, CGM will automatically calculate the risk tolerance for their reference. Continuing to click the button show plan, the page will jump to **show plan** page with the portfolio of that risk tolerance showing.

Risk Tolerance Questionnaire

Tolerance for risk is a key consideration in determining your probable level of comfort with varying investing choices. Your risk tolerance is scored based on three factors: (1) time horizon, (2) long-term goals and expectations, and (3) short-term risk attitudes.

Time Horizon
Your current situation and future income needs.

1. What is your current age?

☐ A. Less than 45

☐ B. 45 to 55

☒ C. 56 to 65

☐ D. 66 to 75

☐ E. Older than 75

2. When do you expect to start drawing income?

☐ A. Not for at least 20 years

☐ B. In 10 to 20 years

☒ C. In 5 to 10 years

☐ D. Not now, but within 5 years

☐ E. Immediately

Long-Term Goals and Expectations
Your views of how an investment should perform over the long term.

3. What is your goal for this investment?

☐ A. To grow aggressively

☐ B. To grow significantly

☒ C. To grow moderately

☐ D. To grow with caution

☐ E. To avoid losing money

4. Assuming normal market conditions, what would you expect from this investment over time?

Scoring

For each question	Your score
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
A=5, B=4, C=3, D=2, E=1	3
Total	21

Score	Result
7-10	Very Conservative
11-17	Conservative
18-24	Moderate
25-31	Aggressive
32-35	Very Aggressive
Your risk tolerance	Moderate

Show plans

Figure 9: Part of Risk Tolerance Questionnaire and Calculation

5.2 User Interface for Managers

The user interface for managers is an interface to build, test and implement new portfolio strategies. It is designed for managers who has some basic knowledge in portfolio construction. Besides the home page which shows the current parameters of the clients interface, there are 6 web pages that the managers need to go through if they want to implement a new strategy. They are Select ETFs, Determine rebalance method, Set taus, Add views, Review your strategy and Implement the strategy.

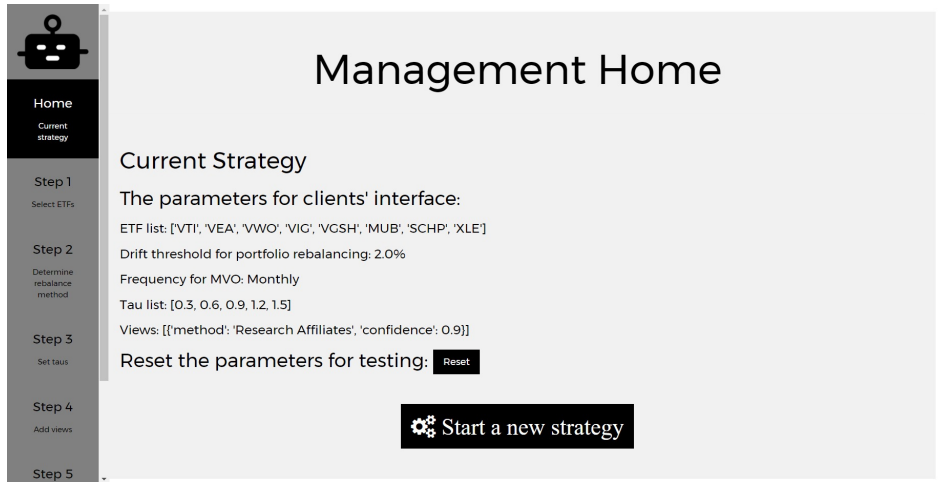


Figure 10: Management Home

5.2.1 Select ETFs

This web page shows all the ETF tickers in collection ETFs in database Robo-Advisor along with their asset type. Managers can select the ETFs for their new portfolio strategy. The default selection is done by the authors of this report, with the consideration of tracking difference, average spread, expense ratio, average daily volume and inception date. Furthermore, if collection ETFs has been updated, for instance, a new ETF is inserted into this collection, the new ETF will also show on this page and be an option to be selected.

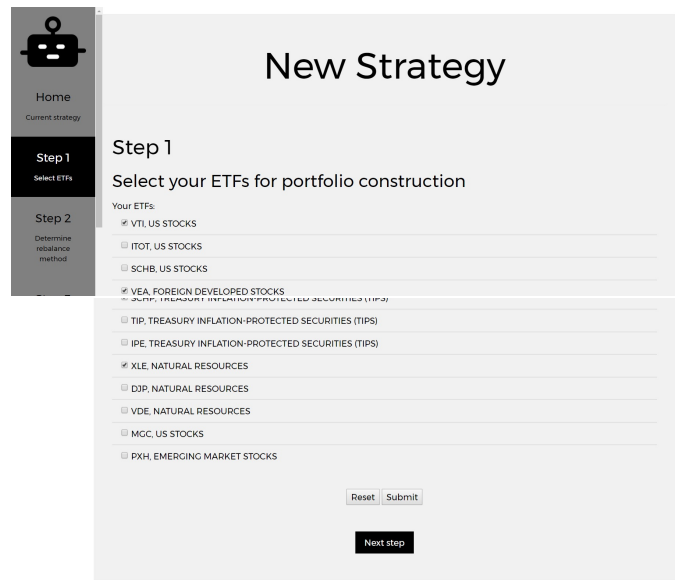


Figure 11: Select ETFs

5.2.2 Determine Rebalance Method

Managers can adjust rebalancing frequency through two inputs on this web page. The first one is to set the drift threshold for portfolio rebalancing. The input is a number between 0 to 100. The number will be converted into percentage after submitting. Small drift threshold may lead to frequently rebalancing and increase the computing time, also potentially increase the transaction cost and tax. Another one is to set the frequency for target weights calculation from the drop-down list. Four options are provided: weekly, monthly, quarterly and annually. By clicking the submit button, collection Backtest will be updated.

The screenshot shows a web interface titled "New Strategy". On the left is a vertical sidebar with a robot icon at the top and four menu items: "Home" (Current strategy), "Step 1" (Select ETFs), "Step 2" (Determine rebalance method), and "Step 3" (Set taus). The main content area is titled "Step 2" and "Adjust rebalancing frequency". It contains two input fields: "Set the drift threshold for portfolio rebalancing: 2 %" and "Set the frequency for MVO (target weights calculation): Monthly". Below these fields are "Reset" and "Submit" buttons. At the bottom center is a "Next step" button.

Figure 12: Determine Rebalance Method

5.2.3 Set Risk Tolerance

Since CGM is designed to generate five portfolios with different risk tolerance, it is essential to match the risk tolerance parameter in the utility function to 5 portfolios. An intuitive solution is to build portfolios with $\tau \in [0.0, 2.5]$, calculate their volatility stand for the portfolio risk, plot the chart on the left and then let mangers manually match tau with 5 portfolios. After filling and submitting the tau values for each risk tolerance, the values will be stored in collection Backtest as a list.



Figure 13: Set Risk Tolerance

5.2.4 Edit Views

Here managers can add or remove views for Black-Litterman model and change their confidence level in the model as well. Currently, CGM only has two views: Research Affiliates and ARIMA. ARIMA may not provide a good result for the strategies has been tested. Despite this, CGM provides an interface to use other models of views for Black-Litterman models.

New Strategy

Step 4
Edit views

Views included in Black-Litterman model

☒ Research Affiliates
☐ ARIMA
☐ Other Models

Confidence Level %
 95

Reset Submit

Next step

Figure 14: Edit Views

5.2.5 Review Your Strategy

This web page shows the parameters and back-testing result of the new strategy. The result includes asset allocation, historical performance, and portfolio analysis. All charts are interactive. For example, when the mouse hovers on the chart of asset allocation, it will show the asset type, ticker and percentage.

The ideal asset allocation has higher percentage of bonds and lower percentage of stocks in a portfolio when tau is small while lower percentage of bonds and higher percentage of stocks when tau is large, which is obtained by the strategy showed in Figure 15.

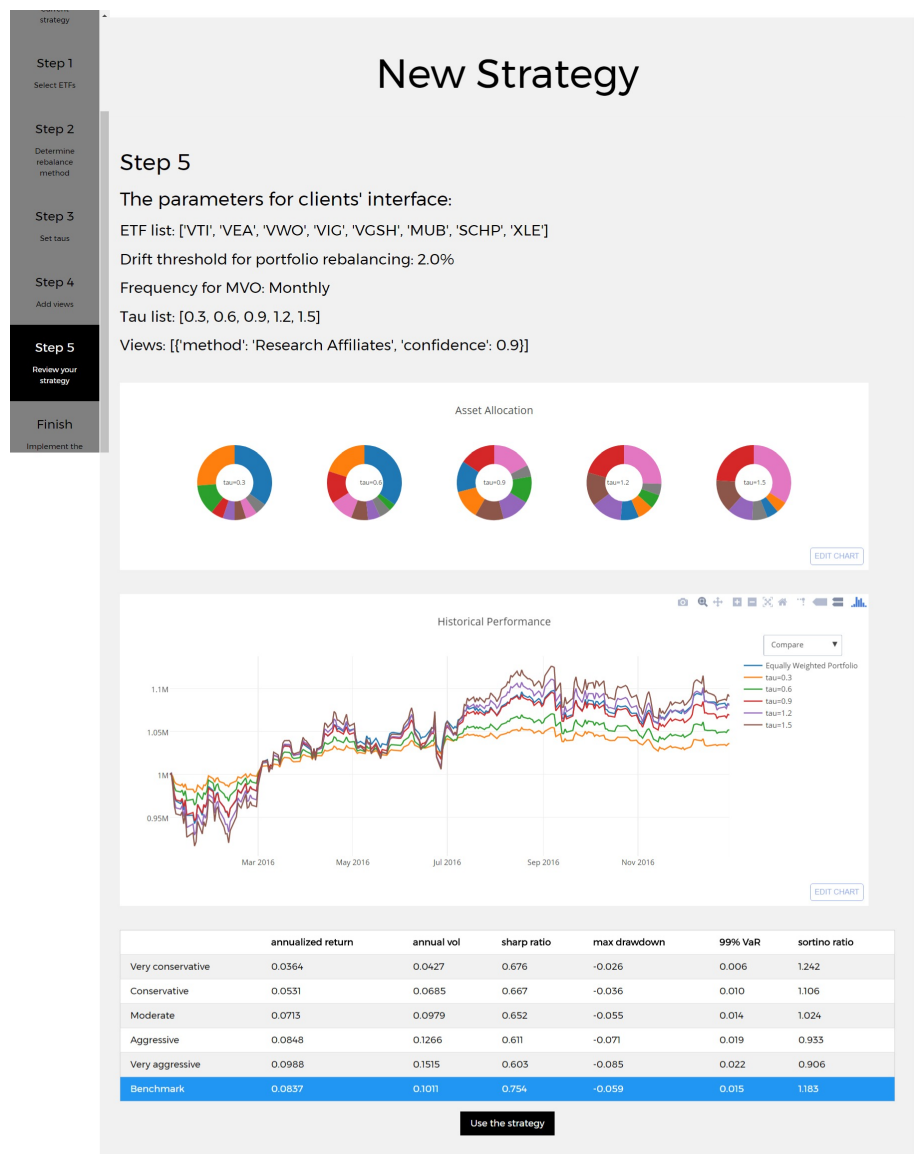


Figure 15: Review Your Strategy

Furthermore, CGMs conducts simple portfolio analysis which includes annualized return, annual volatility, sharp ratio, max drawdown, VaR and Sortino ratio.

If the managers satisfy with the results, they need to click the button Use the strategy. Then a confirmation dialog (shows in Figure 16) pops out and ask the user to check the sentence “I understand that my new strategy will update the interface for clients”. The confirmation dialog secure that the clients interface only can be changed when managers intend to.

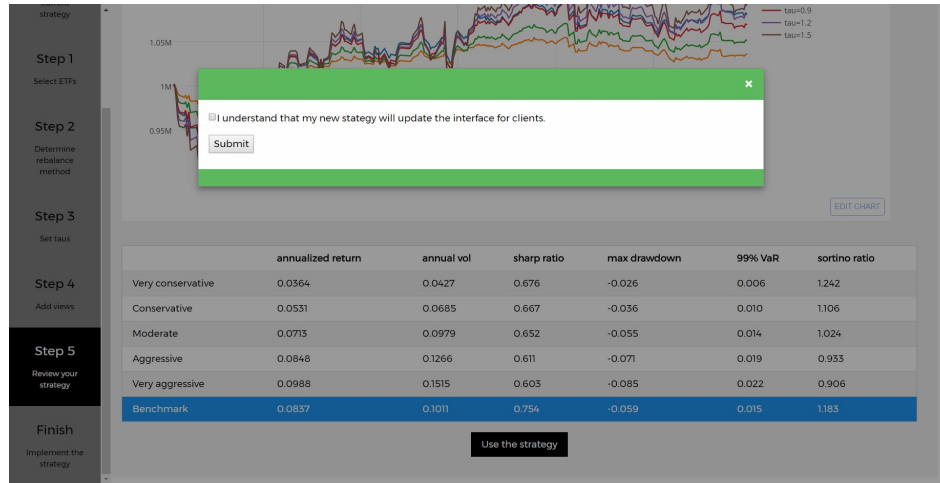


Figure 16: Confirmation Dialog

5.2.6 Implement the Strategy

After clicking submit button in the confirmation dialog, the new strategy will be implemented to clients interface. This web page shows the current parameters for clients interface. Clicking “Go to clients interface” will go to clients interface, and the results in clients interface have already been changed by the new strategy.

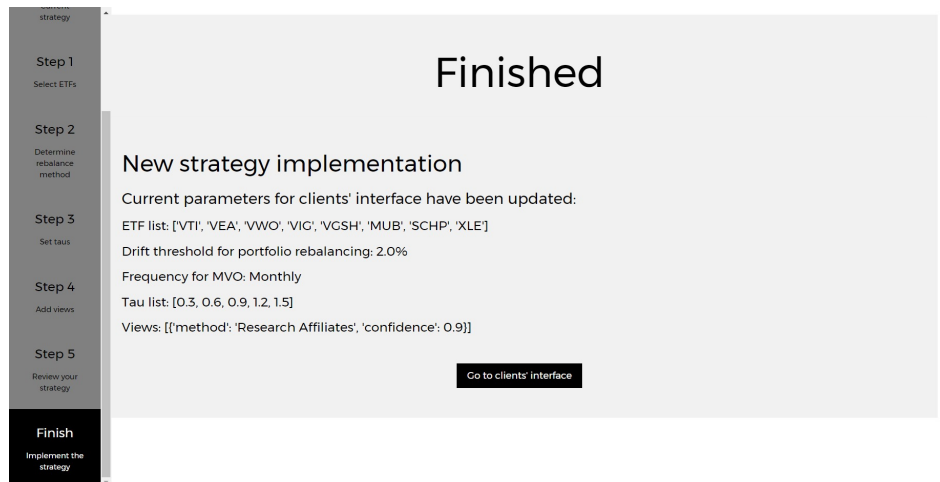


Figure 17: Implement the Strategy

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